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Flexible Sensor-Based Human–Machine Interfaces with AI Integration for Medical Robotics

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ABSTRACT

Medical robotics has revolutionized healthcare by enhancing precision, adaptability, and clinical outcomes. This field has further evolved with the advent of human–machine interfaces (HMIs), which facilitate seamless interactions between users and robotic systems. However, traditional HMIs rely on rigid sensing components and bulky wiring, causing mechanical mismatches that limit user comfort, accuracy, and wearability. Flexible sensors offer a transformative solution by enabling the integration of adaptable sensing technology into HMIs, enhancing overall system functionality. Further integrating artificial intelligence (AI) into these systems addresses key limitations of conventional HMI, including challenges in complex data interpretations and multimodal sensing integration. In this review, we systematically explore the convergence of flexible sensor-based HMIs and AI for medical robotics. Specifically, we analyze core flexible sensing mechanisms, AI-driven advancements in healthcare, and applications in prosthetics, exoskeletons, and surgical robotics. By bridging the gap between flexible sensing technologies and AI-driven intelligence, this review presents a roadmap for developing next-generation smart medical robotic systems, advancing personalized healthcare and adaptive human–robot interactions.

1 | Introduction

Medical robotics has witnessed remarkable growth in recent years, driven by escalating demands to address aging populations, chronic disabilities, and the need for improved patient care, minimally invasive treatments, and enhanced rehabilitation outcomes. Over the past decade, advancements in robotics, materials science, sensors, and artificial intelligence (AI) have accelerated the development of diverse medical robotic systems, including prosthetics, exoskeletons, and surgical robots. Prosthetic devices now offer amputees enhanced limb control and sensory feedback to mimic natural movement and perception, while exoskeleton systems are revolutionizing mobility rehabilitation by providing assisted and adaptive training for stroke patients [1–4]. Additionally, surgical robots provide unprecedented precision and dexterity, facilitating complex procedures with reduced trauma and quicker recovery times [5, 6]. These technologies are increasingly deployed in clinical, rehabilitative, and home-care settings, addressing critical gaps in personalized and accessible healthcare. As technological advancements redefine the capabilities of medical robotics, human–machine interfaces (HMIs) have emerged as critical enablers of intuitive and adaptive interactions between users and robotic systems. HMI systems, reinforced by sensors that capture various biophysiological and external signals, serve to translate human intentions into robotic commands while enabling real-time sensory feedback, thereby enhancing precision, user autonomy, and safety [7–10]. For instance, HMIs can decode signals from the user's muscles to

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control robotic gloves, realizing dynamic and targeted active rehabilitation training [11].

Although there has been considerable progress in integrating HMI systems with robotic equipment, many of these technologies continue to rely on rigid sensing electronics and bulky machines that emphasize robotic control while lacking sufficient feedback. Rigid sensors, typically fabricated from inflexible metals or semiconductors, suffer from mechanical mismatches when interfacing with the human skin, soft biological tissues, and the surface of the robotic body, therefore limiting accuracy, wearability, user comfort, and overall functionalities. These limitations are particularly pronounced in dynamic applications such as prosthetic grip control or exoskeleton joint monitoring, where rigid sensors fail to conform to curvilinear body surfaces or detect subtle force variations. With the rapid advancement of flexible electronics, HMIs are transitioning from conventional bulky equipment to miniaturized, intelligent systems [12]. Flexible sensors can be engineered from stretchable polymers, nanomaterials, or hybrid composites to address these challenges by offering flexibility, biocompatibility, conformability, and high sensitivity to multimodal stimuli, making them ideally suited for HMI systems [8, 13, 14]. Current flexible sensing technologies that detect mechanical stimuli mainly include triboelectric sensors that convert mechanical inputs into electrical signals due to the triboelectric effect, piezoelectric sensors that generate electrical signals in response to mechanical strain, and piezoresistive and capacitive sensors that change resistance or capacitance under deformation [14, 15]. Additionally, electrophysiological sensors can monitor various bioelectric signals based on electromyography (EMG), electroencephalography (EEG), electrooculography (EOG), and electrocardiography (ECG) from activities of the muscles, brain, eyes, and heart, respectively [7, 16]. While these sensors are predominantly based on contact modalities, recent technological advances have enabled the development of noncontact sensing modes for HMIs. For instance, Lu et al. developed a flexible resistive-based humidity sensor for noncontact HMI in medical settings [17]; Le et al. integrated a piezoelectric resonant humidity sensor and a triboelectric sensor for non-contact HMI [18]; Gao et al. proposed a thermoelectric sensor enabling noncontact information transfer and also functioning as tactile electronic skin via piezoresistive effects [19]. Such approaches help reduce mechanical wear, lower cross-infection risk, and enhance environmental adaptability, showing promising potential in medical robotics applications. As medical robots evolve to perform complex tasks in dynamic environments, sensor requirements have expanded to include multimodal sensing fusion, high precision and intelligence, miniaturization, and robustness against environmental interference.

To further optimize user experience and the performance of medical procedures, AI can be integrated into HMIs for medical robotic applications to not only significantly enhance real-time adaptive interactions but also facilitate complex data interpretations from single to multimodal sensing. To fully harness the potential of flexible sensor-based HMIs in medical robotics, AI plays a crucial role in overcoming inherent limitations such as complex signal variations and system uncertainty [20]. In the absence of advanced AI capabilities, these systems may struggle to efficiently extract meaningful patterns from vast and unstructured sensor data, leading to reduced accuracy in detecting subtle physiological changes or executing precise robotic control with solely preset thresholds [21]. Furthermore, the lack of AI-driven learning mechanisms limits adaptability to user-specific variations and real-time decision-making, which are essential for optimizing medical procedures and ensuring seamless interactions between humans and machines. Currently, AI has made great advancements in various aspects of sensing systems for medical robotic HMIs, contributing to advancements in flexible sensing system design, signal processing, and multimodal sensing through numerous machine learning (ML) and deep learning (DL) methods [22]. For intelligent robotic HMIs, one compelling application of AI-driven signal processing techniques is to enable advanced preprocessing and feature extraction of the acquired signals, facilitating intelligent signal augmentation and pattern recognition that enhance system functionality and provide context-aware interpretation of complex physiological and environmental inputs [23]. This fusion integrating AI with flexible sensor-based HMI systems resolves longstanding limitations of conventional HMIs, such as their inability to adapt to dynamic biological environments, lack of nuanced feedback in surgical robots, and mechanical incompatibility of rigid sensors with soft tissues.

There have been numerous published reviews on flexible sensors for HMI applications, focused on sensing mechanisms [8, 24–26], material selection [27–30], design strategies [15, 31, 32], and robotic applications [20, 33]. By contrast, this work distinguishes itself by bridging the gap between flexible sensing technologies and AI-enabled HMI frameworks to strategically advance the development of smart, human-centric medical robotic systems. By systematically exploring sensing mechanisms, AI technologies that enhance HMI systems, and their applications in smart medical robotics, this review provides a comprehensive and unique approach into the synergistic interaction between flexible sensor-based HMI systems and effective AI algorithms that can transform the landscape of modern healthcare (Figure 1).

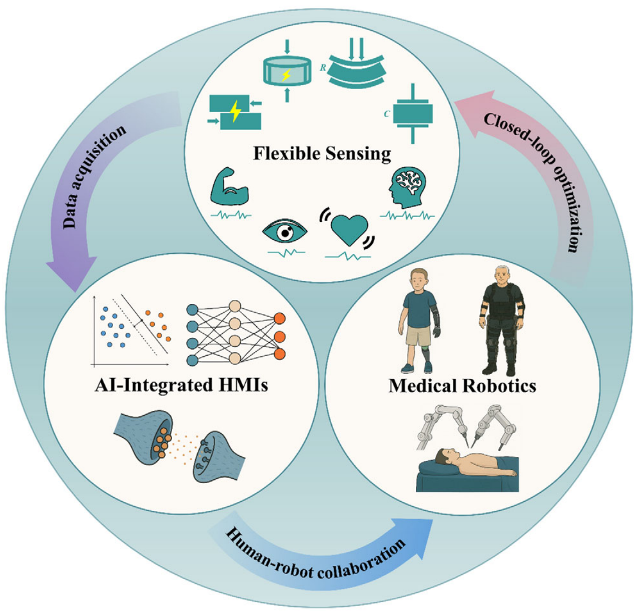

FIGURE 1 | A schematic overview of the flexible sensor-based HMI with AI, categorizing flexible sensing, AI-integrated HMIs, and their applications in medical robotics.

Specifically, we begin by exploring the operational mechanisms of key flexible sensing mechanisms, including triboelectric, piezoelectric, piezoresistive, capacitive, and electrophysiological methods. Next, we methodically address the transformative role of AI in optimizing sensor system design, processing multimodal signals, and enabling context-aware HMIs for healthcare. Then, we emphasize real-world healthcare applications using medical robotics, detailing prosthetics applications with perception and control, adaptive exoskeletons for personalized healthcare and force augmentation, and sensor-integrated surgical robots for enhanced precision and safety. Finally, we conclude with the challenges and future perspectives in this field.

2 | Fundamentals and Advances of Flexible Sensing Technologies

Flexible sensors that rely on physical sensing mechanisms can detect various mechanical stimuli, such as pressure and strain, and convert them into electrical signals. Typically fabricated from soft, stretchable, or bendable materials, these sensors can be seamlessly integrated into various wearable devices. Their high sensitivity, lightweight design, versatile sensing capabilities, and excellent adaptability to complex surfaces enable natural and unobtrusive interactions with the human body while maintaining robustness under dynamic deformations, making them particularly suitable for HMI applications. As the backbone of intuitive, intelligent, and responsive interfaces, these sensors play a critical role in enhancing user experiences and facilitating seamless interactions. In particular, flexible sensing technology can improve precision, functionality, and automation, paving the way for significant advancements in medical robotics. Based on their working mechanisms, flexible sensors can be broadly categorized into several types: triboelectric, piezoelectric, piezoresistive, capacitive, and electrophysiological sensors [34–38]. Herein, we briefly introduce the principles of each sensing technology.

2.1 | Triboelectric Sensors

Triboelectric devices, considered an emerging and pivotal development in the realm of energy technologies, were first introduced in 2012 by Zhonglin Wang [39]. These devices operate based on the coupling of triboelectricity and electrostatic induction, enabling the conversion of diverse mechanical stimuli into electrical signals. This functionality provides significant potential for applications in sensing, where accurate and efficient detection of various stimuli is increasingly in demand. Typically, triboelectric sensors primarily involve two critical components: triboelectric layers and electrodes. When mechanical stimuli such as pressure, vibration, bending, or sliding are applied to triboelectric sensors, they induce contact and separation or relative motion between the triboelectric layers, enabling the generation of triboelectric charges due to the different electron affinity of such materials. As a result, materials that tend to donate electrons acquire positive charges, whereas those that accept electrons attain negative charges. Simultaneously, the electron transfer and separation between the two layers create a potential difference between the electrodes to produce electrical signals. The signal output of triboelectric sensors is typically influenced by the frequency, magnitude, and contact area of the external stimulus, ensuring accurate and real-time feedback. To achieve high sensitivity and enhanced signal generation, triboelectric sensors are often designed with flexible structures to optimize charge transfer efficiency. In particular, flexibility is a critical characteristic of triboelectric sensors for HMI applications, allowing them to conform seamlessly to non-planar or irregular surfaces, such as human skin or textile-based substrates. This adaptability not only enhances user comfort but also facilitates precise signal acquisition, which is essential for effective interaction in HMI. In addition, flexible sensors can withstand prolonged mechanical stress from bending, stretching, or twisting. This is vital for dynamic HMI systems, such as robotic control interfaces, where durability under frequent deformation is needed. Therefore, choosing the appropriate triboelectric layer and electrode material is crucial to enhance the functionality and reliability of HMI technologies.

Typically, synthetic polymers, natural or bio-based materials, and composite materials are widely utilized to fabricate triboelectric layers of flexible triboelectric sensors. Synthetic polymers such as polytetrafluoroethylene (PTFE), polydimethylsiloxane (PDMS), polyimide (PI), polyamide (PA), polyurethane (PU), polyethylene terephthalate (PET), polycaprolactone (PCL), and ecoflex can offer excellent flexibility and ensure the adaptability of triboelectric sensors. Natural or bio-based materials like human skin, silk, and cellulose are also commonly utilized due to their excellent biocompatibility and eco-friendly performance. Composite materials that integrate multiple functionalities and enhanced triboelectric performances are ideal candidates for triboelectric layers of triboelectric sensors. To improve the charge density and sensitivity of the triboelectric layer materials and triboelectric sensor, micro/nano textures or porous structures can also be designed on the surface of flexible triboelectric layers [40, 41]. In addition, the electrodes in triboelectric sensors determine the effect of electrostatic induction and electrical signal transmission in HMI applications. Common electrode materials for triboelectric sensors include pure metals (such as Au, Ag, and Cu), metallic nanostructures (such as silver nanowires), liquid metals (such as eutectic gallium-indium), carbon-based materials (such as graphene, carbon nanotubes (CNTs), and MXenes), conductive polymers (such as polyaniline, poly(3,4-ethylenedioxythiophene):polystyrene sulfonate), and composite conductors (such as graphene and poly(3,4-ethylenedioxythiophene):polystyrene sulfonate composite) that combine these materials for an enhanced electrical performance [42, 43]. Flexible electrodes that demonstrate strong compatibility with triboelectric layers can prevent cracking or delamination under repeated mechanical stress, thus enhancing sensor durability and ensuring reliable HMI performances. Overall, the diverse flexible material options for both the triboelectric layers and electrodes provide extensive functionality for a broad range of HMI applications. For example, Chang et al. developed a highly flexible and self-powered triboelectric tactile sensing array using PDMS, PCL nanofibers, and poly(3,4-ethylenedioxythiophene): polystyrene sulfonate electrodes. This multi-channel array was integrated with a data acquisition system and a computer, creating an HMI system for monitoring pressure distribution within a prosthetic limb [44]. Luo et al. utilized PDMS, silicon rubber, and copper electrodes to fabricate a triboelectric bending sensor-based smart glove toward intuitive multi-dimensional HMI applications, such as controlling robotic hands and functioning as a virtual keyboard with user identification capabilities [45]. These flexible triboelectric sensors enable integration into a wide variety of applications, opening up innovative and unobtrusive HMI solutions.

To achieve optimal performance in these applications, the direction of the polarization change and electrode configuration of the triboelectric sensors give rise to four fundamental working modes, consisting of contact-separation mode, lateral-sliding mode, single-electrode mode, and freestanding triboelectric-layer mode [46, 47]. Each working mode of the triboelectric sensors possesses distinct characteristics and advantages, contributing to its effectiveness in various sensing contexts [9]. For example, contact-separation mode generates an alternating electric field based on repetitive contact and separation between different triboelectric surfaces (Figure 2a①). This mode features a straightforward structure and easy fabrication and can be applied in pressure or impact-based sensing applications. Lateral-sliding mode involves lateral motion and continuous contact and separation of triboelectric materials, enabling enhanced power output, advanced designs, and compact packaging (Figure 2a②). Single-electrode mode requires only one electrode for operation, whereby electron flow occurs relative to the ground potential (Figure 2a③). This approach diminishes the complexity and cost associated with the sensors while improving their design flexibility. Freestanding triboelectric-layer mode operates by utilizing a freely moving triboelectric layer that interacts with two stationary electrodes (Figure 2a④). This interaction creates an asymmetric electric field that induces electron flow between the electrodes. In practical applications, it is essential to select an appropriate working mode tailored to a specific application scenario for better sensing performances. Benefiting from the simplified design and ease of integration, single-electrode mode is one of the most commonly used modes in flexible triboelectric sensors for various HMI applications. For example, a screen-printed single-electrode textile triboelectric sensor was proposed by Zhang et al. for self-powered wearable HMI sensing applications and was customized into a flower pattern with a large surface area [53]. Ma et al. integrated a biomimetic fish lateral line system fiber-based single-electrode triboelectric sensor into textile for constructing HMI interfaces that controlled robotic legs and virtual drone movements (Figure 2b) [48].

Compared to conventional technologies, flexible triboelectric sensors offer diverse materials, ease of fabrication, structural versatility, scalability, and, most importantly, self-powered sensing capabilities. In addition, the sensitive electrical signal response of triboelectric sensors allows them to detect minute mechanical stimuli and provide real-time interactions (Figure 2c) [48]. These attributes position them as promising candidates for HMI applications, where lightweight, cost-effective, adaptable, sensitive, and multimodal sensing capabilities are paramount. However, the output signals of most current triboelectric sensors are generated from dynamic stimuli, limiting their practical application in static sensing. Innovative approaches are required to enhance the capability of triboelectric sensors under static conditions, thereby broadening their applicability in the field of HMI. With advancements in material design and energy harvesting techniques, future developments could overcome these limitations and unlock new possibilities for static sensing applications in HMI systems. By improving the sensor's ability to respond to low or constant stimuli, the integration of triboelectric sensors into diverse human–machine interactive devices may become more seamless and efficient.

2.2 | Piezoelectric Sensors

Piezoelectric materials are inherently self-powered sensing materials, as they can generate electric charges in response to applied mechanical stresses [54]. Specifically, their internal crystal structures become distorted when mechanical stresses, such as vibrations or bending, are applied to piezoelectric materials. This distortion rearranges the charges within the crystal lattice, resulting in polarization due to the asymmetry of the charges. As a result, electric charges are generated on both surfaces of the material (Figure 2d①,②) [55]. This unique feature eliminates the need for an external power source for sensing applications while also enabling force sensing capabilities, making them ideal for self-powered HMIs. Recently, researchers have developed piezoelectric sensors that can placed on various human body parts. The generated piezoelectric signals, which correlate to specific body movement through various forms of mechanical stresses, have been acquired and analyzed for use in diverse HMI applications [56, 57]. Another sensing technology enabled by piezoelectricity is ultrasonic transduction, which includes both sensing and actuating of the piezoelectric material-based ultrasonic transducers. In particular, these ultrasonic transducers utilize the converse piezoelectric effect, where an applied electric field causes mechanical deformation, leading to expansion or contraction based on the field's polarity (Figure 2d③) [55]. This deformation produces high-frequency vibrations, enabling the generation of ultrasound waves. These waves can also be detected by the piezoelectric materials of the transducer, achieving ultrasonic sensing. This dual capability of piezoelectric materials is essential for flexible ultrasonic sensors used in medical imaging and HMI applications [58–60]. When applying piezoelectric sensors to these applications, selecting the appropriate material for specific HMI tasks is crucial to enhancing the sensor's performance. Ensuring a positive user experience also requires selecting piezoelectric materials that optimize the biocompatibility, flexibility, conformability, stability, and durability of the sensors. This section categorizes and summarizes the commonly used piezoelectric materials for HMI applications, including piezoelectric ceramics, crystals, and polymers.

Among these, piezoelectric ceramics are extensively utilized in HMI applications for their superior piezoelectric performance, characterized by their high piezoelectric coefficients and excellent sensitivity. A notable example of this material is lead zirconate titanate ($PbZr_{1-x}Ti_xO_3$, PZT), which features a high piezoelectric coefficient (d_{33}) ranging from approximately 300–1000 pC/N, making it ideal for applications that require high sensitivity and efficient energy conversion [61, 62]. For HMI applications, PZT has been widely used as human motion monitoring sensors or stimulators [63, 64]. However, they still face limitations, such as bulkiness, brittleness, toxicity, and poor biocompatibility, making them unsuitable as wearable sensors for HMI applications. To address concerns about toxicity and poor biocompatibility of lead-based piezoelectric ceramics, researchers have developed lead-free alternatives [65]. These materials primarily feature perovskite (such as $BaTiO_3$, (K, Na)NbO_3,

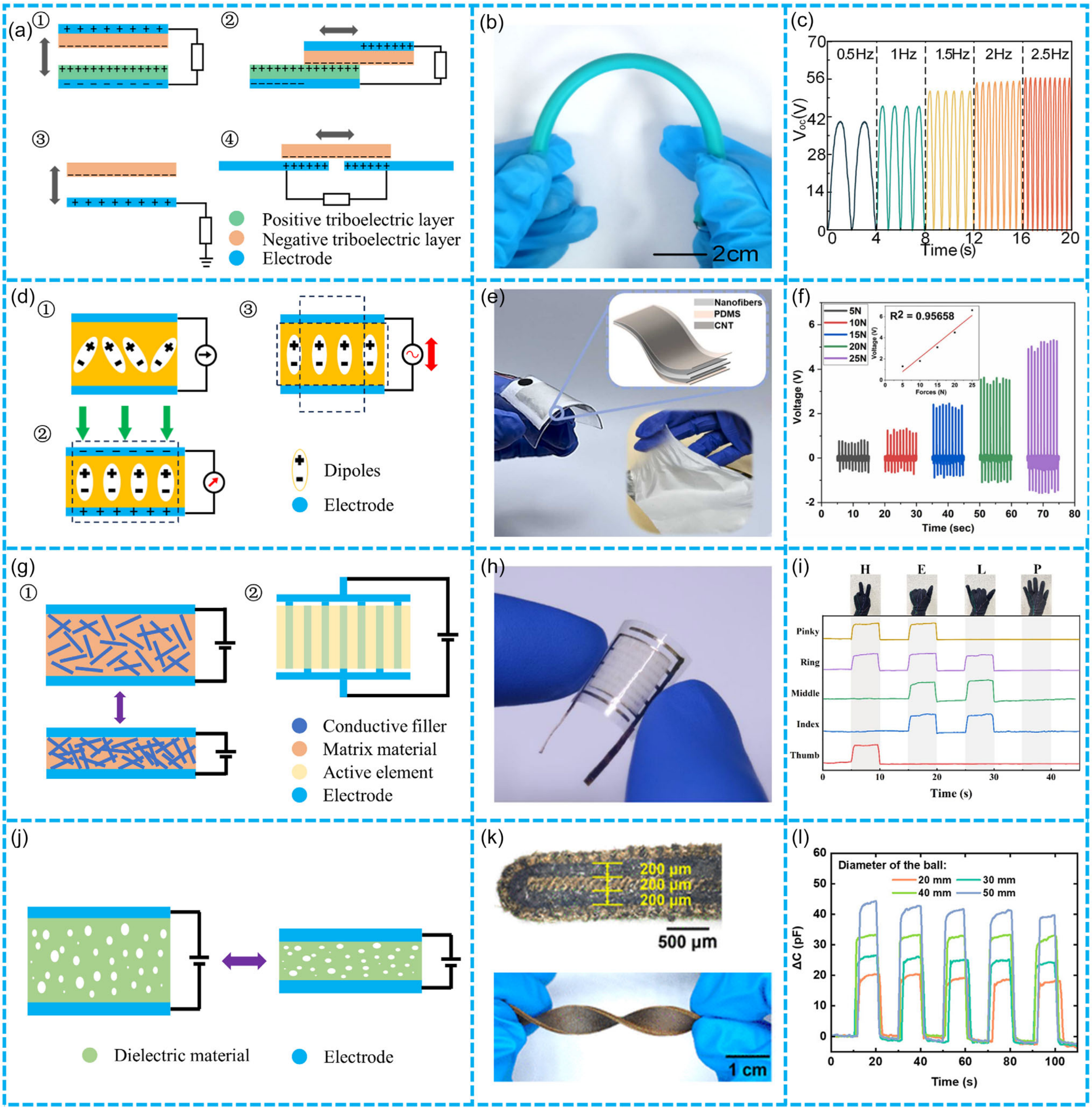

FIGURE 2 | Working mechanisms, examples, and signals generated from flexible sensors. (a) Four fundamental working modes of triboelectric sensors: ① Contact-separation mode, ② Lateral-sliding mode, ③ Single-electrode mode, and ④ Freestanding triboelectric-layer mode. (b) Digital image of a fiber-based single-electrode triboelectric sensor. Reproduced with permission [48]. Copyright 2024, Cell. (c) Open-circuit voltage of a fiber-based single-electrode triboelectric sensor at different compression frequencies. Reproduced with permission [48]. Copyright 2024, Cell. (d) Working mechanisms of piezoelectric sensors: ①,② Direct piezoelectric effect, ③ Converse piezoelectric effect. (e) Digital image of a bioinspired and textured P (VDF-TrFE) nanofibrous piezoelectric sensor. Reproduced with permission [49]. Copyright 2024, Elsevier. (f) Voltage outputs of a bioinspired and textured P (VDF-TrFE) nanofibrous piezoelectric sensor under different forces [49]. Copyright 2024, Elsevier (g) Working mode of piezoresistive sensors: ① Piezoresistive mode with a sandwich structure, ② Piezoresistive mode using interdigital electrodes. (h) Digital image of an all paper-based piezoresistive sensor with interdigitated electrodes. Reproduced with permission [50]. Copyright 2019, ACS. (i) Feedback signals of a glove equipped with piezoresistive sensors performing different hand gestures. Reproduced with permission [51]. Copyright 2024, Elsevier. (j) Working mode of capacitive sensors. (k) Digital image of a liquid metal elastomer-based flexible capacitive sensor. Reproduced with permission [52]. Copyright 2025, ACS. (l) Response signals of a soft gripper with capacitive sensors grasping plastic balls of varying diameters. Reproduced with permission [52]. Copyright 2025, ACS.

$BiFeO_3$) or wurtzite (such as GaN, ZnO) crystal structures, both of which enable piezoelectricity through noncentrosymmetric lattice distortions. While lead-free ceramics are both environmentally and user-friendly, they often exhibit lower piezoelectric coefficients, poor thermal stability, and more challenging manufacturing processes compared to lead-based materials like PZT [66–68]. Despite offering a sustainable alternative, lead-free ceramics still require further research to address their limitations and improve their performance and scalability. Moreover, advanced fabrication methods, including sol–gel, hydrothermal synthesis, electrospinning, and doping, have been widely applied to both lead-based ceramics such as PZT and lead-free ceramic materials such as ZnO, $BiFeO_3$, $BaTiO_3$, (K, Na)NbO_3, and BZT-BCT to realize thin-film structures with flexible substrates like Mica, PI, or PDMS [69–73]. These approaches enable precise control over the morphology, composition, and microstructure of inorganic piezoelectric thin-films, thereby tuning the piezoelectric and mechanical properties to meet the requirements of diverse HMI applications [74].

To further expand the material options for HMI applications, researchers have also explored piezoelectric single crystals. Piezoelectric single crystals are materials with ordered atomic structures and uniform crystal lattices. Compared to piezoelectric ceramics, piezoelectric crystals often show higher piezoelectric and coupling coefficients and exhibit stronger electromechanical responses and sensitivity. One of the most common single crystals is lead titanate $PbTiO_3$ (PT), which has a high piezoelectric coefficient and great thermal stability [75]. Especially, relaxor-based single crystals such as lead magnesium niobate-lead titanate (PMN-PT) and lead zinc niobate-lead titanate (PZN-PT) demonstrate exceptional piezoelectric properties near the morphotropic phase boundary (MPB), exhibiting d_{33} values up to around 2800 pC/N, which is approximately three times higher than that of PZT ceramics [75, 76]. However, the production of piezoelectric single crystals is costly and intricate, involving techniques such as solid-state crystal growth (SSCG) to transform ceramics into single crystals [77], the modified Bridgman method that utilizes directional solidification [78], and the chemical vapor deposition (CVD) that grows crystals directly on substrates through chemical deposition reactions [79]. Moreover, transferring techniques can also be used to relocate single crystal materials on flexible substrates for fabricating piezoelectric single crystals-based flexible sensors [80, 81]. For example, Yang et al. and Zhou et al. fabricated piezoelectric single crystal sensing materials using the CVD growth method, in which the crystals were then transferred onto a flexible PI substrate for fabricating piezoelectric sensors [82, 83]. The proposed sensors demonstrated applications of self-powered HMI by monitoring human hands and controlling robotic prosthetic hands. While piezoelectric single crystals exhibit superior electrical performances, including high electromechanical coupling coefficients, enhanced energy conversion efficiency, and superior sensitivity, ongoing researchers have focused on enhancing their flexibility and usability through innovative fabrication methods and substrate integration for advanced applications. In summary, to overcome the mechanical limitations of bulk piezoelectric ceramics and single crystals, researchers have increasingly focused on developing those inorganic piezoelectric materials in thin film form for flexible and wearable HMI applications. These flexible inorganic thin films retain the superior electromechanical properties of their bulk counterparts while offering enhanced mechanical compliance and compatibility with flexible substrates. By combining inorganic piezoelectric materials with polymeric substrates, piezoelectricity is improved while maintaining flexibility and durability, which makes them highly suitable for next-generation flexible sensor-based HMI applications. These advancements significantly broaden the scope of high-performance inorganic piezoelectric sensing materials for intelligent and adaptive HMIs.

Despite these efforts, achieving mechanical compliance with biological tissues remains a challenge, prompting increased interest in alternative materials. Piezoelectric polymers offer unique advantages over ceramics and single crystals due to their intrinsic flexibility and long-chain molecular structures with weak intermolecular forces, making them inherently flexible and elastic [84]. Among these polymers, polyvinylidene fluoride (PVDF) and its copolymer poly (vinylidene fluoride-co-trifluoroethylene) (P(VDF-TrFE)) are the most commonly used piezoelectric polymeric materials because of their excellent flexibility and biocompatibility [85–88]. These polymers contain molecular structures that impact their piezoelectricity by aligning dipoles within their polymer chains. Specifically, different alignments of polymeric chains form different crystalline phases that significantly influence their piezoelectric properties, in which they exhibit crystalline phases α, β, γ, δ, and ε, with the β, γ, and δ phases primarily contributing to piezoelectricity [89]. As the most dominant electroactive phase, the β phase has the highest dipole moment and the greatest piezoelectric coefficient and is further distinguished by its all-trans chain configuration. Therefore, researchers have developed various processing techniques, including mechanical stretching, high-temperature annealing, and electrical poling, to increase the proportion of the β phase and enhance the piezoelectric performance, thereby improving voltage output [90–92]. For example, Kwon et al. proposed bioinspired piezoelectric nanofibers with textured morphologies to design flexible piezoelectric sensors that were able to detect multiple biophysiological signals (Figure 2e) [49]. The proposed piezoelectric sensor could detect pulse waves by capturing real-time arterial pressure fluctuations on the wrist as well as seismocardiogram (SCG) signals, which measured subtle chest vibrations caused by cardiac contractions, enabling multifunctional monitoring (Figure 2f). Moreover, PVDF-based piezoelectric sensors have also been used in medical HMI applications by controlling robotic prosthetics. Jiang et al. designed flexible piezoelectric sensors capable of harnessing mechanical energy from the bending of multiple finger joints and subtle arm muscle movements into electric signals, enabling efficient and self-powered control of robotic prosthetic hands for amputees [57]. The relatively low d_{33} values of the piezoelectric polymers, such as PVDF ranging from 20 to 33 pC/N, still remain a challenge for achieving efficient sensing [93]. To further enhance the piezoelectric coefficient of polymers, researchers have developed fabrication techniques that introduce microstructures such as porosities and incorporate fillers like piezoelectric ceramic nanoparticles within the polymeric matrix [59–62]. Despite the drawback regarding the low piezoelectric coefficients, piezoelectric polymers exhibit advantageous properties such as biocompatibility, lightweight construction, chemical resistance, and thermal stability, which show extraordinary potential in HMI applications especially for long-term use. As a result, some researchers have further explored the use of piezoelectric polymers for HMI applications, including fluoropolymers, polyureas, polyamides, polypeptides, polysaccharides, and polyesters [94]. The flexibility, biocompatibility, and advanced fabrication processing of piezoelectric polymers make them ideal for biophysiological signals-based medical HMI applications.

Overall, piezoelectric materials can be made into self-powered sensors that convert mechanical stress into electric signals, making them essential for a wide range of HMI applications with a focus in the medical field. These sensors are valued for their ability to function without external power, enabling innovative applications in areas like wearable devices, medical technologies, and robotics without the use of a separate power source. While piezoelectric sensors offer advantages such as sensitivity and adaptability, their performance is often a trade-off between factors like flexibility, durability, and biocompatibility and thus requires thorough consideration of the types of piezoelectric materials used. Advances in design and manufacturing have improved their functionality, addressing limitations like brittleness and biocompatibility concerns, thereby expanding their utility as flexible sensors in medical-based HMI technologies.

2.3 | Piezoresistive and Capacitive Sensors

Piezoresistive sensors operate based on the principle that materials exhibit changes in electrical resistance when subjected to external stimuli such as pressure and strain [95, 96]. These changes can be converted into electrical signals related to the measured physical quantity. The active sensing elements and conductive electrodes are considered the most significant in terms of designing piezoresistive sensors. The active components function by combining with two electrodes to form a sandwich structure (Figure 2g①) or attaching to a pair of planar electrodes such as interdigital electrodes (Figure 2g②). To adapt to the continuous mechanical deformation during the sensing process, the active elements of piezoresistive sensors are usually composed of flexible matrix materials and conductive fillers. The flexible matrix materials serve not only as the supporting structure to respond to the repetitive mechanical stimuli but also as protective layers for conductive fillers to enhance the durability and ensure structure stability of the overall flexible sensor. When embedded into the matrix, conductive fillers form sufficient charge transport paths for electrical current flow to convert mechanical deformation into electrical signals. During the sensing process, conductive paths with varying resistances will form under different matrix deformations, enabling the sensors to generate distinctive resistance responses and the corresponding electrical signals. In particular for piezoresistive sensors, the resistance response in the circuits can be mainly attributed to the variation of volume resistance and contact resistance. The variable volume resistance of sensors is attributed to the formation of diverse conductive pathways, which result from the strain of active elements when combined with conductive fillers under external mechanical stimuli. Regarding volume resistance, the sensitivity of strain-induced sensing can be optimized by adjusting the ratio between the matrix and the conductive fillers. For contact resistance, the mechanical stimuli can increase the contact area between the active materials and the electrodes, thus decreasing the resistance of the sensors that leads to the variation of voltage or current in the circuits. Sensors with contact-induced resistance variation have high sensitivity, which is usually achieved by creating rough structures on the surfaces of the active matrix or fabricating micro- or nanostructured matrices [13]. Overall, the sensing principle of volume resistance-based and contact resistance-based sensors is straightforward, making them easy to design and implement in HMI applications. For example, piezoresistive flexible sensors can be integrated into touch panels for various HMI applications, such as keystrokes, gesture recognition, and tactile sensing [97–99].

To fabricate flexible active components for piezoresistive sensing, various polymers (such as PDMS, PU, PET, and ecoflex), fiber-based materials (such as Kevlar fibers, cotton fabric) and non-conductive hydrogels (such as polyacrylamide) have been used as the flexible matrix. For the electrically active component, metal-based materials (such as Ag and AgNW), carbon-based materials (such as Gr, CNT, MXene, and graphene), conductive polymers (such as PPy, PANI), and conductive hydrogels can be utilized [100, 101]. In addition to serving as conductive components in active sensing elements, these materials can also function as electrodes, enabling sensor integration with external circuitry to measure resistance changes. By integrating advanced conductive materials with flexible active components, piezoresistive sensors can achieve high responsiveness and mechanical adaptability, making them ideal for applications in flexible wearable electronics. For example, Liu et al. proposed a flexible sandwich-structure piezoresistive sensing array based on PI, Au, multiwalled CNT, and PDMS for wearable sensing applications [102]. Gao et al. developed an all paper-based piezoresistive pressure sensor for biodegradable, flexible wearable electronics by utilizing tissue paper coated with AgNWs as the sensing material, nanocellulose paper with printed silver interdigitated electrodes, and nanocellulose paper as the top encapsulating layer (Figure 2h) [50]. When utilized in HMI applications piezoresistive sensors are essential tools due to their simplicity, cost-effectiveness, and versatility. In particular, piezoresistive sensors can provide a stable and continuous signal output under static pressure, ensuring an accurate and consistent signal response in HMI applications (Figure 2i) [51]. However, piezoresistive sensors are not self-powered and thus require an external power source for operation, increasing the energy demands of the system and dependency on batteries. In addition, they are susceptible to environmental factors such as humidity and temperature, which can alter resistance values and reduce reliability.

Similar to piezoresistive sensors, capacitive sensors are generally comprised of two parallel flexible conductive electrodes that are separated by a dielectric material (Figure 2j). This configuration enables the sensor to detect changes in capacitance that result from the variations of applied pressure, displacement of the electrodes, and proximity of an object. The capacitance (C) is determined by the equation $C = \varepsilon_0 \varepsilon_r A/d$, where ε_0 is the permittivity of vacuum, ε_r is the relative permittivity of the dielectric material, A is the overlapping area between the two conductive electrodes, and d is the distance between the two conductive electrodes [103]. Furthermore, flexible capacitive sensors can be constructed from a range of materials, including dielectric substances such as PDMS, PU, and ecoflex, as well as conductive elements such as various metals, CNTs, graphene, gallium indium tin, and indium tin oxide, that allow for variations of designs and configurations for HMI applications. For example, Tchantchane et al. developed a flexible capacitive textile-based sensor using two conductive Ag electrodes sandwiched between a dielectric layer of ecoflex, which was integrated into a glove for real-time control of a commercially available robotic hand and a drone, as well as sign language recognition [104]. Kang et al. utilized gallium-indium-tin, ecoflex, and Ag fiber composite fabric to prepare a liquid metal elastomer-based flexible strain sensor for monitoring human motions, soft gripper electronic skin, and motion posture monitoring of robotic arms (Figure 2k) [52]. It provided continuous and stable changes in capacitance in response to mechanical stimuli variation when used for object grasping with a soft gripper, ensuring precise and responsive sensing capabilities (Figure 2l). In summary, capacitive sensors exhibit high sensitivity, excellent durability, and remarkable capability of noncontact sensing, which present significant potential for HMI applications [105]. Nonetheless, they also face challenges, including sensitivity to external electromagnetic interference and complex circuits, which can limit their applications in certain conditions that require high precision, stability, or operation in harsh environments with strong electromagnetic fields. Overall, both piezoresistive and capacitive flexible sensors leverage the principle of impedance variation to convert external mechanical stimuli into precise electrical responses. Their flexibility, sensitivity, and adaptability allow them to provide responsive and precise interaction in HMI systems, enabling applications such as tactile sensing, gesture recognition, and intelligent robots. However, their power consumption, limited durability, and environmental sensitivity need to be considered and addressed to further enhance the sensing performance and application potential in HMI systems.

2.4 | Electrophysiological Sensors

Triboelectric, piezoelectric, triboelectric, piezoresistive, and capacitive sensors detect mechanical stimuli, converting them into electrical signals, whereas electrophysiological sensors focus on detecting bioelectric signals from biological systems. Electrophysiological signals are electrical impulses generated by biological tissues during physiological activities, providing critical insights into the functional state of the human body. Common types of electrophysiological signals include EEG, EOG, EMG, and ECG, in which each signal type reflects electrical activity from specific bodily systems when in use, such as the brain, eyes, muscles, and heart respectively. As shown in Figure 3, EEG records synchronized electrical signals from brain activity using scalp electrodes placed over specific cortical regions such as the frontal, temporal, central, and occipital lobes [110, 111]. Transitioning to eye-related signals, EOG captures eye movements by detecting voltage changes between the positively charged cornea and negatively charged retina [112]. For muscular signals, EMG monitors the electrical activity of muscle fibers during contraction and relaxation, initiated by neurotransmitter release at the neuromuscular junction following motor neuron stimulation [113]. Lastly, ECG measures the heart's electrical activity through surface or implantable electrodes [114], capturing depolarization and repolarization cycles of the heart chambers. Such biophysiological signals can be captured using implantable or wearable sensors, in which implantable sensors offer high precision and stability due to the proximity of the biological tissue but require surgical procedures to position them safely within the human body. Wearable sensors, on the other hand, are noninvasively attached to the skin surface but may face challenges like noise and reduced signal quality. Although

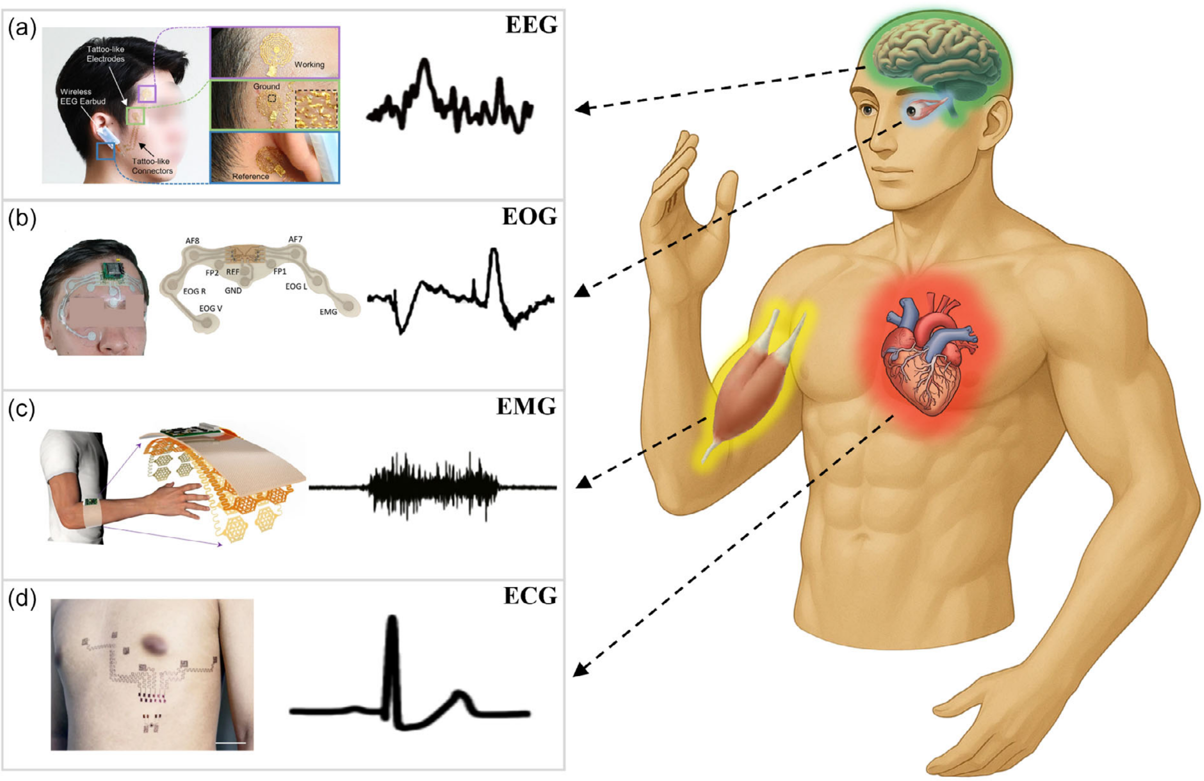

FIGURE 3 | Representative electrophysiological sensors and their signal outputs. (a) Digital image and signal output from an EEG sensor for brain–interface-related application. Reproduced with permission [106]. Copyright 2022, Springer Nature. (b) Digital image and signal output from an EOG sensor for eye-movement controlled application. Reproduced with permission [107]. Copyright 2022, Wiley. (c) Digital image and signal output from an EMG sensor for muscle-movement-related application. Reproduced with permission [108]. Copyright 2023, Springer Nature. (d) Digital image and signal output from an ECG sensor for cardiac monitoring. Reproduced with permission [109]. Copyright 2022, Springer Nature.

electrophysiological sensors are typically powered externally and incorporate rigid electronics like amplifiers and noise filtering chips for signal preprocessing, their integration into HMIs has enabled groundbreaking applications, including prosthetic control, health monitoring, and assistive technologies like exoskeleton manipulation, effectively bridging the gap between humans and machines [20].

Biophysiological sensors used in HMI systems are fundamentally electrodes designed to detect the body's electrical signals during physiological activity. Their effectiveness critically depends on the electrode material's conductivity, biocompatibility, mechanical durability, and ability to conform to the skin with low electrode-skin impedance [115]. While traditional Ag/AgCl wet electrodes remain the clinical standard due to their high signal fidelity, their dependence on conductive gels poses challenges for long-term use, including dehydration, skin irritation, and poor reusability, limiting their practicality in wearable systems. To address these limitations, flexible and stretchable dry electrodes are designed by utilizing materials such as PEDOT:PSS, graphene, MXenes, and metallic nanowires, to be embedded in elastomeric matrices like PDMS [115, 116]. For EEG and EOG, which are typically positioned on the forehead or around the eyes, soft conductive polymers and nanomaterial-based dry electrodes, including microneedle or hydrogel patches, offer enhanced comfort and reduced motion artifacts. EMG electrodes, designed to sense muscle activity from various body regions, employ serpentine or textile-based designs using breathable substrates and conductive nanomaterials to maintain signal quality under skin deformation. Implantable EMG systems further require encapsulation with Parylene-C and use biocompatible metals such as platinum for chronic stability [117, 118]. Moreover, ECG sensors benefit from capacitive-coupled architecture and washable, textile-based electrodes made from CNTs to support unobtrusive and continuous cardiac monitoring [119]. These advancements in material science and device structure are transforming rigid electrode systems into seamless, skin-integrated interfaces that enable reliable, long-term, and comfortable physiological monitoring for next-generation wearable HMIs.

Once the sensing material selection and electrode design are optimized, high-quality and stable biophysiological signals can be reliably acquired for diverse HMI applications. For instance, the EEG signal characteristics of amplitude and frequency reflect various brain states, including relaxation (alpha waves), active thinking (beta waves), light sleep (theta waves), and deep sleep (delta waves) [120], by capturing the degree of synchronization among large populations of neurons (Figure 3a) [121]. EEG can be utilized to enable thought-driven interactions, offering new opportunities for individuals with mobility or muscle impairments while advancing brain-computer interfaces through real-time cognitive signal processing [122]. For example, Kilicarslan et al. proposed a system that uses EEG signals to control a lower-body exoskeleton, allowing a paraplegic user to walk using only their brain activity [123]. Their method demonstrated real-time control of the exoskeleton with minimal training time but with high accuracy, highlighting the potential of noninvasive EEG-based control for assistive walking devices.

In addition to brain signals, EOG provides an eye-movement-based approach for human–machine interaction. EOG signals are capable of characterizing eye movements, in which the lateral and medial rectus muscles govern the horizontal motions, while the superior and inferior rectus muscles control the vertical motions. Meanwhile, the corneal-retinal electric potential shifts to create signals that correspond to the direction and amplitude of the eyeball movements (Figure 3b) [112]. By translating eye movements into control signals, EOG signals can then be widely applied in HMI applications of gaze-controlled interfaces for assistive technologies, such as eye motion-based control of prosthetics and exoskeletons, which are especially valuable for individuals with severe mobility disabilities. For instance, Wang et al. designed a novel eye movement-controlled robotic wheelchair system based on the analysis of EOG signals using a flexible hydrogel biosensor, enabling a high accuracy of 96.3% using ML to detect eye movements for seamless and precise wheelchair navigation [124].

Beyond eye movement tracking, EMG monitors the muscle motor unit by capturing muscle activation patterns. When a muscle motor neuron sends an action potential, it triggers neurons to release neurotransmitters, causing depolarization to generate electric pulses as EMG signals (Figure 3c) [108, 113]. And they can be further applied to control assistive devices like prosthetics and exoskeletons for medical-based HMI applications [125, 126]. To measure EMG signals, electrodes are used for either attaching on the skin above the muscle to acquire surface electromyography (sEMG) or inserting directly into the muscle tissue to get intramuscular electromyography (iEMG) [127]. Hye et al. proposed the sEMG-based robotic hand control by classifying muscular movements via sEMG [128]. By placing the surface electrodes on the upper limbs, they were able to correspond the EMG signals into different robotic hand movements with convenience. In contrast, Vu et al. proposed a prosthetic control system that utilizes implantable electrodes to achieve long-term, reliable upper-limb prosthesis control [129]. The acquired iEMG signals remained stable for over 3 years, allowing participants to control prosthetic hands with high accuracy and without frequent recalibration.

Different from EMG signals, which monitor skeletal muscle activity, ECG signals can accurately represent heart motions on their waveform patterns. An ECG signal has three main wave components: the P wave, the QRS complex, and the T wave. The P wave corresponds to atrial depolarization, reflecting atrial contraction to fill the ventricles; the QRS complex correlates to ventricular contractions to pump blood to the lungs and body; the T wave signifies ventricular repolarization, indicating muscle relaxation and ventricular filling (Figure 3d) [130–132]. The patterns of ECG waves correlate directly to the patient's cardiovascular health in HMI applications. Specifically, wearable ECG devices such as smartwatches and chest straps allow users to track their cardiac health in realtime, providing early detection of abnormalities [133, 134]. Rachim et al. proposed a wearable armband that uses ECG signals to monitor heart activity in real-time while eliminating the need for direct skin contact due to the capacitive-coupled electrodes that measure the signals through clothing or air gaps [135]. In summary, electrophysiological signals play a crucial role in monitoring and analyzing the body's electrical activity of various bodily systems, especially in synergy with HMI-based applications that facilitate enhanced medical diagnostics and personalized care. Through these advancements, electrophysiological sensing technologies are revolutionizing healthcare, rehabilitation, and assistive technology, bridging the gap between biological signals and innovative engineered solutions.

2.5 | Summary of Flexible Sensors

Flexible sensors are innovative devices that can bend, stretch, or conform to different shapes while maintaining functionality in HMI applications, offering advantages such as high sensitivity, adaptability to curved surfaces, and compatibility with not only wearable systems but also robotic sensing and control systems. These sensors offer unique capabilities that enable seamless interaction between humans and machines, but their performance can vary depending on the sensing mechanism. This section summarizes the advantages and disadvantages of various flexible sensing technologies that can be used in the field of HMI, providing insights for selecting optimal solutions based on application-specific requirements, as detailed in Table 1. Flexible triboelectric sensors leverage the triboelectric effect and electrostatic induction to generate electrical signals in response to mechanical stimuli, making them highly suitable for HMI applications. Unlike piezoresistive or capacitive sensing technology, triboelectric sensors possess self-powered sensing capabilities that eliminate the need for external power sources, and their inherent flexible and lightweight characteristics further enhance their suitability by integrating into a variety of flexible

TABLE 1 | Comparison of different flexible sensors.

Sensor type	Sensing mechanism	Key advantages	Limitations
Triboelectric sensors	Triboelectric effect and electrostatic induction	• Self-powered sensing • Capable of sensing dynamic stimuli • Lightweight, scalable, and low-cost • High sensitivity and wide detection range • Diverse material options and working modes • Simple fabrication	• Not capable of sensing static stimuli • Poor durability • Sensitive to environmental factors (such as humidity and temperature)
Piezoelectric sensors	Piezoelectric effect	• Self-powered sensing • Capable of sensing dynamic stimuli • High sensitivity • Simple and diverse designs	• Not capable of sensing static stimuli • Limited by mechanical strain range and need for signal conditioning
Piezoresistive sensors	Variation in resistance	• Broad detecting range • Capable of sensing dynamic and static stimuli • Cost-effective design • Simple and diverse structure	• Require external power source • High energy consumption • Sensitive to environmental factors (such as humidity and temperature)
Capacitive sensors	Variation in capacitance	• Noncontact sensing capability • Capable of sensing dynamic and static stimuli • High sensitivity and durability	• Require external power source and complex circuits • Limited by the need for precise calibration • Sensitive to environmental factors (such as electromagnetic interference)
Electrophysiological sensors	Bioelectric signals	• Reflect physiological conditions of various organs and tissues • Versatile applications and personalized healthcare • Capable of real-time monitoring and feedback	• Require external power source • Complex circuits needed for processing signals • Requires electrodes, signal noise, and interference issues

substrates to ensure the functionality, comfort, and practicability of the overall sensor design. Combined with scalable and low-cost features, triboelectric sensors are well-suited for effective sensing from the human body in HMI applications and can offer high sensitivity and broad detection ranges, which are ideal for detecting touch, motion, or vibration in interactive systems. In addition, the diverse material options and working modes enhance the adaptability of the triboelectric flexible sensors, enabling wider HMI applications that encompass prosthetics, healthcare rehabilitation, surgical environment perception, and much more. However, their reliance on dynamic stimuli limits their functionality in static conditions, and the sensing performance of triboelectric sensors may degrade due to repeated mechanical stimuli. Furthermore, the sensitivity of the triboelectric sensors to environmental factors like humidity and temperature can reduce their reliability in challenging environments governed by such factors.

Piezoelectric sensors, which can be fabricated using ceramics, single crystals, or polymers, detect a wide range of dynamic motions produced by the human body when they are applied as wearable sensors. By employing piezoelectric ceramics and single crystals, the fabricated wearable sensors can demonstrate the advantage of high piezoelectric coefficients to generate large voltage outputs, while piezoelectric polymers can optimize the overall sensor's biocompatibility and flexibility. By selecting the most suitable piezoelectric material for a specific HMI application, the piezoelectric effect can be effectively induced to empower HMI systems to be more ergonomic, scalable, responsive, and reliable. Despite these advantages, piezoelectric sensors possess a fundamental limitation in that they are only capable of detecting dynamic pressure due to the intrinsic dependence of the piezoelectric effect on the rate of change of the applied pressure or force. When pressure or force is maintained or applied constantly, the internal crystal lattice of the piezoelectric material stabilizes, resulting in no additional charge displacement. The sensor fails to produce electrical impulses, hence incapacitating its ability to sense static stress. This trait restricts the application of piezoelectric sensors to scenarios only involving vibrations, impacts, and other swiftly varying mechanical stimuli, necessitating the employment of alternative sensing technologies for effective measurement of both dynamic and static forces for advanced HMI applications.

Piezoresistive and capacitive sensors can monitor deformations or pressure variation through resistance or capacitance changes, enabling precise detection and cost-effective manufacturing. Benefiting from the unique properties of the piezoresistive and capacitive mechanisms, such sensors are capable of detecting and responding to various types of mechanical stimuli that are both dynamic and static. Owing to their flexible and cost-effective design along with their simple yet diverse structural configurations, piezoresistive sensors provide high sensitivity and reliable performances, facilitating seamless integration into a wide range of HMI applications. In addition, piezoresistive sensors offer an extensive detection range from minute to substantial deformations while maintaining remarkable stability and robustness even under extreme strain conditions. Their ability to reliably detect large deformations renders them particularly well suited for HMI applications that involve significant physical interactions, such as in soft robotics and prosthetic devices. However, these sensors often require external power sources for operation, coupled with high energy consumption, which may limit their portability and practicability in long-term wearable use for HMI systems.

Additionally, the resistance is sensitive to environmental factors much like triboelectric sensors, which should be considered in actual HMI applications with varying environmental conditions. While piezoresistive sensors excel in detecting large deformations, capacitive sensors offer distinct advantages in capturing subtle mechanical changes with higher sensitivity and stability, making them particularly suitable for precise measurements. Flexibility and low-power consumption also ensure the output stability and cost-effectiveness of capacitive sensors. Notably, their noncontact capability allows for precise detection of object proximity without requiring direct physical interaction, which is particularly beneficial in noncontact HMI systems such as gesture recognition, virtual reality (VR), and augmented reality (AR). However, flexible capacitive sensors come with some disadvantages that can impact their application and performance in terms of power consumption and design. For example, capacitive sensors often require complex and sensitive electronics for signal processing, leading to bulkiness and redundancy of the overall sensing system, and they are also sensitive to electromagnetic interference, which can introduce noise and affect measurement accuracy.

Electrophysiological signals play a central role in health monitoring applications that utilize HMIs, with different types of signals tailored to specific applications. For instance, EEG is a cornerstone of brain–computer interfaces, while EOG is widely used in gaze-controlled systems. EMG is frequently used in prosthetics and exoskeletons, and ECG is well suited for health monitoring of cardiovascular health. More robust and intuitive HMIs can also be employed when integrating multiple electrophysiological signals to be a multimodal sensing system, providing higher precision, adaptability, and functionality while empowering real-time data processing, personalized user interactions, and enhanced decision-making for advanced medical and assistive technologies. Such systems offer a more comprehensive understanding of human physiological and cognitive states and facilitate adaptive control strategies, optimizing performances in dynamic environments while providing deeper insights into user intent, workload, and physiological that mitigate the limitations of single-sensor systems. For example, Zou et al. introduced an underactuated hand exoskeleton using a multimodal EMG-EEG fusion and a series elastic actuator for a precise and responsive exoskeleton, which accomplished natural grasp restoration with higher robustness due to its multimodal sensing ability [136]. For electrophysiological sensing-based HMI systems, it is also crucial to decide between surface or implantable sensors. Compared to implanted electrophysiological sensors, surface sensors are noninvasive and more accessible, making them ideal for wearable devices. However, they are heavily affected by noise and less reliable than implantable sensors, which offer superior precision and stability but require surgical procedures. To overcome these drawbacks between wearable and implantable electrophysiological sensors, current trends in advanced sensor technologies, including flexible electronics, AI integration, multimodal sensing, and bio-friendly and biodegradable sensors, are bridging these gaps to enable lightweight, biocompatible, stretchable, and smart sensors for wearable and implantable applications. By overcoming the challenges of existing sensor technologies and addressing the diverse requirements of flexible-based sensing applications, these advancements are setting the stage for transformative improvements in medical HMIs.

3 | AI-Driven Advancements in Flexible Sensor-Based HMIs

Recently, HMIs have been revolutionized with the integration of AI and flexible sensing technology, enabling more intelligent, adaptive, and user-centric systems. Traditional HMIs rely on predefined sensor configurations and rule-based processing, limiting their ability to respond dynamically to diverse and evolving user needs. However, with the advent of AI-driven methodologies, flexible sensors can now be optimized, enhanced, and autonomously calibrated to provide superior performance in a wide range of applications, including healthcare, robotics, and assistive technologies. By leveraging AI approaches, flexible sensor-based HMIs can refine the design of flexible sensors, leading to a new generation of intelligent, responsive, and context-aware interactive systems. Specifically, ML and DL algorithms, such as inverse design frameworks and statistic evaluation models, enable rapid optimization of sensor architectures by predicting optimal configurations that maximize sensitivity, durability, and efficiency. By incorporating AI into every stage of sensor development, from initial design to real-time operation, flexible sensor-based HMIs can achieve unprecedented levels of adaptability, making them indispensable in fields ranging from neuroprosthetics to immersive virtual environments. Moreover, AI-assisted digital signal processing (DSP) enhances the interpretation of complex sensor outputs, enabling robust and noise-resistant data extraction, which can be paired with multimodal sensor fusion to synchronize and process diverse physiological and environmental signals for facilitating more intuitive and adaptive system responses. This section explores AI-driven advancements in flexible sensor-based HMIs, covering sensing system optimization along with synaptic transistor design, signal processing, and multimodal integration.

3.1 | AI-Driven Optimization of Sensing Systems

Due to the inherent ability to conform to various surfaces and subsequently capture intricate physiological and biomechanical signals, flexible sensors have gained increasing attention in HMI systems. However, optimizing their morphology, material selection, and functionality has traditionally been a labor-intensive process requiring extensive trial and error. Optimizing the design of flexible sensors with ML and DL algorithms can be leveraged to further synergize with HMI systems for improved performance and interaction in various applications. In this section, cutting-edge AI-driven design technologies for flexible sensing systems are mainly organized into AI-driven flexible sensor design and AI-driven synaptic transistor design, in which AI-driven methodologies effectively optimize the design of flexible sensors that are applied in the field of medical HMIs, allowing for improved sensing capabilities and a more seamless integration with the functionality of HMIs.

3.1.1 | Design Strategies for Flexible Sensors

Flexible sensors are critical components in applications ranging from healthcare and soft robotics to wearable electronics, in which the design plays a crucial role in determining their performance and integration proficiency in HMI systems. Traditional sensor designs often rely on simple structures, in which the sensor optimization is solely based on a repetitive cycle between manual parameter tuning and sensor testing, leading to an overall time consuming and inefficient process. However, AI-driven design of flexible sensors focuses on optimizing the shape, material distribution, material selection, and functionality, aiming to significantly elevate the performance of flexible sensors in real-world applications. Recently, ML has emerged as a powerful tool to accelerate sensor development. By leveraging experimental data and advanced computational techniques, ML-based approaches are enabling the prediction of sensor performances, the rapid discovery of optimal material compositions, and the inverse design of sensors tailored to meet specific functional requirements.

Sensor performance optimization is rapidly emerging as a cornerstone in the development of next-generation intelligent tactile systems. By leveraging ML techniques, researchers are able to fine-tune sensor characteristics such as sensitivity, dynamic range, and response linearity directly from design parameters, thereby drastically reducing the reliance on traditional trial-and-error methods. Lu et al. proposed an ML design strategy for flexible tactile sensors to enhance dynamic touch decoding (Figure 4a) [137]. Statistical learning methodologies were integrated into the design phase of the sensor hardware by introducing an intelligent design approach, in which a support vector machine (SVM)-based method optimized different sensor features such as surface textures and electrode layouts. The proposed ML method increased their classification accuracy among six dynamic touch modalities to 99.58%, demonstrating their advanced capabilities of dynamic texture sensing in their application of AI-optimized robotic HMI.

Additionally, ML-driven sensor design, combined with simulations, can also be applied to optimize sensor microstructures [143, 144]. Li et al. proposed a strategy integrating ML with high-throughput phase-field simulations to optimize the structure of oxide-polymer piezoelectric nanocomposites [145]. By systematically varying oxide filler geometries in a PVA matrix, they generated 400 composite architectures while also assessing the optimal stress distribution, electric field, and material properties. Regression-based ML established predictive relationships between filler geometry and key properties like the piezoelectric coefficient, dielectric permittivity, and elastic stiffness. Furthermore, ML-driven sensor performance optimization can also facilitate systematic inverse design, which is an approach that begins with the desired sensor characteristics and methodically works backward to identify the most effective fabrication method. Liu et al. also proposed a data-driven inverse design framework to achieve optimized sensing properties for capacitive iontronic sensors tailored to specific applications [146]. The approach combined a reduced-order model (ROM) with a 'jumping-selection' technique to efficiently optimize material and structural parameters that designed pressure sensors with a highly linear capacitance response and accuracy across a broad

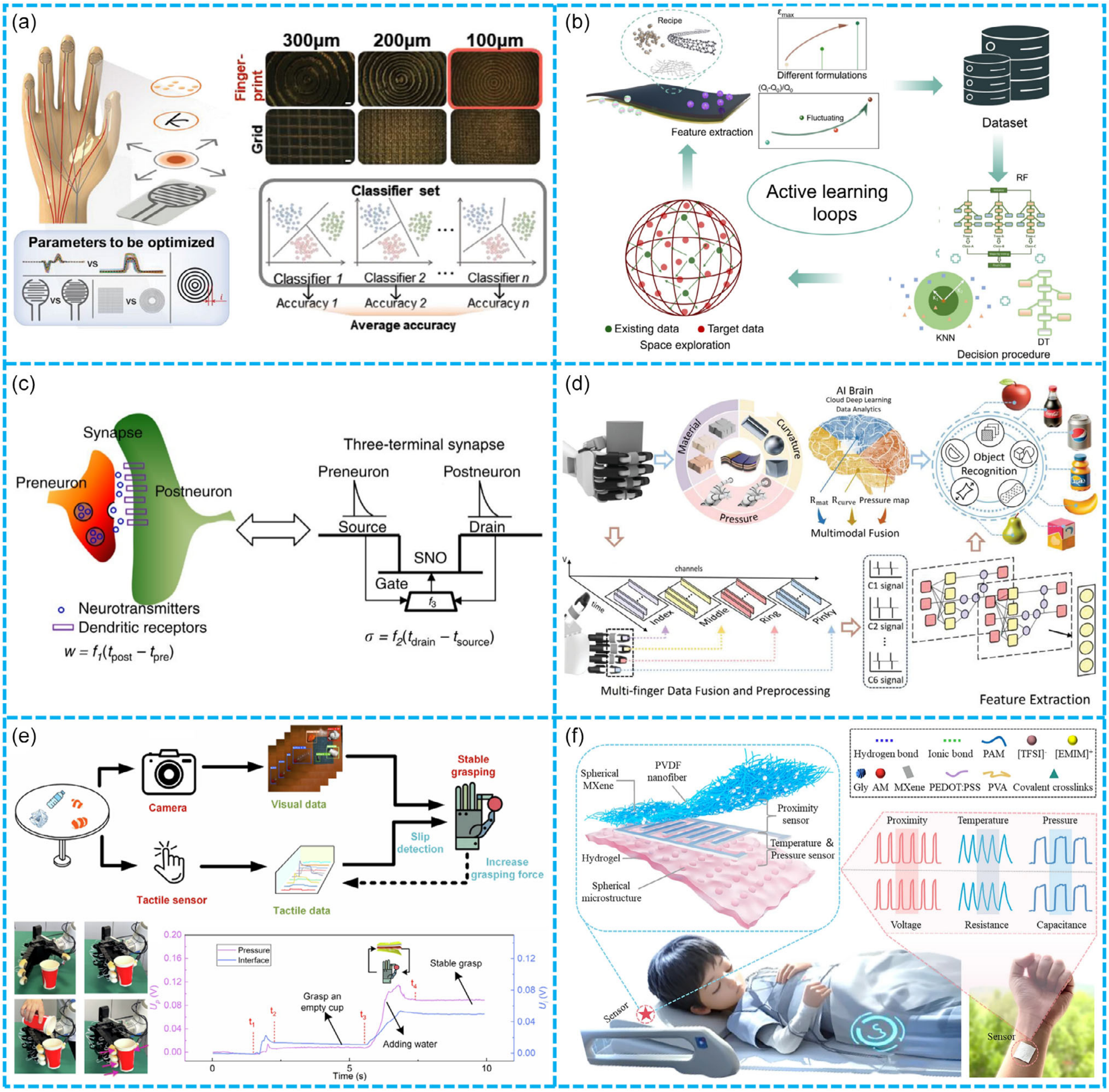

FIGURE 4 | AI-driven optimization, sensor fusion, and MNN integration for flexible sensor-based HMIs. (a) Schematic of the SVM-based sensor design via fabrication parameters optimization. Reproduced with permission [137]. Copyright 2023, Wiley. (b) Active learning-based and automatic sensing material synthesis. Reproduced with permission [138]. Copyright 2024, Lippincott. (c) Bioinspired three-terminal nickelate synaptic transistor device. Reproduced with permission [139]. Copyright 2013, Nature Portfolio. (d) Multimodal triboelectric sensor fusion framework for robotic object recognition. Reproduced with permission [140]. Copyright 2024, Wiley. (e) Multimodal thermistor-based tactile sensor fusion with computer vision in robotic housekeeping. Reproduced with permission [141]. Copyright 2024, Nature Portfolio. (f) MNN for real-time sleep monitoring and posture recognition using a flexible hydrogel sensing patch. Reproduced with permission [142]. Copyright 2025, Springer Nature.

pressure range while also minimizing computational costs. Validation through simulations and experiments confirmed superior performance in the application of robotic tactile sensing and healthcare monitoring. By bridging the gap between sensor material selection and application-driven performance optimization, the research enabled a systematic and scalable approach to developing next-generation flexible sensors in intelligent HMIs.

Active learning, another important ML-driven sensor design strategy, iteratively refines sensor design by strategically selecting the most informative experiments [138, 147, 148]. In this approach, the model initially learns from a limited dataset and then identifies the regions in the design space where uncertainty is highest. By focusing subsequent experiments on the critical areas, the predictive accuracy of the model can dramatically improve and provide direct guidance on which design parameters or configurations to test next. The predictive accuracy can also accelerate the discovery of optimal sensor designs, reduce the number of experiments needed, and minimize costs. Yang et al. proposed a comprehensive ML framework to optimize the fabrication of their strain sensor [147]. The feasible boundaries of their strain sensor design were first established by training an SVM classifier on 351 different sensing material mixtures. Iterative active learning loops were then used to explore the design space, in which a set of fabrication methods was first tested to measure strain sensor metrics, and then a navigation model built with K-nearest neighbor algorithm (KNN) and Random Forest was used to identify the most informative experiments. Over 12 loops, 125 sensors were fabricated, significantly reducing uncertainty and enhancing prediction accuracy. Next, data augmentation was used to expand the dataset points, and a genetic algorithm assisted in determining an optimal model. This ultimate prediction model was then integrated into a reverse design process using Bayesian optimization to recommend the most optimal fabrication method of the strain sensor that met target performance metrics. Further research has also explored utilizing the active learning-aided design of flexible sensors to optimize sensor arrays. Zhao et al. proposed an active learning-assisted approach for optimizing piezoelectric material synthesis by iteratively refining material recipes through ML (Figure 4b) [138]. Using Decision Tree, k-Nearest KNN, and Random Forest algorithms, they trained a model on 300 initial samples, then iteratively fabricated 105 new samples over 10 learning loops, improving prediction accuracy and reducing RMSE by 19.4%. The model selected the most uncertain samples for further testing, efficiently exploring the material space. A Bayesian optimization-based reverse design further refined material selection based on target properties. The optimized materials, applied in flexible wearable sensors, demonstrated the potential of active learning in accelerating material discovery. While active learning does not improve the sensor designs directly, they are capable of effectively optimizing prediction models that can lead to a more efficient, targeted design process for the sensors, guaranteeing that each experiment progressively refines the design with each iteration.

3.1.2 | Design Strategies for Flexible Synaptic Transistors

As the integration of ML and simulation techniques accelerates efficient sensor design, another frontier in smart materials and devices lies in the development of artificial synaptic transistors, which mimic the functionality of biological synapses to enable efficient processing in neuromorphic systems. Artificial synaptic transistors are inspired by the structure and function of biological synapses in the human brain and are considered an emerging class of neuromorphic devices. Shi et al. proposed synaptic transistors made of a thin film of samarium nickelate ($SmNiO_3$) that mimic the signal transmission and adaptive learning capabilities of biological synapses by using materials with unique electrical properties capable of modulating the connection strength (synaptic weight) between the input and output signals (Figure 4c) [139]. Unlike conventional transistors, where input and output signals are distinct and separated by a gate, synaptic transistors utilize flexible materials such as conductive filaments, ion gels, and organic semiconductors to enable non-volatile, analog changes in conductivity in response to input stimuli, mimicking the way neurotransmitters modulate synaptic strength in the brain [149]. By incorporating flexible material technology directly into the design of synaptic transistors, the devices achieve not only enhanced mechanical resilience but also a closer mimicry of the plasticity inherent in biological systems. Such integration enables the transistors to endure conditions commonly encountered in wearable electronics and bio-integrated systems, such as bending, stretching, and twisting, without compromising their non-volatile, analog switching behavior. In addition, the incorporation of flexible sensors presents a transformative opportunity for applications of synaptic transistors, in which flexible sensors can enable more resilient and adaptive sensing architectures that better emulate the adaptability of biological systems, paving the way for next-generation neuromorphic devices to seamlessly integrate sensing and processing functionalities.

Flexible sensors such as triboelectric sensors can be connected to synaptic transistors with direct electrode contact, in which the voltage signal output provides a waveform similar to biological synaptic responses. Common materials used in these devices include transition metal oxides such as zinc-oxide, organic polymers, 2D materials like graphene, and ion-conductive electrolytes such as Se doped lithium phosphate [150–152]. By integrating with sensors to receive their output signals, these artificial synapse transistors can transform the acquired sensing signals into voltage outputs that mimic the human synaptic response. This significantly enhances flexible sensor-based HMIs by enabling real-time, adaptive signal processing. Sultan et al. proposed a synaptic sensing system by connecting triboelectric sensors with artificial synaptic transistors [153]. This convergence allowed their flexible sensing systems to emulate synaptic functions like short-term plasticity (STP) and long-term potentiation (LTP), which are critical for intelligent learning and memory. Alternatively, they also proposed a tactile sensory synapse based on organic electrochemical transistors (OECTs) monolithically integrated with an ionogel triboelectric layer to mimic biological mechanoreceptors. The device utilized triboelectric coupling to generate output voltage signals upon mechanical stimulation to modulate ion movement in the PEDOT:PSS channel, enabling synaptic functionalities such as spike number-dependent plasticity (SNDP) and spike duration-dependent plasticity (SDDP). This integration allowed the synaptic device to sense, adapt, and recognize various materials using ML algorithms, demonstrating significant advancements in self-powered, bioinspired artificial tactile systems.

Ultimately, AI-driven design technologies have the potential to significantly refine the development process of flexible sensors and synaptic transistors, substantially boosting their adaptability, efficiency, and integration into HMIs. Traditional sensor design relies on repetitive manual tuning and trial-and-error testing, making sensor development slow and resource-intensive. Alternatively, AI-driven flexible sensor design leverages various AI algorithms to optimize material selection, structural configuration, and sensor performance. To effectively accelerate the development of flexible sensors, techniques such as inverse design, which determines the optimal fabrication process based on desired sensor characteristics, and active learning, which strategically refines sensor designs by selecting the most informative experiments, can be utilized. Additionally, computer simulations combined with ML enable precise microstructural optimization, further improving sensing efficiency and leading to high-performance, AI-optimized sensors for applications in wearable electronics for healthcare monitoring and medical robotics.

Moreover, AI-driven synaptic transistor design also introduces a paradigm shift in neuromorphic computing by mimicking the biological synapses of the human brain. These transistors, built with materials such as transition metal oxides, organic polymers, and ion-conductive electrolytes, enable adaptive, low-power signal processing that can dynamically learn and respond to sensory inputs. By integrating flexible sensors with artificial synaptic transistors, researchers can develop bioinspired HMIs capable of real-time signal adaptation, allowing for enhanced prosthetics, soft robotics, and self-powered tactile sensing systems.

3.2 | AI-Enhanced Signal Processing

By conformably attaching to the human skin, flexible sensors generate output signals that are not only more complex but also richer in unique characteristics, offering deeper medical insights into individuals. Specifically, ongoing research is increasingly focused on applying multimodal flexible sensors in HMIs to enhance the perception dimension of the sensing, thereby outputting larger data sets from the overall more comprehensive HMI system. Therefore, it is crucial to apply effective statistical methods for processing and analyzing these larger and more complex data sets in HMI applications. A method that can be applied in most flexible sensor-based HMI systems is DSP, which is a mathematical algorithm that can analyze, modify, and optimize the acquired digital signals in real-time. Owing to the adaptive capability, efficiency, automation, and intelligence of AI algorithms, AI-enabled DSP has greatly improved the advancement of flexible sensor-based HMIs.

The first stage of AI in HMI applications is signal preprocessing. Initially, time-series raw signals from flexible sensors are filtered in the frequency domain to remove unwanted noise. The filtering algorithms applied are mostly the traditional Fast Fourier Transform (FFT)-based filtering algorithms, specifically low-pass, high-pass, or band-pass filters, which are used to cut noises from different frequency domains. Some researchers use AI algorithms such as Convolutional Neural Network (CNN) to do highly precise filtering of output signals from flexible sensors [154, 155]. After filtering, normalization is applied, which rescales all the filtered signals to a fixed range by applying mapping calculation. This step can scale the filtered signals to a common range, so that their features are now contributed equally to the pattern recognition AI model, thus preventing features with larger values from dominating the learning process and ultimately improving the accuracy and stability of the intelligence in HMIs [156]. The last step in signal preprocessing, signal segmentation, further divides the filtered and normalized signals into smaller and more manageable data sets that are studied in the analyzing model. Specifically, the traditional sliding window method is mostly used for dividing signals by extracting a window of fixed length along with a defined step size. For example, Liu et al. systematically evaluated how varying window sizes affect fall detection accuracy by inputting wearable tri-axial accelerometers into different ML models such as SVM and KNN [157]. Their findings emphasize that careful tuning of window length is crucial for maximizing model accuracy in wearable-based HMI systems. Following signal segmentation, some researchers also implement extra signal augmentation, which can enhance data quality and diversity by applying transformations such as employing pitch shifting, adding controlled noise, or performing Principal Component Analysis (PCA). For instance, Wu et al. applied PCA to reduce the dimensionality of windowed multichannel strain sensor data [158]. They extracted the top 30 principal components, capturing 97.3% of the variance, and used them as input features for gesture classification. These techniques simulate real-world variations, improving the robustness and generalization of AI models. For limited data sets, signal augmentation is especially useful, as it increases training data, reduces overfitting, and improves the model's ability to adapt to new conditions in HMI applications.

Signal feature extraction serves as an essential intermediate step in the data analysis process, where meaningful and representative attributes are identified and extracted from the preprocessed signals to facilitate efficient pattern recognition and decision-making. This crucial step transforms filtered and normalized signals into a set of discriminative features that capture the essential characteristics of the data, enabling the AI model to learn and interpret patterns more effectively. Various AI algorithms have been developed over the years, including traditional ML, which uses structured statistic models to evaluate different data characteristics, and DL, which applies multi-layered neural networks for higher-level learning of implicit data features. Within small sets of data, ML classification algorithms, including SVM, Random Forest, and KNN, are often deemed effective at dealing with such signals. This is particularly beneficial during the early prototyping stage of the proposed sensors when only a limited number of experiments have been conducted, such as in cases when signal data sets are small. For example, SVM identifies optimal decision boundaries in high-dimensional signal spaces, excelling at separating complex or overlapping classes by maximizing the margin between them, even in small datasets. Zhao et al. applied an SVM algorithm to classify signals from a triboelectric patch that was applied for object recognition in their HMI sensing system [159]. The SVM model effectively distinguished 11 objects with an accuracy of approximately 94%. Furthermore, KNN classifies signals based on local similarity metrics, dynamically adapting to intricate or non-linear patterns in sparse datasets without requiring assumptions about underlying data distributions. Yu et al. proposed an AI-powered multimodal robotic sensing system (M-Bot) with an all-printed soft electronic skin-based HMI [160]. Using KNN, sEMG signals were decoded for robotic hand control, achieving a 97.29% gesture recognition accuracy. In addition, by projecting data into a lower-dimensional space, linear discriminant analysis (LDA) maximizes the separation between signal classes, thereby preserving discriminative features critical for classification while reducing computational complexity. Wu et al. used LDA for signal pattern recognition in their wearable sensor-enabled sign language translation system, specifically used to analyze the signal patterns by maximizing class separability based on these extracted features [158]. After applying PCA, the trained model was validated using five-fold cross-validation, and its performance was tested on unseen gesture data, contributing to high accuracy in recognizing both single and combined sign language gestures.

For large-scale, high-dimensional data with complex patterns, DL classification algorithms, including Artificial Neural Networks (ANN), CNN, and Recurrent Neural Networks (RNN), are particularly effective at processing them, making them indispensable for advanced sensor systems and applications requiring hierarchical feature extraction. To enable the robust modeling of intricate signal patterns even with moderately sized datasets, ANN employs interconnected layers of neurons to approximate non-linear relationships in data by using activation functions and backpropagation to iteratively refine weights. Wang et al. proposed a flexible and stretchable flexible triboelectric sensor fabricated from graphene oxide and polyacrylamide hydrogels for high-precision gait recognition in hemiplegic patients and people with Parkison's disease [161]. They used ANN to classify gait patterns from sensor data, achieving 99.5% accuracy for daily-life gait recognition and 98.2% for pathological gait recognition. Moreover, CNN specializes in spatial and temporal signal analysis through convolutional layers that automatically detect local features such as edges, textures, and pooling operations that reduce dimensionality, excelling in tasks like image recognition or spectral signal classification by preserving spatial hierarchies. Xie et al. proposed an ML-integrated flexible sensor using a triboelectric design for real-time tactile detection and voice recognition [162]. They employed CNN to analyze sensor signals, achieving 94.6% accuracy in speech recognition. The flexible sensor was integrated into a facemask to capture vocal vibrations, enabling hands-free voice recognition for HMI applications. Furthermore, RNN processes sequential, time-series signals such as sensor readings over a specified time period, using recurrent connections to maintain the memory of previous inputs, leveraging architectures like Long Short-Term Memory (LSTM) to handle long-range dependencies and temporal dynamics critical for real-time or continuous monitoring applications. Wajahat et al. developed an AI-enabled sign language-predicting glove integrating 3D-printed triboelectric sensors with DL for advanced gesture recognition [163]. They employed the LSTM model to process sequential sensor data, achieving 99% accuracy in classifying hand gestures corresponding to the alphabet from A to J. The ability of the applied LSTM model to capture temporal dependencies enabled precise and reliable interpretation of finger movements. Overall, while DL algorithms demand larger datasets and computational resources compared to traditional ML methods, their ability to autonomously learn abstract representations makes them powerful tools for deploying refined sensor systems or analyzing complex, multimodal data streams.

3.3 | AI-Augmented Multimodal Sensing Systems

The evolution of flexible HMIs has ushered in a paradigm shift toward multiple modality sensing systems, where heterogeneous signals such as pressure, temperature, and bioelectrical inputs are synergistically combined to enrich interactions between humans and machines. By effectively processing a diverse range of sensory inputs, AI-driven approaches empower multimodal sensing systems to seamlessly combine heterogeneous data sources, transcending the limitations of single-modal sensing that only captures signals one modality at a time. In contrast, multimodal sensing systems have the potential to capture diverse and comprehensive physical and physiological phenomena, improving the accuracy, robustness, and adaptability in complex environments. Here, two main AI-based techniques, sensor fusion and multimodal neural networks (MNNs), are explored in detail for their significant applicability in the field of multimodal flexible sensor-based HMIs in healthcare.

The technique of sensor fusion plays a pivotal role in extracting cross-modal correlations, suppressing noise, and resolving conflicts between data sources, ultimately enabling systems to infer user intent with higher fidelity. Specifically, sensor fusion refers to the process of integrating heterogeneous data streams from multiple sensors to generate a unified, context-rich representation of a system or user state [164–166]. In multimodal flexible sensor-based HMIs, this involves harmonizing inputs from diverse modalities such as sEMG, pressure, strain, optical, and temperature sensors to capture comprehensive physiological, kinematic, and environmental insights [167–170]. Furthermore, sensor fusion can be categorized as early fusion, intermediate fusion, or late fusion depending on the integration stage. Early fusion combines raw sensor data at the feature level, maximizing cross-modal correlations but requiring precise synchronization. Intermediate fusion merges partially processed data, balancing cross-modal dependencies while preserving unique modality-specific features. Late fusion, on the other hand, integrates information at the decision stage, where independent classifiers analyze different sensor inputs before aggregating their outputs, ensuring flexibility at the cost of losing fine-grained interactions. The choice of fusion strategy depends on the requirements of the specific application since it can greatly influence the robustness, adaptability, and accuracy of user intent recognition.

Unlike traditional HMIs that rely on isolated sensor signals, sensor fusion leverages the complementary strengths of each modality to overcome individual limitations. For example, sEMG sensors track muscle clenching conditions, and flexible pressure sensors detect tactile interactions or posture shifts [140, 141, 168, 171]. By fusing these multimodal sensing signals, HMIs achieve enhanced accuracy, robustness, and adaptability, such as compensating for motion artifacts in ECG signals using SCG signals, utilizing multimodal sensing systems to handle sensor failures, and enabling real-time calibration to user-specific biomechanics. Recently, Zhao et al. proposed a flexible triboelectric multimodal tactile sensor (TMTS), which is composed of PI and PTFE layers with ecoflex and Cu shielding, that integrates AI-based sensor fusion to enhance robotic tactile perception (Figure 4d) [140]. Specifically, through the triboelectric effect, the TMTS is capable of detecting material properties, curvature, and pressure. To achieve high-precision perception, the system employs DL-based fusion by transmitting multimodal tactile signals from robotic fingertips to a cloud-based AI processor. An LSTM neural network extracts features, decouples sensing modalities, and compensates for variations in pressure, enabling robust object classification with 99.2% accuracy and softness recognition with 94.1% accuracy. This AI-driven fusion framework significantly enhances robotic object manipulation, intelligent grasping, and dexterous material recognition, paving the way for advanced human-like robotic interactions. Moreover, Mao et al. proposed a flexible tactile sensor based on thermosensation, integrating pressure, temperature, thermal conductivity, texture, and slip detection for multimodal sensor fusion with vision in robotic housekeeping (Figure 4e) [141]. To enhance robotic perception, a tactile-visual fusion framework combines camera-based vision for object localization and tactile sensing for real-time grip adjustment, ensuring stable handling of fragile objects like a cup with liquid. A cascade AI classifier first applies You Only Look Once (YOLO) for visual object detection, then refines recognition using tactile features (pressure, thermal conductivity, texture) to distinguish visually similar items. This fusion enables robots to autonomously perform object sorting, stable grasping, and desktop cleaning, demonstrating human-like dexterity in real-world environments. Through the seamless integration of heterogenous signals, sensor fusion frameworks that employ AI models can enable HMIs to deliver durable healthcare solutions that bridge the gap between clinical precision and daily usability.

Other than sensor fusion, MNNs are also applied uniquely in multimodal sensor-based HMIs [140, 141, 172, 173]. Built by combining branches of single-model neural networks, MNNs differ from standard neural networks by their ability to process multiple input modalities and generate several types of outputs simultaneously. Unlike traditional neural networks that typically handle a single type of data and output a single prediction, MNNs are designed to fuse and interpret heterogeneous signals such as electrophysiological signals, tactile feedback, and vision data, to allow for more comprehensive decision-making in HMIs. Typically, neural networks can be transformed into an MNN by introducing separate input branches for different data types, each optimized with modality-specific feature extraction layers (such as CNNs for spatial data, RNNs for sequential data, and attention mechanisms for contextual learning). These modality-specific features are then fused at a shared representation layer, enabling the network to understand complex relationships between different sensor inputs. Finally, a multi-output architecture can be implemented, where different fully connected layers or task-specific decoders generate multiple predictions simultaneously, such as gesture classification, force estimation, and fatigue detection.

For flexible sensor-based HMI applications, MNNs have been mainly used in tactile sensing systems for healthcare. Yu et al. proposed an alterable robotic skin that leveraged material gene expression modulation to dynamically adjust its mechanical and electrical properties [172]. The multi-layered robotic skin integrated position and pressure sensing to recognize multi-dimensional touch patterns, in which their tactile sensing system simultaneously outputted semantic labels such as 'light tap' or 'firm press' and quantitative motion characteristics by using MNN. By fusing data through CNNs for spatial features and RNNs for sequential patterns, they demonstrated accurate haptic recognition and adaptive robotic responses, advancing intelligent HMIs and interactive robotics. Ongoing research has also applied MNNs for monitoring human movements in medical applications using flexible sensor-based HMIs [142, 174, 175]. Wang et al. proposed a multimodal CNN for processing signals from a flexible hydrogel sensing patch (Figure 4f) [142]. The system collected and processed pressure, temperature, and proximity signals through different sensing mechanisms and integrated them into a one-dimensional CNN for real-time sleep monitoring. The neural network outputs three distinct information types: pressure changes from tracking head movement, temperature variations from body heat monitoring, and proximity data through non-contact detection. By analyzing these multimodal signals together, the system demonstrated accurate sleep posture recognition and real-time detection of sleep quality patterns, facilitating comfortable and unobtrusive sleep monitoring solutions. By enabling real-time processing of heterogeneous sensor data, the MNN approach allows HMIs to dynamically adjust to variations in user input, improving response precision and facilitating more intuitive, context-aware interactions.

3.4 | Summary of AI-Driven Progress in Flexible Sensor HMI

In the field of flexible sensor-based HMIs, AI can assist throughout the entire workflow from sensor design and signal processing to final application deployment. However, tremendous AI algorithms have been developed over the decades, each tailored to specific statistical challenges within diverse flexible sensor-based HMI datasets. Therefore, it is crucial to select the most appropriate and effective AI algorithms for optimizing different phases of flexible sensor-based HMI research, as using inappropriate algorithms may lead to suboptimal and even incorrect outcomes. At the end, Table 2 summarizes and organizes the algorithms discussed in the above sections.

During the sensor design phase of flexible sensor-based HMIs, AI algorithms have been widely applied to optimize material selection, structure, and functionality. On the one hand, statistical learning models of SVM and regression analysis are used to directly predict and enhance sensor performance metrics like sensitivity, linearity, and durability. On the other hand, active learning algorithms, including KNN, Random Forest, and Bayesian optimization, are leveraged to iteratively refine sensor configurations by analyzing experimental datasets, thus accelerating development while minimizing cost and trial-and-error.

Signal feature extraction is a critical intermediate step that transforms preprocessed signals into meaningful features for efficient classification and decision-making in HMI systems. For small datasets, traditional ML algorithms such as SVM, KNN, LDA, Random Forest, and PCA are commonly used due to their simplicity and effectiveness. These models have been successfully applied in object recognition, gesture decoding, and sign language translation. For large-scale or high-dimensional data, DL algorithms such as ANN, CNN, and RNN/LSTM are employed. These models are capable of learning hierarchical, abstract representations from complex signal patterns, making them suitable for signals such as gait analysis and speech recognition in wearable sensor applications.

For signal preprocessing, most algorithms are traditional methods that do not inherently involve AI. Filtering, normalization, and segmentation are primarily conventional techniques. However, they play a critical role in enabling AI applications by ensuring that the input data is clean, consistent, and well-structured for accurate learning, unbiased analysis, and effective pattern recognition. In addition, signal augmentation methods such as PCA are increasingly used to extract the most informative features from complex sensor signals, reducing computational complexity and enhancing learning efficiency and performance for improving model generalization and robustness.

TABLE 2 | Comparison of different AI algorithms.

AI algorithm	Type	Key features	Application in Flexible Sensor-based HMIs
PCA	Signal preprocessing	• Unsupervised learning • Reduces input dimensionality • Preserves principal variance	Applied to reduce dimensionality of sensor signals in gesture recognition, enhancing machine learning model efficiency.
SVM	Classification	• Supervised learning • Effective for small datasets	Used for object/texture recognition in triboelectric sensors.
Random Forest	Classification	• Ensemble learning • High accuracy • Robust to overfitting	Used for flexible sensor design, and applied in activity recognition using triboelectric or piezoresistive sensors.
KNN	Classification	• Instance-based learning • Computational cheap • Low complexity	Used for real-time motion classification in resistive sensor-based wearables.
LDA	Classification	• Supervised dimensionality reduction • Efficient for linearly separable data	Utilized in multi-gesture recognition systems based on piezoresistive or capacitive sensors.
ANN	Classification	• Multi-layer perceptron • Learns complex nonlinear relationships • High accuracy with enough dataset	Used for classifying gait signal patterns, and employed in EMG signal interpretation for prosthetic control interfaces.
CNN	Classification	• Convolution layers for spatial feature extraction • High accuracy in image-like data	Used for suppressing noise, spatial signal classification. Application in handwriting or gesture recognition from capacitive and resistive sensor arrays.
RNN	Classification	• Efficient for sequential pattern recognition	Used for classifying sequential signals in speech or continuous gesture recognition from wearable sensors.
LSTM	Classification	• Efficient for sequential pattern recognition with higher accuracy but computational expensive • Long-term sequence learning	Used for classifying hand gesture-based sequential signal. Application in time-series analysis of biosignals (such as heartbeat and EMG) for adaptive HMI systems.
YOLO	Object Detection	• Real-time spatial pattern recognition • Computational expansive	Real-time visual object detection. Application in vision-based HMIs for tracking gestures and objects in real time.
MNN	Multimodal data integration	• Cross-domain learning • Sensor fusion ability	Enhances decision-making in systems combining multiple sensor types (such as EMG and pressure sensors).

In addition, advancements in flexible sensor-based HMIs can harness AI-driven multimodal sensor fusion and neural networks to seamlessly integrate diverse sensor inputs and create cohesive and adaptive systems that enhance real-time decision-making, improve interaction precision, and dynamically respond to user intent and environmental changes. For sensor fusion, heterogeneous signals are synthesized to enhance accuracy, resilience, and context awareness, enabling applications like surgical robotics and prosthetics to dynamically compensate for noise or sensor failures. MNNs process these heterogeneous inputs through specialized architectures and fuse features to generate simultaneous outputs, offering real-time, context-sensitive interactions for applications that involve gesture recognition and force estimation. Innovations like robotic skins with MNNs demonstrate multimodal touch interpretation, blending spatial and sequential data for responsive haptic feedback. Collectively, these AI techniques transform fragmented flexible sensor-based data into intelligent, personalized, and highly adaptable HMIs, critical for advancing healthcare, rehabilitation, and interactive robotic prosthetics that effectively bridge clinical precision with real-world adaptability.

Table 2 compares and summarizes various AI algorithms applied in flexible sensor-based HMIs, categorizing them by type, key features, and specific applications. ML methods such as PCA are primarily used for signal preprocessing to reduce input dimensionality, thereby enhancing downstream ML/DL performance. ML classification algorithms like SVM, Random

Forest, KNN, and LDA are effective for analyzing small datasets, with applications ranging from object recognition in triboelectric sensors to sign language interpretation using piezoresistive sensors. In contrast, DL algorithms such as ANN, CNN, RNN, and LSTM utilize multi-layered neural networks capable of learning complex patterns directly from large datasets, often achieving higher accuracy than traditional ML methods but at the cost of greater computation and data size demands. CNNs are particularly suited for spatial pattern recognition, while RNNs and LSTMs are designed for handling sequential signals. Advanced DL-based algorithms like YOLO enable real-time object detection, while MNNs support cross-domain sensor fusion, enhancing the intelligence and adaptability of multimodal HMI systems.

4 | Flexible Sensor-Based HMIs in Medical Robotics

4.1 | Advancing Prosthetic Perception and Control

Traditional prosthetics rely heavily on mechanical structures and rigid sensor systems that typically struggle to conform to the user's body movements, making it difficult to accurately translate the user's intent. To address such issues, flexible sensor technologies have been applied to significantly transform prosthetics. When attaching flexible sensors to the user's body parts, they can seamlessly integrate with the prosthetic socket or conform to the human skin, not only enhancing user comfort but also improving the ability of prosthetics to interpret biological signals. This leads to more intuitive, adaptive, and precise interactions between the user and the artificial limb. Furthermore, integrating prosthetics with flexible tactile sensors enhances artificial limbs with advanced sensory capabilities, enabling them to perceive and detect objects and their surroundings with greater precision that closely emulates human-like perception. For flexible sensor-based prosthetic applications, this section categorizes their operation through two key aspects: sensing of surroundings and user intent, and control of limb motion. Sensing mechanisms detect and capture the user's biosignals, which are generated through the dynamic interactions between the prosthetics and nearby objects or environmental factors. The signals are then converted into meaningful data for advanced prosthetic perception and user monitoring. The other fundamental aspect involves the control mechanisms, which process the acquired human biosignals using techniques such as threshold-based control, proportional control, and pattern recognition to successfully translate the signals into prosthetic motion.

4.1.1 | Prosthetic Perception

In flexible sensor-based prosthetics, sensing perception is a crucial enabler for overcoming the inherent limitations of conventional prosthetics, which often struggle with inadequate human–prosthetics interaction and reduced functionality. Traditional prosthetics often force users to rely on visual compensation and inferred proprioception, leading to compromised dexterity, safety risks, and heightened cognitive loads. To address such issues, smart prosthetics can be integrated with various sensors to enable real-time environmental perception and translate these signals into electrical, mechanical, or neurostimulatory feedback. Coupled with AI-driven adaptive algorithms, these advancements in sensing systems pave the way for prosthetics with biomimetic sensory autonomy, bridging the gap between artificial devices and biological sensory–motor integration. In particular, pressure sensing within the field serves as an essential sensing modality to detect and quantify mechanical forces between the prosthetic device and its environment, enabling adaptive control and real–time interaction for the user. Owing to their mechanical flexibility, conformability, and rapid response characteristics, flexible sensors are exceptionally well-suited for pressure detection in these applications.

Various flexible sensors have been developed to augment tactile pressure feedback by facilitating real-time monitoring and enhancing user comfort. For example, Chang et al. developed a highly flexible triboelectric tactile sensing array with PDMS, PCL nanofiber membrane, and PEDOT:PSS electrodes to quantify the pressure distribution between an amputee's residual limb and the socket's internal environment for improving prosthetic fit [44]. Li et al. developed a cost-effective and large-area capacitive pressure sensor array that achieved high sensitivity and fast responses, which could be integrated into prosthetic hands to enable an object recognition system assisted by convolutional neural networks [176]. In contrast to single-mechanism sensors in the applications of prosthetics, which are often constrained by trade-offs between sensitivity, bandwidth, and environmental stability, pressure sensors integrated with multiple-mechanism sensing capability combine complementary sensing modalities such as piezoresistive, capacitive, piezoelectric, and triboelectric mechanisms to achieve expanded dynamic range, enhanced environmental robustness, and multidimensional force characterization. This shift toward multimodal systems improves user-prosthesis interactive authenticity in diverse real-world scenarios. Wang et al. utilized porous nanocomposites to fabricate a stretchable hybrid pressure sensor that combines piezoresistive and capacitive mechanisms [177]. This sensor offered high sensitivity to pressure while minimizing sensitivity to stretch or shear, ensuring accurate pressure sensing in dynamic and stretchable environments in the applications of soft robotics and prosthetics. In addition, other flexible pressure sensors utilizing both piezoresistive and capacitive sensing for prosthetic applications were developed by Ha et al. and Huang et al. [13], by minimizing stretching interference for enhanced sensitivity and enabling wide-range detection through capacitive-piezoresistive dual-mode conversion, respectively [178, 179].

While pressure sensing has equipped artificial limbs with some degree of sensing capability, the evolution toward multimodal sensing has significantly enhanced the performance of smart prosthetics especially when integrated into prosthetic hands. By integrating diverse sensor inputs, multimodal sensing systems can accurately interpret user intent and environmental interactions in real time, allowing natural and responsive limb perception. Han et al. developed a hierarchical bimodal sensor consisting of a laser-induced graphene/silicone rubber layer for pressure-sensing and a NiO layer for temperature sensing, integrated into the fingertips of a smart glove (Figure 5a) [180]. Their smart glove differentiated objects by size, shape, and temperature using resistance variations and also achieved over 92% classification accuracy through DL algorithms,

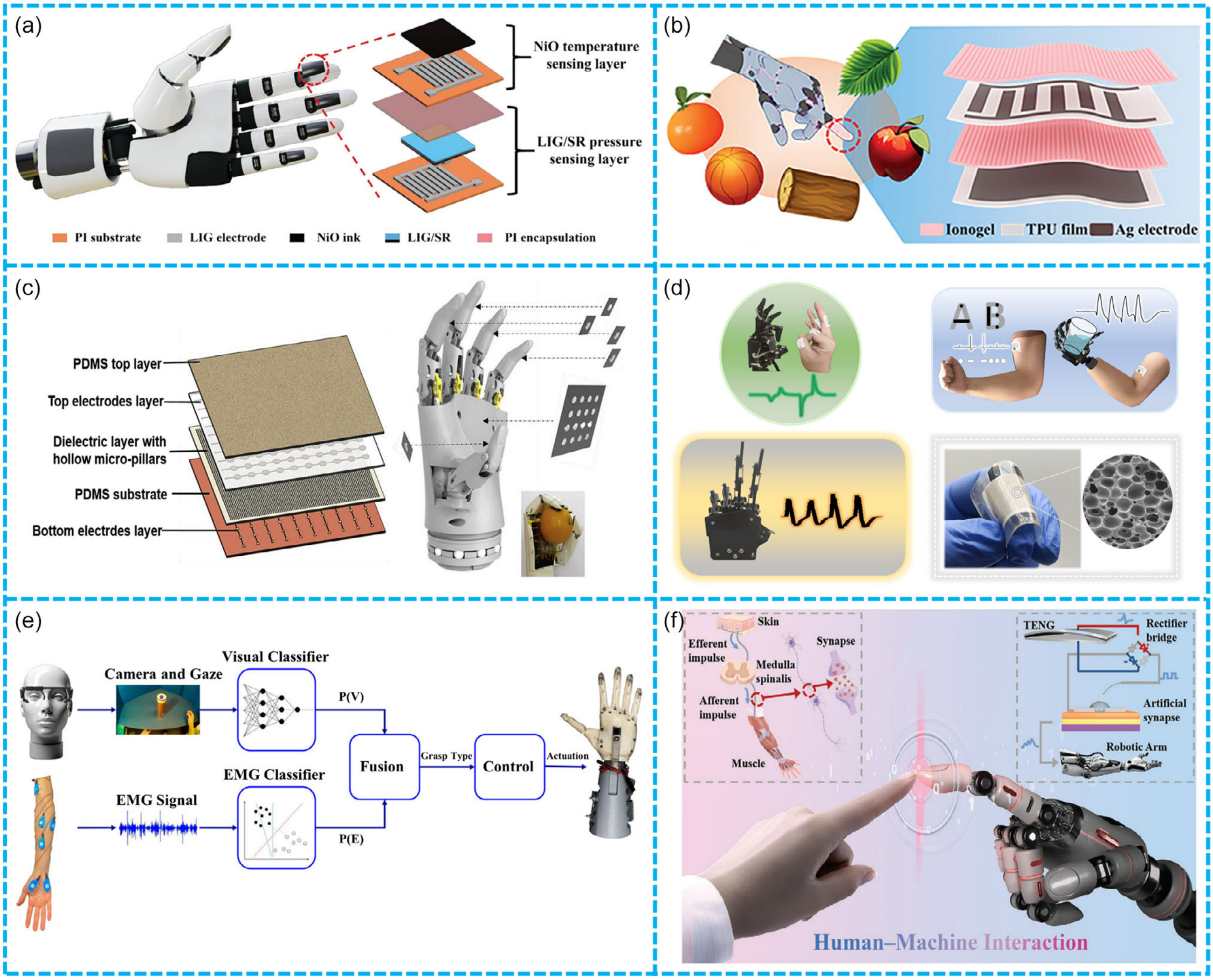

FIGURE 5 | Various sensing and control systems for prosthetic applications. (a) Hierarchical pressure-temperature bimodal sensing system for accurate object classification. Reproduced with permission [180]. Copyright 2023, Wiley. (b) An artificial sensory system emulating human touch for recognition of material types, surface roughness, and contact pressure. Reproduced with permission [181]. Copyright 2024, Wiley. (c) A stretchable dual-mode sensor array integrated into a prosthetic hand for proximity, pressure, and strain sensing. Reproduced with permission [182]. Copyright 2019, Elsevier. (d) Piezoelectric sensor-based prosthetic control using smart threshold-based algorithms. Reproduced with permission [57]. Copyright 2024, Wiley. (e) Multimodal tactile sensing fused with computer vision. Reproduced with permission [183]. Copyright 2024, Frontiers Media SA. (f) Triboelectric based artificial synaptic transistor for controlling prosthetics biomimetically. Reproduced with permission [184]. Copyright 2023, Wiley.

demonstrating a huge prospect in intelligent prosthetics. Moreover, Sundaram et al. designed a scalable tactile glove with 548 piezoresistive sensors and deep convolutional neural networks for object recognition, weight estimation, and tactile pattern analysis [185]. Recent advancements in triboelectric technology have also spurred the development of diverse multimodal sensing systems for prosthetics by integrating triboelectric mechanisms with other sensing modalities. For example, Ma et al. developed a smart skin that integrated triboelectric-hygroelectric sensing with ML to simultaneously detect pressure, vibration, and humidity for applications in robotics and prosthetics [186]. Xia et al. proposed a biomimetic electronic skin based on a micro-frustum ionogel, leveraging iontronic capacitive and triboelectric mechanisms alongside ML to achieve high-sensitivity multimodal perception of material properties and contact pressures (Figure 5b) [181]. In addition, Li et al. proposed a flexible dual-modal sensor using a 'neutral surface' structural design technique to integrate a capacitive PDMS/$BaTiO_3$-based temperature sensing layer and a resistive $Ni_{80}Cr_{20}$-based strain sensing layer, thereby enabling independent detection and effective decoupling of temperature and strain signals [187]. This sensor exhibited excellent temperature and strain sensing capabilities with high sensitivity, broad measurement ranges, and fast response time, highlighting its potential for advanced tactile perception in intelligent prosthetics. Zhang et al. also developed a stretchable dual-modal sensor array integrating cross-grid liquid metal electrodes with micro-structured dielectric layers for multifunctional prosthetic robotic systems, providing complementary capacitive sensing for high-pressure and proximity detection and triboelectric sensing for highly sensitive low-pressure tactile measurements (Figure 5c) [182]. In addition, Osborn et al. developed a bioinspired multilayered electronic dermis that mimicked mechanoreceptor and nociceptor functions to enable continuous tactile perception of both innocuous and harmful stimuli [188]. The neuromorphic interface integrated sensory feedback and pain reflex controls to allow amputees to distinguish object curvature and sharpness while advancing naturalistic tactile perception in prosthetic systems.

In summary, innovative sensing strategies have evolved prosthetic perception from basic, unimodal systems to sophisticated, multimodal platforms that facilitate real-time environmental awareness and adaptive interaction. By integrating diverse sensor modalities with flexible materials and AI-driven adaptive algorithms, these sensing systems provide enhanced sensory–motor integration and natural user–prosthesis interaction. Future advancements will prioritize seamless human–device integration through self-powered systems and AI-enhanced cognitive haptics, advancing prosthetics toward biomimetic sensory autonomy in dynamic environments.

4.1.2 | Prosthetic Control

Early stages of prosthetics primarily served as decorative replacements for missing body parts, such as rudimentary wooden limbs [189]. Technological advancements eventually led to body-powered prosthetic limbs, such as shoulder-driven controlled prosthetics. Today, advances in electronics and power systems have enabled amputees to use externally powered prosthetics by equipping the affected limb with sensors, enhancing functionality and synergizing user control. In addition, flexible sensors further evolve the control system of prosthetics by conformably attaching to different body parts and outputting adaptive signals. The use of flexible sensors enables a more scalable and customizable sensing system that gathers unique biosignals from users that are then converted into commands for controlling prosthetics. Control algorithms play a crucial role in translating these biosignals into precise and responsive prosthetic movements by processing the acquired signals. These algorithms enable seamless interaction between the user and the prosthetic device, ensuring that movements are accurate, effective, and intuitive. With the majority of flexible sensor-based prosthetic control systems categorized as either electromechanical or electrophysiological sensing systems, their control algorithms can be mainly divided into four parts: threshold-based control, proportional control, proportional-integral-derivative (PID) control, and pattern recognition.

Control strategies for prosthetic movement vary in complexity, ranging from basic to advanced approaches. Threshold control is the simplest method for prosthetic movement, relying on signal value-based ‘if statement’ commands to trigger ON-OFF responses for basic binary activation [190–192]. Jiang et al. introduced a porous piezoelectric sensor that uses muscle clenching to generate voltage pulses, which are translated into preset commands for Morse Code or multi-clench gestures for object manipulation (Figure 5d) [57]. Despite its versatility, threshold control lacks real-time adaptability and proportional force modulation, making it unsuitable for complex flexible sensor-based prosthetic applications. To enhance adaptability and user intent recognition, proportional control builds upon threshold-based methods by adjusting prosthetic forces based on biosignal intensity to allow for more fluid and natural interaction [193, 194]. However, precise tuning is necessary to maintain an accurate proportional relationship between sensor signals and prosthetic output. As a more advanced closed-loop control strategy, PID control continuously refines prosthetic movement through proportional, integral, and derivative terms, ensuring smoother and more stable operation [195]. Duan et al. implemented a PID-based EMG or EEG controller for stable grip force regulation [196], while Gohain et al. developed an adaptive PID system integrating force-sensing resistors and kinematic sensors for real-time slip prevention [197]. Although more effective than threshold and proportional control algorithms, some traditional PID control methods still require manual tuning and need carefully dealing with nonlinear sensing systems [198, 199]. Beyond that, advanced strategies like Fuzzy Logic and self-tuning PID can enhance adaptability, improving responsiveness and reliability in prosthetic applications.

While traditional control algorithms improve reliability and precise feedback-based adaptation, their limitations in handling dynamic, nonlinear interactions and individual user variations highlight the need for more advanced approaches. To overcome these challenges, AI-driven closed-loop pattern recognition methods leveraging ML algorithms such as nonlinear regression (NLR), multilayer perceptron (LP), LDA, Decision Tree, and SVM have emerged, offering adaptive, predictive, and personalized control for flexible sensor-based prosthetics [200–204]. Among these, SVM can achieve the highest accuracy with specialized kernels but demands significant computational resources, limiting its suitability for embedded applications. MLP similarly delivers high accuracy yet requires substantial memory and processing power. LDA is computationally efficient and widely used but struggles to capture nonlinear relationships, restricting adaptability for complex movements, and conversely, NLR provides an optimal trade-off between accuracy and computational cost, making it particularly suitable for embedded systems despite needing careful optimization to prevent overfitting. Marinelli et al. comparatively evaluated these algorithms for controlling the Hannes prosthetic hand, demonstrating that NLR offered performance comparable to LDA while significantly reducing sensor quantity and system complexity, thus highlighting its effectiveness for real-time prosthetic control [205]. Recently emerging as more sophisticated solutions, DL methods including CNN, RNN, and LSTM have expanded beyond ML to further enhance prosthetic control through advanced feature extraction, adaptability, and superior responsiveness to complex neuromuscular signals. Zbinden et al. developed a DL-based system comparing shallow and deep neural networks for real-time motor intent decoding [206]. Their study demonstrated that deep models, integrating CNN with squeeze and excitation module (CNN-SE) architectures, significantly outperformed shallow networks, achieving superior precision and robustness in real-time prosthetic limb control during human-in-the-loop testing. Furthermore, DL methods excel in multimodal sensor integration, significantly benefiting flexible sensor-based prosthetics [207, 208]. Zandigohar et al. proposed a multimodal fusion framework combining CNN-based visual grasp intent classification with sEMG-based gesture recognition via an extra-trees ensemble, achieving an impressive accuracy of 95.3% through Bayesian fusion (Figure 5e) [183]. These results underscore the transformative impact of integrating AI algorithms and multimodal sensor fusion, enabling prosthetic systems to achieve unprecedented adaptability, precision, and real-time responsiveness.

Despite advances in these control algorithms, conventional flexible sensor-based prosthetics still rely on external hardware computing and predefined processing frameworks, limiting their biological realism and real-time processing efficiency. To overcome these challenges, flexible synaptic transistors, which integrate memory and computation at the hardware level, are gaining attention for enabling more seamless and biomimetic prosthetic control by mimicking biological synapses. This is due to those artificial synaptic transistors that can similarly transform the input pulse signals into real synaptic-like responses. Moreover, to potentially offer self-learning abilities for prosthetics, the artificial synaptic transistors can mimic synaptic plasticity, which is the ability of biological synapses to strengthen or weaken over time in response to neuron activity levels [209]. Currently, researchers have increasingly utilized triboelectric sensors to trigger synaptic responses that precisely control the prosthetics, in which the sensors simultaneously work as both the flexible sensing system and input pulse suppliers [210]. Geng et al. proposed an artificial neuromuscular system for bimodal HMI by integrating triboelectric sensors, SnErOx neuromorphic transistors (SENTs), and a signal-converting system (Figure 5f) [184]. The system mimicked biological neuromuscular processes, enabling muscle contraction, muscle fiber shift, muscle movements, and transformation of neuron communication from the input signals of the triboelectric sensor. Both contact-based and non-contact-based HMI were employed using sEMG decoding and supercapacitive iontronic effects respectively. The proposed system achieved real-time gesture recognition and robotic manipulation, offering a pathway for next-generation interactive electronics with multimodal interaction capabilities. Similarly, Park et al. developed a multi-layered triboelectric sensor that generated multiple voltage pulses from a single touch for low-power artificial synaptic devices [211]. By integrating micropatterned PDMS and $BaTiO_3$ composite films, the triboelectric sensor enhanced charge generation and storage, and coupled with an organic electrochemical transistor (OECT), it also replicated biological synaptic plasticity to enable memory training in robotic hands and to further provide huge potential in neuromorphic computing, human–machine interfaces, and self-powered electronic applications. Overall, such advancements lay the foundation for next-generation bioinspired interactive electronics, facilitating seamless real-time decision-making and adaptive multimodal interaction to help realize the development of intelligent,

In summary, flexible sensor-based HMIs have demonstrated significant potential in advancing prosthetic applications by integrating adaptive mechanisms with high-performance sensing and control capabilities, as summarized in Table 3. The sensing systems exhibit key features such as reliable sensing responses with minimal hysteresis, high accuracy in real-time signal acquisition, and multimodal signal detection comprising of pressure, strain, temperature, and electrophysiological modalities for comprehensive perception and closed-loop movement control. Their applications span precise gesture recognition for natural prosthetic movements, real-time force feedback for enhanced control precision, and neural signal interpretation to support seamless closed-loop operation, thereby improving prosthetic responsiveness and functionality significantly. For flexible sensor-based prosthetic systems, they achieve response times typically ranging from 10 to 170 milliseconds (ms), enabling near real-time adaptation to dynamic user inputs. Enhanced stability is also attained through advanced structural engineering techniques, with engineered devices enduring over 10,000 cycles, thereby ensuring long-term durability and reliability. Furthermore, the integration of ML-augmented signal processing substantially improves control accuracy, effectively overcoming traditional limitations in conventional prosthetics and paving the way for more natural and responsive user interactions. The convergence of these attributes enables natural replication of limb movements and bidirectional sensory feedback that provide a transformative pathway for developing intuitive, patient-specific prosthetic solutions.

Despite promising performances in laboratory settings, such as rapid response, high sensitivity, and robust durability, current evaluations of flexible sensor-based HMIs remain largely confined to controlled environments, with limited validation in real medical robotic contexts. Key performance metrics like sensitivity and durability are often derived from idealized tests that do not reflect complex, real-world conditions. Dynamic loading scenarios such as joint movement, repeated deformation, and multidirectional stress may degrade sensor performance over time, yet these effects remain underexplored. Similarly, prolonged use can introduce sensitivity decline, signal drift, material fatigue, and delamination, yet long-term reliability data under real-use conditions remain scarce. In addition, biocompatibility remains a critical yet often overlooked aspect in current research. Although many sensors employ biocompatible materials or encapsulation layers such as PDMS, most sensing systems have not undergone standardized or clinical-level biocompatibility testing, leaving their long-term safety with skin-contact or implantable applications uncertain. Furthermore, sterilization compatibility remains a challenge, as most sensors can withstand only basic disinfection, with few capable of enduring clinical sterilization protocols without functional degradation, thus limiting their suitability for prosthetic applications. To advance clinical translation, future work must prioritize comprehensive validation under realistic conditions, integrating biocompatibility certification, dynamic mechanical testing, long-term performance monitoring, and sterilization resilience, which can ensure that flexible sensor-based HMIs are safe, durable, and effective for real-world medical robotics applications. In addition to these application-related gaps in developing flexible sensor-based prosthetics, there are ongoing technical hurdles in reconciling sensor miniaturization with high-resolution signal capture, maintaining robust signal interpretation under mechanical and environmental noise, and optimizing energy efficiency without compromising computational performance. Addressing these limitations requires future research to focus on innovative material and structure design, multimodal sensor fusion, adaptive control systems driven by ML algorithms, and bioinspired neural interfaces to improve prosthetic responsiveness and emulate natural human movement.

4.2 | Adaptive Exoskeleton Systems

Robotic exoskeletons represent an emerging technology within the field of HMI, functioning in tandem with flexible sensors to effectively assist human users. Exoskeletons, also referred to as exosuits, are wearable assistive devices designed to augment the user's musculoskeletal system by exerting external

TABLE 3 | Comparison of flexible sensor-based HMI for prosthetic applications.

References	Sensing Mechanism	Key feature	Application	Response time	Sensitivity	Detection range	Durability	Accuracy	Biocompatibility
[44]	Triboelectric	• Cost-effective • Scale-up capable • Highly stable	• Pressure detecting	—	• 7.78 mV kPa^{-1}	• 40–200 kPa	• 10000 cycles	—	Yes
[176]	Capacitive	• Large area • High performance	• Pressure sensing • Object recognition	• 90 ms	• 0.141 kPa^{-1}	• 0–190 kPa	• 7000 s	• 95.14%	—
[179]	Piezoresistive-capacitive	• Wide detection range • Low cost • Simple fabrication	• Proximity detection • Human behavior monitoring • Ultra high-pressure detection	• 120 ms	• Capacitive mode: 1.65 kPa^{-1} (<0.1 kPa), 0.051 kPa^{-1} (0.1-25 kPa), and 0.0054 kPa^{-1} (25-600 kPa) • Piezoresistive mode: −0.0043 kPa^{-1} (600-800 kPa), −0.0004 kPa^{-1} (800-1100 kPa), and −0.000004 kPa^{-1} (1100-2000 kPa)	• 0–2000 kPa	• Capacitive mode: 2000 times • Piezoresistive mode: 1000 times	—	—
[181]	Capacitive-triboelectric	• High sensitivity • Wide detection range • High accuracy	• Material recognition • Surface roughness • Contact pressure	• 10 ms	• 357.56 kPa^{-1}	• 0–500 kPa	• 10000 cycles	• Capacitive mode: 94.8% • Triboelectric mode: 100%	—
[187]	Capacitive-resistive	• Cost-effective		• 54 ms	• −160.90 fF °C^{-1}	• 30–200°C	• 200°C	—	—

(Continues)

TABLE 3 | (Continued)

References	Sensing Mechanism	Key feature	Application	Response time	Sensitivity	Detection range	Durability	Accuracy	Biocompatibility
		• High resolution • High sensitivity and linearity	• Temperature and strain sensing			• 20–1000 με	• 1000 cycles		
[182]	Capacitive-triboelectric	• High sensitivity and linearity • Multifunctionalit • Facile fabrication	• High-pressure sensing • Proximity detection • Low-pressure tactile measurement	• Capacitive mode: ~170 ms • Triboelectric mode: ~140 ms	• Capacitance mode: 1.4 MPa^{-1} (10 kPa-20 kPa) and 0.5 MPa^{-1} (20 kPa-120 kPa) • Triboelectricity mode: 1.04 V kPa^{-1} (<5 kPa) and 0.16 V kPa^{-1} (5–10 kPa)	• 0–120 kPa	• 500 cycles	—	—
[57]	Piezoelectric	• Smart threshold control • Increased computational efficiency • High flexibility and breathability	• Gesture conveying • Object manipulation • Morse Code communication	• 65ms	• 38.4 mV kPa^{-1}	—	• 10000 cycles	—	—
[211]	Triboelectric, artificial synaptic transistor	• Synaptic memory	• Robotic prosthetics control	—	• 0.38 V kPa^{-1} (0.098–9.8 kPa) and 0.01 V kPa^{-1} (9.8–98 kPa)	• 0.098–98 kPa	• 10000 cycles	—	—

mechanical forces through actuators that enhance the user's strength, endurance, or mobility [212]. While exoskeletons are primarily utilized in medical applications such as physical rehabilitation, they also hold significant potential in industrial settings, where mechanical performance can be enhanced and the risk of injury can be reduced by targeting the exoskeleton to specific areas of the body, including the upper and lower limbs and back muscles. For exoskeleton applications, HMI is crucial for capturing and interpreting the user's physiological signals such as muscle activity and joint movements to enable intuitive control and seamless integration between the user and the device. Central to this interaction are flexible sensors, which serve as a key enabling technology for HMI-enabled exoskeletons and play a vital role in healthcare and rehabilitation. These soft, adaptable, and durable devices excel at detecting physical phenomena like force and pressure, allowing for precise detection of user inputs while maintaining compatibility with clothing and wearable systems, ensuring both functional performance and ergonomic integration [213]. They are also instrumental in recording critical data for both monitoring user progress during rehabilitation and assisting in actuating exoskeletons for task-specific operations [214]. The implementation of flexible sensors constructed from soft, lightweight materials alleviates these issues, thereby enhancing comfort, wearability, and ergonomic acceptance during prolonged exoskeleton applications. When further integrated with AI technologies, such as DL algorithms, these systems enable accurate intention recognition and fast response, effectively reducing muscular effort and facilitating intuitive user control in real-world scenarios [215]. For this section, the application of flexible sensors in robotic exoskeletons will be further explored across healthcare, mobility support, and industrial domains.

4.2.1 | Enhancing Healthcare and Rehabilitation

Robotic exoskeletons play a pivotal role in enhancing healthcare and rehabilitation by augmenting mobility restoration in impaired or injured individuals. They usually integrate advanced sensor technologies and real-time control systems to continuously monitor and regulate movements, allowing for personalized and adaptive rehabilitation protocols that significantly improve therapeutic outcomes. Exoskeletons serve multifaceted roles in healthcare and rehabilitation, with muscular rehabilitation considered a core function that enhances muscle strength, coordination, and functional recovery through mechanized assistance or resistance training. These systems enable quantitative functional sensing assessment through various flexible sensors, which can detect electrical signals or mechanical movements in the user's body.

Specifically, the hand exoskeleton can sense movement in the user's body and provide a physical therapy in the form of strength training if the user lacks muscular control, thus retraining muscles and neural pathways and enabling proper muscular rehabilitation. Kladovasilakis et al. developed a soft robotic hand exoskeleton system using flexible sensors for physical therapy based on mirror therapy principles (Figure 6a) [216]. The system included a control glove and a soft exoskeleton glove, where soft flexible sensors captured finger motions in the healthy hand, and actuators replicated them in the affected hand using pneumatic control. Clinical trials demonstrated the system's ease of use, comfort, and effectiveness in improving force output and motion accuracy for stroke and neurological disorder patients. Chen et al. introduced a wearable hand rehabilitation system combining mirror therapy and task-oriented therapy using sensory and motor gloves made of soft, flexible materials for enhanced comfort and safety [220]. ML enabled accurate gesture recognition (93.32% for 16 finger gestures) and real-time task-oriented rehabilitation (89.4% accuracy), allowing for precise, fine-grained finger training and coordinated movements. Building on these advancements, integrating flexible sensors with exoskeleton systems further augments virtual reality (VR)-based rehabilitation by immersive exercise environments, accurate motion monitoring and correction, tailored training programs, and increased patient engagement through gamification. In addition, Wang et al. developed a fully flexible multimodal HMI interface using hydrogel-based sensors and a flexible circuit board to accurately collect and decode EMG and FMG signals with AI assistance (Figure 6b) [11]. This system achieved a gesture recognition accuracy of 91.28% with only two channels, enabling precise control of a pneumatic robotic glove for stroke rehabilitation and broader applications in intelligent robotic systems.

In addition to exoskeletons centered around the hands, other upper-body exoskeletons have also proven effective in rehabilitation for neurological disorders or afflictions, aiming to assist in muscular support, resistance training, and corrective therapy. Paredes-Acuña et al. developed a lightweight upper-limb exoskeleton with sEMG sensors and robotic skins to monitor user intent and enhance therapy, serving as an alternative to traditional physical therapy [221]. The device reduced muscular load by 40% during assisted exercises and increased muscular activation by 30% during resistive therapy, demonstrating its dual role in muscular assistance and rehabilitation. In addition, Bhatia et al. designed a gravity support device for shoulder rehabilitation using an origami-based structure integrated with foldable triboelectric sensors [222]. The rehabilitation tasks were based on the exercise-gaming approach, where the triboelectric sensors served as self-powered sensors for gaming tasks and energy harvesters for exercise tasks. This device effectively demonstrated an improved range of motion for the upper arms of stroke patients, indicating its potential for home-based tele-rehabilitation. Along with the advancements of upper limb exoskeletons, lower limb exoskeletons are also in high demand to address mobility challenges and enhance gait performance.

Another major challenge for lower limb exoskeleton design is ensuring a sustainable and lightweight energy supply, as high-precision sensors and power-outputting machinery require significant energy. To resolve this, Hu et al. developed a knee joint exoskeleton with a magnetic-driven piezoelectric cantilever generator that converted mechanical energy to electrical energy during usage (Figure 6c) [217]. This system not only powered sensors but also integrated a joint angle sensing module for joint activity and rehabilitation tracking, improving efficiency while reducing battery dependency. Pan et al. electrospun piezoelectric PVDF fibers to develop a mechanomyography sensor, which was integrated with interdigitated electrodes and applied to detect the human body motion for the lower limb rehabilitation exoskeleton [223]. This sensor demonstrated a high signal amplitude and signal-to-noise ratio, thereby enhancing the sensitivity and

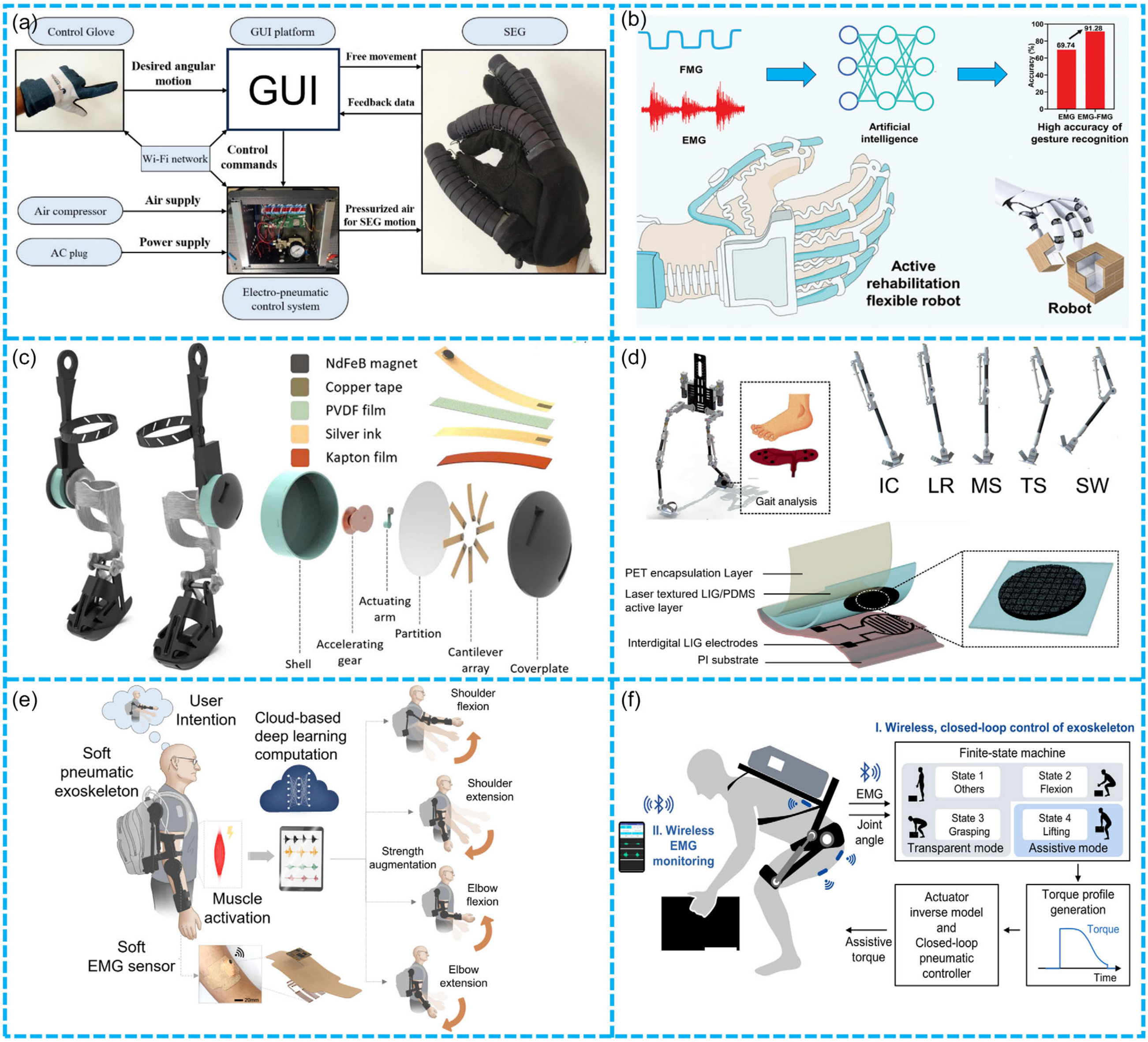

FIGURE 6 | Flexible sensor-based HMIs for adaptive exoskeleton applications. (a) A soft exoskeleton glove for hand rehabilitation and assistance purposes. Reproduced with permission [216]. Copyright 2022, MDPI. (b) Multimodal HMI integrated with hydrogel-based EMG and pressure sensors for active rehabilitation. Reproduced with permission [11]. Copyright 2024, Wiley. (c) Wearable exoskeleton system integrated with a magnetic-driven piezoelectric cantilever-based generator for energy harvesting and knee joint rehabilitation training. Reproduced with permission [217]. Copyright 2022, ACS. (d) Flexible LIG-based wearable exoskeleton for walking gait recognition. Reproduced with permission [218]. Copyright 2024, Springer Nature. (e) DL-driven upper-body exoskeleton for force augmentation. Reproduced with permission [215]. Copyright 2024, Springer Nature. (f) Stretchable microneedle adhesive patch-based lower-body exoskeleton for lifting leg force support. Reproduced with permission [219]. Copyright 2024, American Association for the Advancement of Science.

effectiveness of the lower limb rehabilitation exoskeleton in movement assistance. Li et al. also developed an HMI-enabled lower limb exoskeleton that integrated multimodal biosignals, specifically EEG and sEMG signals, to accurately interpret user motion intentions [224]. Through precise, adaptive, and personalized interventions, flexible sensor-based robotic exoskeletons are transforming healthcare and rehabilitation by bridging real-time sensing with personalized therapeutic actions. Future advances in AI-driven control, lightweight energy-harvesting designs, and multimodal sensor integration will further boost responsiveness and precision of robotic exoskeletons.

4.2.2 | Human-Centric Mobility Assistance and Augmentation

Other than for rehabilitation purposes, exoskeletons can also be designed for mobility support to enhance human movement by reducing physical strain, improving gait efficiency, and providing adaptive assistance. These systems aim to enhance gait efficiency, stability, and endurance by integrating sensors that monitor muscle activation, foot pressure distribution, and joint kinematics [218, 225, 226]. By leveraging wearable gait recognition sensors and tactile-based gait phase detection, mobility-assisting exoskeletons can dynamically adjust joint torque and support levels based on real-time feedback, enabling natural and intuitive movement patterns for users [218]. Unlike force augmentation exoskeletons, which primarily target upper-limb applications, mobility-assisting exoskeletons prioritize lower-limb function, making them particularly valuable for elderly individuals [227, 228]. To develop flexible sensing systems for lower-limb exoskeletons, researchers have explored triboelectric, and piezoresistive pressure sensors to provide high-resolution force detection and muscle activity monitoring while also maintaining comfort and durability [212, 226]. These sensors are often embedded in smart insoles, or sensor-integrated exoskeleton joints, enabling continuous gait phase classification and movement adaptation [218, 226]. With flexible sensing systems delivering real-time physiological and biomechanical data, advanced control strategies such as fuzzy logic control and other DL-based motion predictions are progressively being utilized to improve gait pattern recognition and optimize assistance levels [226, 228]. For instance, Sun et al. developed laser-engraved wearable gait recognition sensors that demonstrated an accuracy of 99.85% in real-time gait classification, significantly improving human–exoskeleton interaction for mobility assistance (Figure 6d) [218]. Moreover, adaptive actuation mechanisms, such as soft pneumatic actuators, variable stiffness actuators (VSAs), and cable-driven actuators, are central to the functionality of mobility-assisting exoskeletons since they can modulate joint support based on real-time sensor feedback [216, 225]. A recent study proposed by Zhang et al. introduced a hip exoskeleton controlled via soft pneumatic force sensors, enabling seamless transition between gait assistance, resistance, and transparent modes for daily mobility assistance [227]. Similarly, triboelectric bidirectional sensors have also been incorporated into exoskeletons to provide multi-degree-of-freedom motion tracking, allowing users to navigate real and virtual environments with improved precision [212].

Unlike mobility-supporting applications, exoskeletons designed for force augmentation focus on enhancing a user's strength, endurance, and load-carrying capabilities. These systems provide mechanical reinforcement to the musculoskeletal system, enabling individuals to lift heavier loads, sustain physically demanding tasks for extended periods, and reduce muscle fatigue. By utilizing flexible sensors for real-time biomechanical feedback and adaptive force-distribution mechanisms that dynamically adjust load assistance, force-augmenting exoskeletons help redistribute strain across multiple muscle groups, reducing localized fatigue and minimizing the risk of overexertion-related injuries. Such exoskeletons are particularly valuable in industrial, military, and labor-intensive work environments. The majority of force augmentation exoskeletons are designed for the upper limbs, as many physically demanding tasks such as lifting and carrying heavy loads and tool operation primarily rely on arm and shoulder strength [229]. Recently, soft exoskeletons, defined as a lightweight, flexible wearable system that provides assistive force augmentation using soft materials, have been gaining increasing attention due to the ongoing need for ergonomic solutions [230]. To build flexible sensing systems for soft exoskeletons, various flexible sensors such as piezoresistive, piezoelectric, and capacitive sensors have been developed, facilitating accurate and responsive sensing and motion control [231–233]. The working process for upper-limb exoskeletons typically involves sensor input, signal processing, actuation, and feedback loop control. With flexible sensing systems providing real-time data, control algorithms play a crucial role in processing these signals to generate precise and adaptive assistance, ensuring smooth and intuitive exoskeleton performance. Upper-limb exoskeletons employ various control algorithms to ensure precise, adaptive, and intuitive assistance, in which PID-based controls are commonly used for trajectory stabilization and movement tracking while adaptive impedance control dynamically adjusts stiffness and force based on user interaction [234–237]. Currently, more advanced systems integrate ML and AI-based prediction to anticipate user intention using bioelectronic signals, enhancing real-time responsiveness. At the end of each control cycle, different actuation mechanisms, such as pneumatic actuators or cable-driven actuators will then be triggered to assist users for force augmentation. Lee et al. proposed an intelligent DL-driven control algorithm for an upper-limb exoskeleton that enables real-time, intention-driven strength augmentation (Figure 6e) [215]. Their system leveraged soft wearable bioelectronic sensors to capture muscle activity, which was processed through a cloud-based DL model to predict user intentions with an accuracy of 96.2% within 500–550 ms. The predicted motion commands were then executed by soft pneumatic artificial muscles, providing a force of 897 N and a displacement of 87 mm to assist upper-limb movements and significantly reducing muscle activity by a factor of 3.7, ultimately highlighting its potential to enhance mobility control based on user intentions.

While upper-limb exoskeletons focus on enhancing arm strength for various daily tasks, lower-limb exoskeletons also play a crucial role in force augmentation for lower-body endurance and load-bearing support, particularly in industrial applications. By leveraging flexible sensing systems, lower-limb exoskeletons can continuously monitor a user's motion conditions in real time, assessing parameters such as joint angles, muscle activity, posture stability, and force exertion. This real-time motion analysis enables the exoskeleton to accurately interpret the user's intention and biomechanical state, ensuring that the assistance is adaptive, natural, and seamlessly integrated into their movement. Kim et al. proposed a stretchable microneedle adhesive patch (SNAP) for reliable electrophysiological sensing and exoskeleton robot control, which integrated a stretchable platform with serpentine interconnects and silicon microneedle arrays to penetrate the stratum corneum without reaching pain receptors (Figure 6f) [219]. The electrically conductive adhesive composed of silver flakes and high-tack silicone ensured secure skin adhesion and low impedance even under dynamic motion and skin contamination. Compared to existing gel-based and flexible microneedle electrodes, SNAP exhibited superior mechanical adaptability, reduced motion artifacts, and improved user comfort during long-term use. After processing the user's movement patterns, exoskeletons precisely control actuators to reduce fatigue during prolonged activity or enhance force while lifting heavy loads to prevent overexertion. Compared to upper-limb exoskeletons that provide supplementary strength for lifting and carrying objects, lower-limb exoskeletons assist in walking long distances, providing leg force support, navigating uneven terrain, and reducing joint stress. These capabilities are particularly beneficial in physically demanding fields such as construction, military operations, and healthcare. Additionally, the integration of flexible sensors into exoskeleton systems has revolutionized the sensing accuracy, exoskeleton responsiveness, and overall user experience. By embedding such sensors into the exoskeleton's joint structures and limb attachments, real-time motion detection, force distribution, and biomechanical feedback can be improved to provide more precise and adaptive assistance, making the overall integrated system an invaluable tool for enhancing human–machine interfacial performance in everyday tasks.

4.3 | Human–Robot Synergy in Surgical Systems

As a medical intervention, surgery is a procedure involving invasive manual or instrumental techniques to diagnose, treat, or repair physiological conditions through targeted alteration of tissues or organs. Traditional open surgery, characterized by relatively large incisions, offers direct access to internal organs but is associated with significant drawbacks such as increased trauma, extended recovery periods, and higher risks of infection and postoperative complications for patients [238]. Minimally invasive surgery, including techniques such as laparoscopic and endoscopic procedures, reduces these issues by minimizing incision sizes and facilitating faster recovery. However, they still highly rely on the surgeon's manual dexterity, which may fall short in achieving the micro-level precision required for complex or delicate procedures due to factors like hand tremors and fatigue. To address those issues, robotic-assisted surgeries are presented as an advanced evolution of minimally invasive surgery, incorporating a patient-side robotic platform, a surgeon's console, and an integrated sensing and feedback system. They can enhance surgical precision and enable complex procedures with minimal tissue trauma, reduced postoperative pain, accelerated recovery, and lower infection risks while simultaneously improving surgeon ergonomics, mitigating fatigue, and ensuring real-time adaptability during prolonged operations [239]. In the robotic-assisted surgical context, flexible sensors serve as critical components that can facilitate seamless interaction between surgeons and robotic instruments. Their superior flexibility and mechanical conformability allow them to closely interface with various tissues, enabling precise monitoring of tool-tissue interactions and accurate quantification of the mechanical properties of biological tissues, which in turn improves tactile feedback. Additionally, these sensors enable real-time monitoring of physiological signals to improve surgical control and reduce the impact of tremors and fatigue. Furthermore, they can continuously track surgeon performance and patient vital signs, ensuring optimal clinical outcomes and patient safety. This section systematically examines flexible sensor-based surgical robotics through two distinct functional paradigms: surgical tactile perception and force feedback, and electrophysiological monitoring for surgical control and safety.

4.3.1 | Sensor-Integrated Tactile Perception and Force Feedback for Precision Surgery

In conventional open surgeries, surgeons have direct access to the surgical site and can diagnose tissue abnormalities through physical palpation. This direct tactile interaction provides essential feedback that aids in nuanced tissue assessment. However, in traditional robot-assisted minimally invasive surgeries, the absence of direct haptic feedback poses a significant challenge in accurately identifying various tissue structures. To address such issues, tactile sensing has emerged as an effective surrogate for palpation in advancing surgical robotics, which can offer the ability to perceive and interpret physical interactions during surgery operations. By mimicking the sense of touch, tactile sensors provide crucial mechanical information such as stiffness and elasticity when embedded in robotic surgical systems, enabling surgeons to detect anomalies by remotely differentiating between soft and hard tissues, as it is essential for delicate and minimally invasive procedures. For example, tissue stiffness, often increased in cancerous tissues, serves as a key marker for malignancy due to changes in tissue composition and heterogeneity during cancer development [239]. Real-time detection of tissue stiffness via surgical robot systems allows surgeons to precisely delineate tumor margins and assess cancer progression during surgeries. This capability provides a significant advantage over blood tests and imaging procedures, which often fall short in capturing local tissue mechanical properties.

Building on these clinical benefits, researchers have introduced a range of flexible sensor-based innovations to seamlessly integrate tissue stiffness assessment into robotic surgery. Nguyen et al. developed a single-chip elasticity sensor using microelectronic-mechanical systems (MEMS)-based piezoresistive cantilevers with different tactile properties for use in robotic hand manipulation and tissue stiffness discrimination in minimally invasive surgery (Figure 7a) [240]. Talasaz deployed DL models to characterize tissue stiffness properties during telerobotic palpation and localization of tissue abnormality while estimating its depth [246]. This method utilized a minimally invasive probe with a mounted capacitive tactile sensor at the tip to capture the pressure distribution map and the indentation depth for each tactile element, thereby generating a stiffness map for the palpated tissue. To overcome the challenge of precisely localizing tumors and identifying their boundaries in minimally invasive en bloc tumor resection, Hong et al. proposed a piezoelectric-based tactile sensor integrated onto a robotic endoscopic injection needle to detect tissue hardness through changes in resonant frequency [247]. They developed an autonomous boundary recognition algorithm to improve the accuracy of tumor localization and boundary identification. In addition to the advances in real-time tissue stiffness monitoring, some innovative approaches that integrate advanced robotic technology with precise tissue detection have also demonstrated enormous potential. For example, continuum robots have garnered significant attention in recent years owing to their high flexibility and multiple degrees of freedom that have led to potential applications in confined-space procedures and minimally invasive surgery. However, they face limitations in accurately detecting and responding to collisions due to their lack of advanced tactile perception. To address this, Sun et al. proposed a self-powered triboelectric tactile perception ring that can sense tiny collision pressures in four directions [248]. This sensor can be integrated into each joint of the continuum robot to detect collisions and adjust posture, demonstrating the ability of obstacle avoidance and adaptive crawling. For high sensitivity, durability, and real-time feedback in robotic surgeries through physical palpitation, tactile sensing technologies can empower robotic systems to interact safely and effectively with the complex and variable environments within the human body. Future developments are expected to focus on integrating multimodal tactile sensing with AI technology to enable real-time,

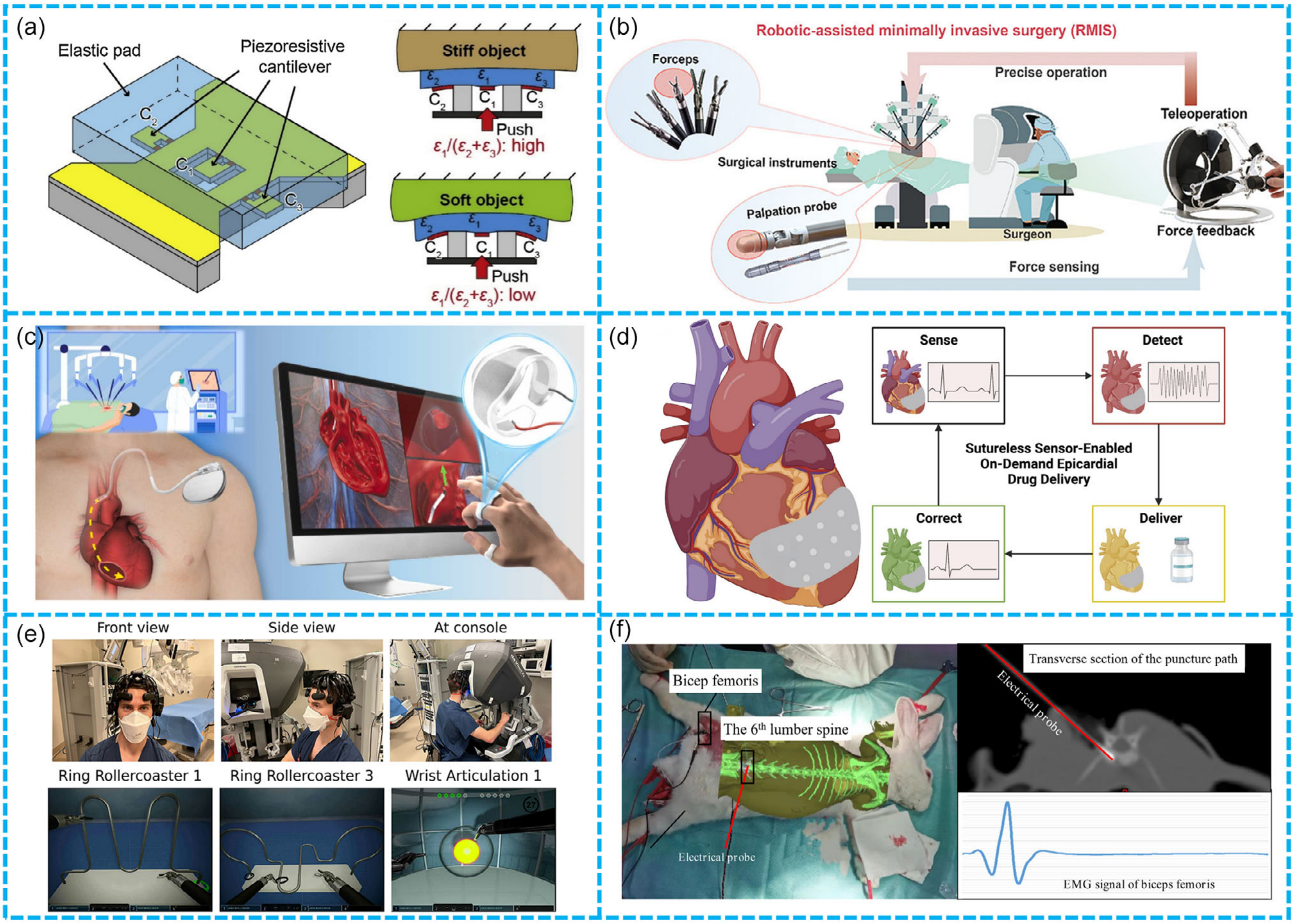

FIGURE 7 | Advanced sensor-integrated technologies for surgical robotic applications. (a) A single-chip elasticity sensor using MEMS-based piezoresistive cantilevers for robotic hand manipulation and tissue stiffness discrimination in minimally invasive surgery. Reproduced with permission [240]. Copyright 2019, Elsevier. (b) A highly integrated 3D MEMS force sensing module with variable sensitivity for robotic-assisted minimally invasive surgery. Reproduced with permission [241]. Copyright 2023, Wiley. (c) VR-directed pacemaker lead implantation surgery enabled by using the smart piezoelectric hydrogel ring as a self-powered wearable HMI. Reproduced with permission [242]. Copyright 2025, Elsevier. (d) A sutureless soft robotic epicardial device for drug delivery during surgery. Reproduced with permission [243]. Copyright 2024, Cell Press. (e) Evaluation of a surgeon completing various tasks on the da Vinci simulator with an EEG headset and eye-tracking glasses. Reproduced with permission [244]. Copyright 2023, Frontier Media SA. (f) EMG-based proximity assessment of surgical instruments to the patient's nerve roots. Reproduced with permission [245]. Copyright 2022, Wiley.

adaptive decision-making and predictive tissue characterization during surgery. Advancements in biocompatible, high-density sensor arrays, coupled with closed-loop robotic control systems, could further enhance spatial resolution, dynamic responsiveness, and autonomous surgical precision, ultimately transforming robot-assisted platforms into intelligent, context-aware partners in complex clinical interventions.

In addition to tactile perception, force feedback is another important parameter in robotic-assisted surgeries since it can improve precision and stable surgical control to ensure safer and more intuitive surgical operations enabled by flexible sensor-based HMIs. This capability is achieved by converting minute mechanical interactions into real-time haptic signals through advanced flexible sensors and sophisticated control algorithms, thereby ensuring meticulous manipulation of delicate tissues. As exertion of inappropriate amounts of force in surgeries can lead to the risk of unintended tissue injuries, incorporating a force feedback system would allow the surgeon to have a more natural interaction between surgical tools and biological tissues, closely resembling the tactile experience of open surgery. With an additional sensing and feedback system that provides real-time quantitative measurements of exerted force, delicate manipulation of surgical tools during operations would drastically improve.

Various technologies and methods have been developed to design force feedback sensors for robotic surgery with careful consideration of the precision, safety, and integration needs of the surgical environment. To facilitate surgeons with force telepresence during surgery, Hou et al. proposed a MEMS-based piezoresistive 3D force sensing module with variable sensitivity integrated at the end of palpation probe tips and forceps to achieve a high precision perception of the salve manipulator for robotic-assisted minimally invasive surgery (Figure 7b) [241]. Oh et al. implemented advanced ZnO piezoelectric field-effect transistors on flexible substrates for high-speed switching elements and tactile sensing to demonstrate slip and grip with robotic fingers across various scales [249]. The fabricated array exhibited excellent spatial and temporal resolution with strong sensitivity to normal force, and with an additional 3D pillar structure fabricated from PDMS, excellent sensitivity was also demonstrated to the magnitude and direction of shear force, highlighting its potential in surgical robotic applications. To achieve triaxial force detection in surgery, Hou et al. applied orthogonal membrane arrangements of the piezoresistance-sensing and PDMS cap to develop a miniature force sensor and integrated it in the grasping head of a continuum robot to provide force feedback [250]. The biocompatible PDMS cap enhanced the measurement range of the sensor and enabled triaxial force detection. Arshad and Hussain et al. also demonstrated their multi-axis capacitive tactile force sensors with high sensitivity, presenting a good prospect in robot-assisted surgery [251, 252].

In addition to detecting tissue mechanical properties and monitoring the state of applied surgical forces, force feedback in robotic-assisted surgeries can also be used for precise control to enhance the surgeon's ability to perform delicate and accurate operations, thus ensuring safer and more positive surgical outcomes. To minimize the risks of tissue trauma and improve surgical performance, Aubeeluck et al. proposed an ultrathin and flexible screen-printed capacitive tactile sensor for the interior jaws of a disposable surgical magnetically-controlled microgripper [253]. It could monitor and regulate tool-tissue manipulation of pressure and forces in real time to improve grasping performances and quality of surgical procedures. Puneetha et al. developed an ultra-flexible self-powered graphene/nylon/PDMS coaxial fiber-shaped multifunctional robotic-hand controlled sensor [254]. Due to its piezoresistive mechanism, this sensor boasted a fast response of 120 ms and recovery time of 55 ms, offering promising applications in robotic-hand controlled medical surgeries. Arabagi et al. utilized a stacked multi-lamina design and a mechanical amplification technique to develop a flexible and biocompatible cylindrically-packaged piezoresistive pressure sensor array [255]. It was incorporated into robotic endoscopes and catheters to create a co-robotic controller that facilitated shared motion control between the clinician and the robot. Zhang et al. developed a smart piezoelectric hydrogel ring as a self-powered and wearable HMI for operating pacemaker lead implantation surgery in a VR interface (Figure 7c) [242]. Through simple finger motions, users could control the movements of the lead from the superior vena cava to the right ventricle, highlighting the potential of HMI for surgical guidance and training and also paving the way for advancements in robotic surgery, where robotic instruments perform procedures under VR-based HMI control. In summary, force feedback in robotic-assisted surgeries significantly enhances precision, control, and safety by providing surgeons with a natural and intuitive interaction with tissues. By remotely enabling the meticulous manipulation of delicate anatomical structures, tissue trauma can be minimized while also refining surgical outcomes for an overall improved patient recovery and reduced risk of complications.

4.3.2 | Electrophysiological Monitoring for Surgical Control and Surgeon-Patient Safety

In surgical settings, electrophysiological sensors have been employed on surgeons or patients to obtain various bioelectrical signals during operation for the purpose of medical instrument control. For surgeons, the upper limb muscles play a crucial role in performing precise and dexterous movements during surgery, enabling them to manipulate instruments with accuracy and control. Their forearm muscles are heavily utilized to operate surgical instruments, often leading to fatigue during prolonged surgeries. To address this issue, muscle contraction-induced surgical robotic control systems based on EMG signals have been used to provide real-time, intuitive control of robotic instruments by directly translating muscle activity into movement commands. This approach reduces physical strain on surgeons, minimizing fatigue during prolonged procedures while enhancing precision and stability. Compared to manual operations, EMG-driven robotic control enables consistently steadier movements, reduces tremors, and allows for enhanced dexterity in minimally invasive surgeries, ultimately improving surgical outcomes.

Moreover, this technology opens new opportunities for individuals with physical disabilities to pursue surgical careers, as EMG-based control systems can compensate for limited hand function, permitting disabled surgeons to operate surgical robots effectively. Yang et al. demonstrated the integration of EMG signals into teleoperated robotic surgery systems, showing the potential of utilizing EMG signals for improving automation level of the robotic surgery [256]. Furthermore, Yang et al. introduced a proportional control system that maps EMG signal intensity to robotic gripper movement, facilitating hands-free surgical operations and providing accessibility for surgeons with physical disabilities [257]. To further advance hands-free surgical operations, EEG signal-based surgical robotic control has been developed. Such systems assess the surgeon's cognitive workload during robotic-assisted surgeries, improving performance in sophisticated procedures requiring heightened concentration. For example, Yang et al. designed an mental workload-based adaptive automation system using EEG-based workload level sensing to reduce perceived workload and enhance surgeons' task outcomes [258]. By utilizing DL, the surgeon's variable cognitive patterns were identified and used as the workload status to trigger a higher automation level of the surgical robots. Barragan et al invented a semi-autonomous blood suction system for robotic surgery that activates based on the surgeon's cognitive workload detected via EEG and eye tracking [259]. Their system improved task efficiency and reduced mental demands compared to manual suction control. In contrast, ECG signal-based surgical robot control technologies have also been utilized on patients to analyze their cardiac signals in real time during surgery, which are then integrated into closed-loop control algorithms that synchronize robotic movements with the heart signals. For instance, Cheng et al. developed a teleoperated robotic system that utilized ultrasound-guided, neural network-based motion prediction and impedance control to enable non-oscillatory force feedback and real-time heart motion compensation [260]. Their simulated heart motion was temporally matched to ECG rhythms to replicate realistic cardiac dynamics during evaluation. Mendez et al. also proposed a sutureless soft robotic system called SmartSleeve that used the patient's ECG signals to trigger the closed-loop real-time epicardial drug delivery (Figure 7d) [243]. Their ECG-integrated robotic system ensured precise and timely administration of medication during cardiac surgeries, highlighting its potential for responsive and targeted treatment of various cardiac conditions.

Robotic-assisted technologies have also developed advanced monitoring systems to ensure optimal surgeon performance and well-being. Biophysiological signal-based surgeon monitoring has emerged as a powerful approach to assess the physical and cognitive states of surgeons during real-time surgery. These systems support applications such as ergonomic assessments, cognitive workload evaluations, and stress monitoring by leveraging biophysiological signals derived from the entire biological system, such as EMG, EEG, and ECG signals. For instance, applications of monitoring physical workload and muscle fatigue during surgeries are effectively supported by EMG signals, which have been obtained from surgeons by placing sEMG sensors on different body parts. For example, Niu et al. evaluated the ergonomics of robotic-assisted laparoscopic surgery versus traditional laparoscopic surgery by monitoring sEMG signals from the surgeon's upper limb muscles, which are heavily utilized for surgeries requiring fine motor control [261]. They demonstrated the potential of EMG-based systems in identifying ergonomic challenges and optimizing surgical robot design by analyzing muscle activation in robotic-assisted laparoscopic surgery (RALS), with their data showing that the RALS system reduced shoulder strain while increasing wrist engagement. These findings highlight the need for ergonomic refinements, such as adjustable consoles and wrist support, to enhance surgeon comfort and efficiency. Assessing the cognitive workload of surgeons during robotic-assisted surgeries has also been significantly advanced through EEG-based systems. For example, Shafiei et al. utilized EEG and eye-tracking data to develop ML models for evaluating surgical performance and distraction levels in robot-assisted surgery [262]. D'Ambrosia et al. developed a system integrating EEG-based neurophysiological metrics with real-time error detection in robotic-assisted surgery simulations to assess cognitive and affective responses to intraoperative errors (Figure 7e) [244]. These applications emphasize the utility of EEG to address cognitive challenges in demanding surgical environments that require high levels of concentration and skills. In addition, monitoring the surgeon's cardiac status and workload in surgical scenarios is effectively achieved using ECG signals. For example, Pérez-Salazar et al. invented ECG-based technology to monitor ergonomics and stress during conventional and robotic-assisted laparoscopic surgeries, revealing reduced stress levels with robotic systems and highlighting their potential to enhance surgical performance [263].

From the perspective of the patient, biophysiological signals-based monitoring in real-time also plays a pivotal role in optimizing clinical outcomes and ensuring patient safety during robotic-assisted surgeries. Applications such as neuromuscular monitoring and cardiovascular health assessment have been greatly advanced by such systems by leveraging signals from muscle activity and cardiovascular responses to provide detailed and objective insights during surgery. These monitoring methods enable patient-centric surgeries and are adaptable to various clinical needs such as drug delivery management, early detection of surgical complications, and real-time assessment of physiological stress responses. Specifically, EMG monitoring has emerged as a critical tool in advancing patient safety and surgical strategies, offering precise insights into the patient's neuromuscular activity and enabling tailored interventions in clinical settings. For instance, Li et al. invented an EMG-integrated robotic system to assess the proximity of surgical instruments to nerve roots during spinal surgeries (Figure 7f) [245]. By providing real-time feedback to surgeons, risk of nerve damage was reduced and surgical precision was enhanced by attaching EMG sensors to the biceps femoris muscles of a rabbit. Alternatively, Hislop et al. conducted a meta-analysis, a statistical approach of combining results from two or more separate studies, to compare the muscle activation of patients during traditional and robot-assisted laparoscopic surgeries [264]. ECG-based monitoring systems have also been instrumental in monitoring the patient's cardiac stress levels during surgical procedures. Ivanova et al. introduced a novel wireless ECG sensor integrated into a robotic modular laparoscopic instrument, enabling real-time cardiac monitoring during minimally invasive surgeries [265]. The ECG-integrated robotic system continuously assessed the patient's vital parameters throughout the entirety of the surgical procedure. Overall, to bridge physical recovery and stress management for holistic patient care, utilizing electrophysiological signal-based systems can comprehensively offer complementary insights to the patient's overall health status during surgery. In particular, combining muscle activity and heart rate variability data could also enhance post-surgical monitoring, addressing both physical and autonomic recovery needs after surgery.

Surgical robot interaction systems vary in their adaptability and precision, each with its own advantages and challenges. Some approaches are highly sensitive to external noise and environmental factors, requiring advanced signal processing and machine learning techniques to maintain reliability. Additionally, variations in signal patterns from its sensing system may necessitate individualized calibration and extended training, which can be impractical in high-demand clinical settings. In contrast, certain sensor-based methods provide robust, consistent measurements, making them well-suited for real-time force feedback and motion detection. However, these systems may have limitations in adapting to dynamic surgical conditions. A hybrid approach that integrates multiple sensing modalities could enhance precision, adaptability, and intuitive control in surgical robotics. Overall, flexible sensor-based HMIs, integrated with AI-driven technologies, are revolutionizing medical robotics by enhancing prosthetic perception and control, optimizing adaptive exoskeletons, and advancing human–robot synergy in surgical systems, ultimately enabling more intuitive, precise, and adaptive human–machine interactions in healthcare applications.

5 | Conclusions and Future Perspectives

This review provides a comprehensive overview of flexible sensor-based HMI and AI-driven technologies in advancing medical robotics. By leveraging various sensing mechanisms that include triboelectric, piezoelectric, piezoresistive, capacitive, and electrophysiological sensing technologies, such HMI systems enhance the sensitivity and responsiveness of robotic systems to enable adaptive, real-time interactions between humans and machines. AI technology further strengthens the functionality and intelligence of HMI and robotic systems by improving sensing system designs including AI-driven synaptic transistors, optimizing signal processing performances, and enhancing multimodal sensing systems. Moreover, flexible sensor-based HMIs are transforming medical robotics by enhancing prosthetic perception and control, optimizing adaptive exoskeletons, and refining human–robot synergy in surgical systems. These advancements enable seamless interaction, precise control, and enriched sensory feedback, driving the evolution of intelligent, patient-centered robotic solutions for safer and more intuitive healthcare applications. Although significant progress has been made in this field, several critical challenges persist and need to be addressed in the near future through multiple perspectives.

5.1 | Material Innovation

As the performance demands for flexible sensor-based HMI in medical robotic applications intensify and are driven by the need for enhanced functionality, reliability, and adaptability, the material requirements are becoming increasingly stringent and sophisticated. As the fundamental building blocks of sensors, materials play a critical role in defining device performance in physiological environments, which is essential for flexible sensors to seamlessly integrate with the human or robotic body while achieving superior functionality and high-fidelity signal acquisition. To fulfill specific requirements, a diverse range of materials has been explored to optimize sensor performance. For example, flexible substrates like biocompatible PDMS can provide mechanical adaptability and mitigate inflammatory risks, ensuring seamless integration and safety with the human body. Conductive nanocomposites such as graphene-elastomer hybrids and CNT-infused polymers allow for high-fidelity signal acquisition, while ionic materials like ionogels enable high-sensitivity detection of multimodal signals by mimicking the bioelectrical properties of human tissues. Transitioning to stimuli-responsive functional materials such as thermoresponsive hydrogels provides dynamic adaptability, allowing sensors to autonomously modulate mechanical properties or thermally tune their response to physiological changes, enhancing flexibility and user interaction in HMI applications.

While individual material functionalities are relatively easy to achieve, integrating multiple essential properties, such as flexibility, durability, stability, biocompatibility, and biodegradability, into a single material remains a significant challenge since the development of these advanced materials usually faces persistent trade-offs between the desired properties. For example, stretchable polymers and nanocomposites provide mechanical adaptability but often suffer from material fatigue and interfacial delamination. Biocompatibility and biodegradability add further complexity, necessitating materials that balance functional longevity with physiological safety and sustainability. Moreover, environmental interference can hinder sensing stability, requiring appropriate material encapsulation and adaptive AI algorithms for compensation. Future advances will likely focus on multi-scale material innovations, such as bioresorbable conductive polymers and self-healing composite materials, to maintain a balance between mechanical resilience and eco-friendly degradation. AI-driven computational modeling will also accelerate the discovery of materials with tailored degradation kinetics and strain-insensitive electrical properties. Collaborative efforts across materials science, AI, and clinical disciplines will be pivotal to translating these innovations into scalable, clinically viable solutions, ultimately enabling intelligent HMIs that seamlessly adapt to human physiology while aligning with global sustainability goals.

5.2 | Structural Design of Sensors

Both biological tissues and active robotic systems exhibit complex, time-varying mechanical properties. However, conventional rigid sensors lack the necessary mechanical compliance to seamlessly interface with these dynamic environments, resulting in signal inaccuracies, user discomfort, and limited long-term usability. In contrast, flexible sensors offer superior mechanical adaptability and biocompatibility, showing great promise in various long-term HMI applications. However, the integration of flexible sensors with HMI for medical robotic applications usually requires real-time, high-precision detection of various physical and physiological signals and operational intent to enable advanced AI-enabled systems, placing higher demands on the overall performance of flexible sensors. Thus, innovative structural designs of sensors remain pivotal in achieving seamless interactions between soft sensors and dynamic biological systems. Advanced structures, such as serpentine layouts, kirigami-inspired patterns, and porous architectures, enable sensors to move in harmony with tissues or human–machine interfaces, ensuring stable conformal contact for accurate signal acquisition. In addition, hierarchical and gradient-based structural configurations can not only enable sensors to distribute external mechanical stimuli more uniformly but also facilitate controlled deformations that accommodate large strains without compromising the sensor's electrical performance while maintaining stable conformal contact with irregular and moving surfaces.

Concurrently, the miniaturization of the sensor design is also critical for unobtrusive integration into flexible HMI systems for medical robotic applications. However, this objective must be carefully balanced with preserving signal-to-noise ratios and managing power budgets in constrained physiological environments. Emerging nanofabrication techniques such as transfer-printing and laser-assisted patterning can enable submillimeter-scale sensors to achieve highly sensitive sensing ability for micron-level variations. Additionally, energy harvesting innovations are overcoming limitations in sustainable power delivery for flexible sensors. For example, leveraging energy harvesting methods that hybridize multiple mechanisms, such as tribo-piezoelectric synergy technology, could redefine the durability and stability of sensor-based HMI applications. Such hybrid approaches can strategically decouple the energy supply from external charging infrastructure while enhancing device longevity. In addition, AI-driven customization holds transformative potential in advancing flexible sensor design that enables adaptive, user-specific solutions tailored to diverse physiological and environmental demands. By employing various machine learning algorithms, sensors can be structurally optimized through predictive modeling of material properties and geometric configurations, enhancing sensitivity, stretchability, and durability while minimizing mechanical mismatch with biological tissues.

5.3 | System Integration and Power Supply

The seamless integration of flexible sensors, AI algorithms, and wireless communication/control modules is key to achieving functional, closed-loop HMI systems in medical robotics. Effective integration enables real-time data acquisition and bidirectional interaction between humans and machines, as seen in biomimetic prosthetics. Flexible sensors capture physiological signals, which are then processed by embedded AI to generate control commands for soft actuators, while wireless modules transmit feedback to external devices. However, achieving this synergy involves overcoming significant challenges, including mechanical compatibility between heterogeneous components (such as rigid electronics and soft substrates), signal interference in densely integrated systems, and the development of unified communication protocols for low-latency data exchange. Advances in hybrid fabrication techniques such as 3D printing of multifunctional materials or laser-assisted heterostructure assembly can embed sensors and wireless components into conformable, miniaturized platforms. Furthermore, the rise of edge computing and ultra-low-power wireless standards can enable localized data processing, rapid signal response, and reduced reliance on external infrastructure. This approach supports the seamless integration of flexible sensor-based HMIs enabled by AI by enhancing real-time responsiveness, energy efficiency, and overall system reliability.

Integrating multiple modules, sensors, and control units provides superior functionalities but increases overall power consumption, necessitating a more robust and stable power supply to maintain reliable operation under fluctuating load conditions. Furthermore, certain sensors based on piezoresistive, capacitive, and electrophysiological principles inherently rely on a stable power supply to uphold continuous operation and sensing accuracy, making a sustainable energy source crucial for long-term performance and system stability. Traditional power solutions, such as tethered connections or bulky batteries, impose significant limitations on user mobility and long-term usability. Emerging wireless energy transfer methods such as near-field communication and self-powered technologies such as piezoelectricity, triboelectricity, and biofuel cells offer promising alternatives by harvesting energy from body movements, environmental vibrations, or biochemical processes. These innovations enable untethered power management and reduce dependency on frequent recharging and battery replacements. However, challenges persist in scaling these technologies for applications with high energy demands, such as soft prostheses or active exoskeletons, where significant improvements in power density and efficiency are critical. Future research should focus on hybrid energy systems that combine multiple harvesting mechanisms, adaptive power management algorithms, and advanced energy storage materials such as flexible supercapacitors to balance energy autonomy with device performance. Additionally, integrating energy-efficient AI-driven control systems could optimize power consumption dynamically, extending operational lifetimes while maintaining responsiveness.

5.4 | Intelligent Sensing and Interaction

In HMI applications, intelligent sensing and interaction enables systems to perceive, process, and respond to environmental and user inputs in an adaptive and autonomous manner. In particular, medical robotic systems demand high precision, real-time adaptability, and comprehensive physiological monitoring to ensure safe, personalized, and context-aware interventions for improved clinical outcomes. Multimodal sensing, which integrates multiple signals, offers holistic insights into user intent, physiological states, and environmental conditions, thereby improving system performance and reliability in diverse medical environments. For instance, hybrid sensor arrays embedded in prosthetic limbs can simultaneously detect pressure distribution, muscle activity, and temperature, providing nuanced and more comprehensive control signals for prosthetic movement actuation. However, multimodal sensing systems face inherent challenges in signal entanglement, in which separation of the different subsets of data is necessary, but very few AI-driven algorithms have been used for robust signal decoupling. Currently, multimodal sensing systems rely on traditional signal-processing techniques, which have difficulty managing the dynamic, nonlinear multimodal outputs of flexible sensors. To effectively extract meaningful insights from multimodal data, AI techniques such as sensor fusion and predictive analytics can be used to decode these heterogeneous data streams, allowing for real-time interpretation, robust decision-making, and intelligent adaptation by simultaneously assessing various physiological parameters of the user. For instance, physics-informed neural networks could disentangle multimodal signals by embedding sensor-specific physical constraints such as strain-response relationships into the training process. Future research can prioritize a universal AI algorithm to enable real-time, robust decoupling of different flexible multimodal sensing systems.

In addition, the majority of the flexible sensor-based HMIs rely on supervised learning for most current medical robotic applications with AI-integration, which requires extensive labeled datasets. Yet, unsupervised learning remains underexplored within the premise of intelligent sensing and interaction despite its potential to expand healthcare-related applications to detect subtle anomalies in biosignals like irregular heartbeats and muscle tremors. This capability is significant since advanced sensing systems can detect unknown disease patterns that may indicate underlying health issues. When compared to supervised learning ML algorithms, unsupervised techniques such as variational autoencoders (VAEs) could assist in identifying deviations in unlabeled physiological data, flagging patterns that elude traditional diagnostic thresholds. By leveraging unsupervised techniques, flexible sensor-based HMIs could evolve into proactive health-monitoring tools that can also be integrated into medical robotic applications by allowing robots to autonomously detect early signs of health issues, thereby enabling personalized and adaptive interventions without relying on predefined disease models. Especially in the field of medical robotics, the future of intelligent flexible sensor-based HMI will be driven by trends such as advanced multimodal decoupling and self-learning AI models, in which the integration of AI will significantly expand healthcare potential and facilitate dynamic and intuitive interactions across a range of healthcare applications.

5.5 | Data Security and Model Reliability

In AI-enabled medical robotic applications, flexible sensor-based HMIs continuously collect and process highly sensitive personal medical data, such as physiological signals, movement patterns, and biochemical markers. To protect user autonomy and advance data security, integrated frameworks should incorporate dynamic consent management and transparent, context-aware interfaces. These systems enable precise control over data-sharing permissions and translate complex data usage policies into linguistically accessible formats through adaptive visualizations. For example, a prosthetic user might permit motion data sharing for calibration but block cloud-based analytics. Given the critical nature of medical-related sensing data in clinical decision-making, which is collected and processed during system operations, it is essential to implement robust encryption mechanisms and safe communication protocols during data transmission and storage to prevent unauthorized access, data breaches, and cyber threats. In addition, limiting data collection to only what is essential for system functionality and decision-making can significantly reduce personal data security risks. Failure to implement adequate security measures may not only compromise patient confidentiality but also undermine the reliability of AI-driven diagnostic and therapeutic interventions.

Additionally, flexible sensors often produce highly individualized signal patterns due to material variations, body morphology, and environmental factors, complicating the collection of large, standardized datasets. Since the signals are often small, domain-specific, and require labeling, this data scarcity limits the direct applications between the sensing signals and large language models (LLMs), which typically require massive training corpora and process with texts instead of sequential signals. To resolve this dilemma, transfer learning can offer a potential solution by leveraging pre-trained neural networks. Simple neural networks can be initially trained with smaller, domain-specific datasets from flexible sensors and subsequently modify their output layers to be compatible with texts, which can then be connected to LLMs for advanced applications. For example, a lightweight neural network could be trained to map physiological signals to a structured format compatible with an LLM's Application Programming Interface (API). This network could continuously adapt via online learning as it collects data from new users, optimizing neuron weights to account for inter-subject variability. Such a framework could enable novel applications, such as coupling LLMs with real-time biometric data from passengers in autonomous vehicles. Here, the LLM could analyze both sensor-derived health metrics, such as stress levels and vehicle telemetry, to enhance safety and could alert the system if a passenger's vital signs indicate distress during an emergency maneuver. This approach could effectively democratize the use of LLMs in flexible HMI contexts, provided that challenges like computational efficiency and privacy-preserving data aggregation are addressed. Thus, to ensure the safety of highly sensitive personal medical data, the integration of flexible sensor-based HMIs in AI-enabled medical robotics necessitates a robust focus on data security, user autonomy, and dynamic consent management. Addressing challenges related to computational efficiency, standardized data collection, and privacy-preserving frameworks remains crucial, but the successful implementation of these measures can not only advance medical robotic applications but also pave the way for broader real-time biometric data analysis across diverse human–machine interface contexts.

5.6 | Commercialization toward Market Demands

The commercialization of flexible sensor-based HMIs for medical robotic applications is propelled by increasing market demands for precision, minimally invasive procedures, and personalized healthcare. However, the majority of current performance claims regarding flexible sensor-based HMI systems are still based on theoretical modeling, benchtop experiments, or short-term simulations. Quantitative data from clinical trials or user-centered studies remain scarce, making it difficult to assess real-world effectiveness, user comfort, and learning adaptability. Therefore, experimental validation involving human participants, especially over extended periods of use, will be essential to achieving true commercial translation of these systems. In particular, reliability and long-term stability must be verified under dynamic conditions such as mechanical deformations, repeated usage, and exposure to biological environments. Biocompatibility and safety of the overall system must also be validated to prevent adverse reactions and ensure compliance with medical regulations. Optimizing signal accuracy and implementing noise reduction strategies are also crucial for precise physiological monitoring and minimizing motion artifacts and external interferences. In addition, validation of user comfort, such as breathability, wearability, and skin compatibility, should be conducted, especially for long-term prosthetic or exoskeleton use. Furthermore, assessing the learning adaptability of AI-driven control systems in real users is crucial for ensuring effective human–machine coordination over time. To support these comprehensive validation efforts, future systems must be grounded in multifunctional materials, scalable manufacturing processes, and intelligent AI algorithms that collectively enhance system performance and adaptability. Moreover, power supply demands and energy efficiency necessitate innovative and sustainable energy solutions like energy harvesting or low-power electronics to enable continuous operation without the need for bulky batteries. Finally, the fabrication of current advanced flexible electronics is predominantly confined to laboratory settings and relies heavily on manual processes, resulting in performance variability and impeding scalable mass production. Scalable, cost-effective manufacturing methods, such as roll-to-roll printing, laser processing, 3D printing, and inkjet techniques, should be considered to facilitate the transition from lab prototypes to mass production while ensuring batch-to-batch consistency.

Before progressing towar commercialization, regulatory standards must also be met. The integration of AI-driven flexible sensor-based HMIs for medical applications demands strict adherence to rigorous regulatory standards to safeguard patient safety, ensure ethical AI deployment, and secure personal data. Existing frameworks, such as the U.S. Food and Drug Administration's Software as a Medical Device (FDA's SaMD) guidelines, the European Union Medical Device Regulation (EU MDR), and the Health Insurance Portability and Accountability Act (HIPAA), need to be met for pre-market validation and post-market surveillance. However, traditional static approval processes often struggle to accommodate the constantly evolving nature of self-learning AI systems. In response, innovative approaches such as regulatory sandboxes and adaptive compliance models have emerged, while global harmonization remains a significant challenge, with organizations like the International Medical Device Regulators Forum and the World Health

Organization working toward standardized AI governance. In addition, achieving market readiness for successful entry into the market further demands a comprehensive strategy that integrates regulatory, technical, and commercial imperatives. A strategic, phased go-to-market approach should encompass a series of clinical trials ranging from early feasibility studies to large-scale validations that demonstrate safety, efficacy, and tangible user benefits such as reduced surgical times and enhanced patient mobility. Equally important is the development of scalable, cost-effective manufacturing processes and the seamless integration of these systems into existing clinical workflows. Robust stakeholder education through pilot programs, demonstration projects, and case studies will be crucial to build user trust and drive adoption. Additionally, targeted strategies such as subscription-based AI updates for premium healthcare institutions, expansion into telemedicine, and the integration of advanced materials like self-healing materials will position these technologies to meet evolving clinical demands and realize commercial viability. Ultimately, by aligning research and development with regulatory milestones, incorporating user feedback, and fostering rapid iteration through strategic partnerships, flexible sensor-based AI systems can successfully transition from laboratory prototypes to widely adopted commercialized clinical solutions, addressing unmet needs in surgical robotics, rehabilitation, and diagnostic wearables.

In summary, the integration of flexible sensor-based HMIs with AI for medical robotic applications represents a transformative frontier in clinical technology. This interdisciplinary field leverages advances in sensor design, including novel structures and multifunctional materials, to achieve high sensitivity, long-term durability, and seamless conformity with dynamic biological interfaces. Concurrently, breakthroughs in system integration, power management, and edge computing are facilitating real-time data acquisition and energy autonomy, while sophisticated AI algorithms enhance multimodal signal processing and user-specific adaptation. Robust data security also measures and adheres to rigorous regulatory frameworks, such as FDA's SaMD, EU MDR, and HIPAA, which are critical to ensuring patient safety and ethical AI deployment that follow healthcare privacy and security regulations. Furthermore, as commercialization strategies evolve to include scalable manufacturing and phased clinical validations, ongoing collaborative efforts across material science, AI, and clinical disciplines promise to translate laboratory prototypes into widely adopted, clinically validated solutions. Ultimately, the synergistic advancements in flexible sensor-based HMIs, AI-driven analytics, and robust system integration herald a transformative era in medical robotics, promising to deliver intelligent, adaptive, and patient-centric solutions for enhanced clinical outcomes.

Finally, several critical challenges must be resolved or at least partially addressed to enable the real-world deployment and commercialization of AI-integrated flexible sensor-based HMIs. These include flexible sensing system integration, material selection with sensor structure design, and AI compliance. Among these, material selection, system integration, and power supply strategies are the most immediate priorities, as the realization of any specific medical application depends on a stable, well-powered, and fully integrated sensing system, and short-term progress can be made through rapid prototyping from ongoing research efforts. Sensor structure design is also pivotal in influencing signal fidelity, mechanical durability, sensor scalability, and overall system conformability. Extensive research in solid mechanics and material science has made single modal flexible sensor design converge into maturity, as various sensor structure strategies like serpentine or kirigami architectures have been developed. However, advanced sensing systems such as multimodal flexible sensors often require longer development cycles due to the need for comprehensive optimization to achieve enhanced sensing performance and multi-functionality. The emergence of AI-driven sensor design techniques has the potential to accelerate this process, yet this field remains underdeveloped and needs further validation and standardization. Long-term challenges persist in the broader landscape of AI-assisted flexible HMIs, including decoupling AI-aided multimodal signals, establishing standardized datasets for AI training, and ensuring compatibility with LLMs. While these issues currently hold a lower implementation priority due to the availability of traditional alternatives or dependencies on progress in adjacent fields, they may become major barriers to achieving artificial general intelligence (AGI) in future HMI systems. By prioritizing feasible research efforts, researchers can accelerate the translation of flexible HMI technologies from conceptual prototypes into clinically impactful, intelligent, and adaptive medical robotic systems.

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Conflicts of Interest

The authors declare no conflicts of interest.

References

1. I. Fagioli, A. Mazzarini, C. Livolsi, et al., "Advancements and Challenges in the Development of Robotic Lower Limb Prostheses: A Systematic Review," *IEEE Transactions on Medical Robotics and Bionics* 6 (2024): 1409.

2. P. Aqueveque, E. Germany, F. Pastene, and R. Osorio, "Exploring Silicone Rubber Skin with Embedded Customizable Shape Capacitive Sensors to Enable Haptic Capabilities on Upper Limb Prosthetics," in 2022 44th Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC) (IEEE, 2022), 4241. https://doi.org/10.1109/EMBC48229.2022.9871761.

3. S. Guo, F. Zhang, W. Wei, F. Zhao, and Y. Wang, "Kinematic Analysis of a Novel Exoskeleton Finger Rehabilitation Robot for Stroke Patients," in 2014 IEEE International Conference on Mechatronics and Automation (IEEE, 2014), 924. https://doi.org/10.1109/ICMA.2014.6885821.

4. K. Xia, X. Chen, X. Chang, et al., "Hand Exoskeleton Design and Human-Machine Interaction Strategies for Rehabilitation," *Bioengineering* 9 (2022): 682.

5. M. T. Thai, P. T. Phan, T. T. Hoang, S. Wong, N. H. Lovell, and T. N. Do, "Advanced Intelligent Systems for Surgical Robotics," *Advanced Intelligent Systems* 2 (2020): 1900138.

6. Q. Wan, Y. Shi, X. Xiao, X. Li, and H. Mo, "Review of Human-Robot Collaboration in Robotic Surgery," *Advanced Intelligent Systems* 7 (2025): 2400319.

7. L. Zongxing, Z. Jie, Y. Ligang, C. Jinshui, and L. Hongbin, "The Human-Machine Interaction Methods and Strategies for Upper and

Lower Extremity Rehabilitation Robots," *A Review, IEEE Sensors Journal* 24 (2024): 13773.

8. R. Yin, D. Wang, S. Zhao, Z. Lou, and G. Shen, "Wearable Sensors-Enabled Human-Machine Interaction Systems: From Design to Application," *Advanced Functional Materials* 31 (2021): 2008936.

9. W. Ding, A. C. Wang, C. Wu, H. Guo, and Z. L. Wang, "Human-Machine Interfacing Enabled by Triboelectric Nanogenerators and Tribotronics," *Advanced Materials Technologies* 4 (2019): 1800487.

10. Z. L. Rao, F. Ershad, A. Almasri, L. Gonzalez, X. Y. Wu, and C. J. Yu, "Soft Electronics for the Skin: From Health Monitors to Human-Machine Interfaces," *Advanced Materials Technologies* 5 (2020): 2000233.

11. H. Wang, Q. Ding, Y. Luo, et al., "High-Performance Hydrogel Sensors Enabled Multimodal and Accurate Human-Machine Interaction System for Active Rehabilitation," *Advanced Materials* 36 (2024): 2309868.

12. Y. Liu, C. Yiu, Z. Song, et al., "Electronic Skin as Wireless Human-Machine Interfaces for Robotic VR," *Science Advances* 8 (2022): eabl6700.

13. Y. Huang, X. Fan, S.-C. Chen, and N. Zhao, "Emerging Technologies of Flexible Pressure Sensors: Materials, Modeling, Devices, and Manufacturing," *Advanced Functional Materials* 29 (2019): 1808509.

14. S. Pyo, J. Lee, K. Bae, S. Sim, and J. Kim, "Recent Progress in Flexible Tactile Sensors for Human-Interactive Systems: From Sensors to Advanced Applications," *Advanced Materials* 33 (2021): 2005902.

15. C. Xu, J. Chen, Z. Zhu, et al., "Flexible Pressure Sensors in Human-Machine Interface Applications," *Small* 20 (2024): 2306655.

16. P. Won, J. J. Park, T. Lee, et al., "Stretchable and Transparent Kirigami Conductor of Nanowire Percolation Network for Electronic Skin Applications," *Nano Letters* 19 (2019): 6087.

17. L. Lu, C. Jiang, G. Hu, J. Liu, and B. Yang, "Flexible Noncontact Sensing for Human-Machine Interaction," *Advanced Materials* 33 (2021): 2100218.

18. X. Le, Q. Shi, Z. Sun, J. Xie, and C. Lee, "Noncontact Human-Machine Interface Using Complementary Information Fusion Based on MEMS and Triboelectric Sensors," *Advanced Science* 9 (2022): 2201056.

19. F.-L. Gao, P. Min, Q. Ma, et al., "Multifunctional Thermoelectric Temperature Sensor for Noncontact Information Transfer and Tactile Sensing in Human-Machine Interaction," *Advanced Functional Materials* 34 (2024): 2309553.

20. W. Heng, S. Solomon, and W. Gao, "Flexible Electronics and Devices as Human-Machine Interfaces for Medical Robotics," *Advanced Materials* 34 (2022): 2107902.

21. N. Parajuli, N. Sreenivasan, P. Bifulco, et al., "Real-Time EMG Based Pattern Recognition Control for Hand Prostheses: A Review on Existing Methods, Challenges and Future Implementation," *Sensors* 19 (2019): 4596.

22. T. Sun, B. Feng, J. Huo, et al., "Artificial Intelligence Meets Flexible Sensors: Emerging Smart Flexible Sensing Systems Driven by Machine Learning and Artificial Synapses," *Nano-Micro Letters* 16 (2023): 14.

23. A. Subasi, S. M. Qaisar, and H. Nisar, Artificial Intelligence and Multimodal Signal Processing in Human-Machine Interaction (Elsevier, 2024), 0443291519.

24. J. T. Nguyen and W. Cheng, "A Review on Epidermal Nanogenerators: Recent Progress of the Future Self-Powered Skins," *Small Structures* 3 (2022): 2200034.

25. K. K. Kim, Y. Suh, and S. H. Ko, "Smart Stretchable Electronics for Advanced Human-Machine Interface," *Advanced Intelligent Systems* 3 (2021): 2000157.

26. Y. Chen, Z. Gao, F. Zhang, Z. Wen, and X. Sun, "Recent Progress in Self-Powered Multifunctional E-Skin for Advanced Applications," *Exploration* 2 (2022): 20210112.

27. S. Y. Xu, Z. G. Xu, D. Li, et al., "Recent Advances in Flexible Piezoresistive Arrays: Materials, Design, and Applications," *Polymers* 15 (2023): 2699.

28. X. Chen, H. Li, Z. Xu, L. Lu, Z. Pan, and Y. Mao, "Electrospun Nanofiber-Based Bioinspired Artificial Skins for Healthcare Monitoring and Human-Machine Interaction," *Biomimetics* 8 (2023): 223.

29. P. W. Sayyad, S. J. Park, and T. J. Ha, "Bioinspired Nanoplatforms for Human-Machine Interfaces: Recent Progress in Materials and Device Applications," *Biotechnology Advances* 70 (2024): 108297.

30. N. Han, X. Yao, Y. Wang, et al., "Recent Progress of Biomaterials-Based Epidermal Electronics for Healthcare Monitoring and Human-Machine Interaction," *Biosensors* 13 (2023): 393.

31. M. Haghayegh, R. Cao, F. Zabihi, R. Bagherzadeh, S. Y. Yang, and M. F. Zhu, "Recent Advances in Stretchable, Wearable and Bio-Compatible Triboelectric Nanogenerators," *Journal of Materials Chemistry C* 10 (2022): 11439.

32. G. Dandegaonkar, A. Ahmed, L. Y. Sun, B. Adak, and S. Mukhopadhyay, "Cellulose Based Flexible and Wearable Sensors for Health Monitoring," *Materials Advances* 3 (2022): 3766.

33. J. Jie, W. Shihang, Z. Zhongtan, M. Deqing, and W. Yancheng, "Progress on Flexible Tactile Sensors in Robotic Applications on Objects Properties Recognition, Manipulation and Human-Machine Interactions," *Soft Science* 3 (2023): 8.

34. J. Zhu, S. Ji, J. Yu, et al., "Machine Learning-Augmented Wearable Triboelectric Human-Machine Interface in Motion Identification and Virtual Reality," *Nano Energy* 103 (2022): 107766.

35. M. Zhang, W. Wang, G. Xia, L. Wang, and K. Wang, "Self-Powered Electronic Skin for Remote Human-Machine Synchronization," *ACS Applied Electronic Materials* 5 (2023): 498.

36. W. Liu, F. Xiang, D. Mei, and Y. Wang, "A Flexible Dual-Mode Capacitive Sensor for Highly Sensitive Touchless and Tactile Sensing in Human-Machine Interactions," *Advanced Materials Technologies* 9 (2024): 2301685.

37. J. Li, N. Li, Y. Zheng, et al., "Interfacially Locked Metal Aerogel Inside Porous Polymer Composite for Sensitive and Durable Flexible Piezoresistive Sensors," *Advanced Science* 9 (2022): 2201912.

38. X. Du, L. Yang, and N. Liu, "Recent Progress on Poly(3,4-Ethylenedioxythiophene): Poly(Styrenesulfonate) Bioelectrodes," *Small Science* 3 (2023): 2300008.

39. F.-R. Fan, Z.-Q. Tian, and Z. Lin Wang, "Flexible Triboelectric Generator," *Nano Energy* 1 (2012): 328.

40. X. Ge, N. Hu, F. Yan, and Y. Wang, "Development and Applications of Electrospun Nanofiber-Based Triboelectric Nanogenerators," *Nano Energy* 112 (2023): 108444.

41. Y. Mi, Z. Zhao, H. Wu, Y. Lu, and N. Wang, "Porous Polymer Materials in Triboelectric Nanogenerators: A Review," *Polymers (Basel)* 15 (2023): 4383.

42. I. Aazem, D. T. Mathew, S. Radhakrishnan, et al., "Electrode Materials for Stretchable Triboelectric Nanogenerator in Wearable Electronics," *RSC Advances* 12 (2022): 10545.

43. G. Khandelwal, N. P. Maria Joseph Raj, and S. J. Kim, "Materials Beyond Conventional Triboelectric Series for Fabrication and Applications of Triboelectric Nanogenerators," *Advanced Energy Materials* 11 (2021): 2101170.

44. K.-B. Chang, P. Parashar, L.-C. Shen, et al., "A Triboelectric Nanogenerator-Based Tactile Sensor Array System for Monitoring Pressure Distribution inside Prosthetic Limb," *Nano Energy* 111 (2023): 108397.

45. Y. Luo, Z. Wang, J. Wang, et al., "Triboelectric Bending Sensor Based Smart Glove towards Intuitive Multi-Dimensional Human-Machine Interfaces," *Nano Energy* 89 (2021): 106330.

46. Z. L. Wang, "Triboelectric Nanogenerators as New Energy Technology and Self-Powered Sensors - Principles, Problems and Perspectives," *Faraday Discussions* 176 (2014): 447.

47. C. Wu, A. C. Wang, W. Ding, H. Guo, and Z. L. Wang, "Triboelectric Nanogenerator: A Foundation of the Energy for the New Era," *Advanced Energy Materials* 9 (2019): 1802906.

48. G. Ma, M. Zhang, F. Gao, et al., "Bioinspired, Fiber-Based, Flexible Self-Powered Sensor for Wearable Applications," *Device* 2 (2024): 100508.

49. S. H. Kwon, C. Zhang, Z. Jiang, and L. Dong, "Textured Nanofibers Inspired by Nature for Harvesting Biomechanical Energy and Sensing Biophysiological Signals," *Nano Energy* 122 (2024): 109334.

50. L. Gao, C. Zhu, L. Li, et al., "All Paper-Based Flexible and Wearable Piezoresistive Pressure Sensor," *ACS Applied Materials & Interfaces* 11 (2019): 25034.

51. W. Zhao, J. Natsuki, V. Dinh Trung, et al., "AgNPs/CNTs Modified Nonwoven Fabric for PET-Based Flexible Interdigitated Electrodes in Pressure Sensor Applications," *Chemical Engineering Journal* 499 (2024): 156252.

52. X. Kang, L. Sun, Y. Wu, L. Chen, D. Zhang, and J. Yang, "Liquid Metal Elastomer-Based U-Shaped Electrode Flexible Strain Sensors with Enhanced Stability and Sensitivity," *ACS Applied Materials & Interfaces* 17 (2025): 5527.

53. C. Zhang, L. Zhang, B. Bao, et al., "Customizing Triboelectric Nanogenerator on Everyday Clothes by Screen-Printing Technology for Biomechanical Energy Harvesting and Human-Interactive Applications," *Advanced Materials Technologies* 8 (2023): 2201138.

54. M. C. Sekhar, E. Veena, N. S. Kumar, K. C. B. Naidu, A. Mallikarjuna, and D. B. Basha, "A Review on Piezoelectric Materials and Their Applications," *Crystal Research and Technology* 58 (2022): 2200130.

55. Y. Wu, Y. Ma, H. Zheng, and S. Ramakrishna, "Piezoelectric Materials for Flexible and Wearable Electronics: A Review," *Materials & Design* 211 (2021): 110164.

56. C. Bouyam and Y. Punsawad, "Human-Machine Interface-Based Wheelchair Control Using Piezoelectric Sensors Based on Face and Tongue Movements," *Heliyon* 8 (2022): e11679.

57. Z. Jiang, C. Zhang, S. H. Kwon, and L. Dong, "Self-Powered, Soft and Breathable Human-Machine Interface Based on Piezoelectric Sensors," *Advanced Sensor Research* 3 (2024): 2400086.

58. X. Xue, H. Wu, Q. Cai, et al., "Flexible Ultrasonic Transducers for Wearable Biomedical Applications: A Review on Advanced Materials, Structural Designs, and Future Prospects," *IEEE Transactions on Ultrasonics, Ferroelectrics, and Frequency Control* 71 (2024): 786.

59. X. Bai, D. Wang, L. Zhen, et al., "Design and Micromanufacturing Technologies of Focused Piezoelectric Ultrasound Transducers for Biomedical Applications," *International Journal of Extreme Manufacturing* 6 (2024): 062001.

60. Q. Zhou, K. H. Lam, H. Zheng, W. Qiu, and K. K. Shung, Piezoelectric Single Crystal Ultrasonic Transducers for Biomedical Applications,"*Progress in Materials Science* 66 (2014): 87.

61. A. Khorsand Zak, S. T. Yazdi, M. E. Abrishami, and A. M. Hashim, "A Review on Piezoelectric Ceramics and Nanostructures: Fundamentals and Fabrications," *Journal of the Australian Ceramic Society* 60 (2024): 723.

62. M.-G. Kang, W.-S. Jung, C.-Y. Kang, and S.-J. Yoon, "Recent Progress on PZT Based Piezoelectric Energy Harvesting Technologies," *Actuators* 5 (2016): 5.

63. D. Pan, "Lead Zirconate Titanate (PZT) Piezoelectric Ceramics: Applications and Prospects in Human Motion Monitoring," *Ceramics - Silikaty* 68 (2024): 444.

64. M. Zhu, Z. Sun, Z. Zhang, et al., "Haptic-Feedback Smart Glove as a Creative Human-Machine Interface (HMI) for Virtual/Augmented Reality Applications," *Science Advances* 6 (2020): eaaz8693.

65. Y. Zhang, H. Kim, Q. Wang, et al., "Progress in Lead-Free Piezoelectric Nanofiller Materials and Related Composite Nanogenerator Devices," *Nanoscale Advances* 2 (2020): 3131.

66. J. Koruza, A. J. Bell, T. Frömling, K. G. Webber, K. Wang, and J. Rödel, "Requirements for the Transfer of Lead-Free Piezoceramics into Application," *Journal of Materiomics* 4 (2018): 13.

67. F. Ali, W. Raza, X. Li, H. Gul, and K.-H. Kim, "Piezoelectric Energy Harvesters for Biomedical Applications," *Nano Energy* 57 (2019): 879.

68. J. Zou, M. Song, X. Zhou, et al., "Enhancing Piezoelectric Coefficient and Thermal Stability in Lead-Free Piezoceramics: Insights at the Atomic-Scale," *Nature Communications* 15 (2024): 8591.

69. H. Qi, X. Xia, C. Zhou, P. Xiao, Y. Wang, and Y. Deng, "Ferroelectric properties of the Flexible Pb(Zr0.52Ti0.48)O3 Thin Film on Mica," *Journal of Materials Science: Materials in Electronics* 31 (2020): 3042.

70. C. Li, J. Si, X. Yuan, et al., "Flexible All-Inorganic BiFeO3-Based Film with High Piezoelectric Coefficient for Energy Harvesting and Sensing," *Journal of Materials Science: Materials in Electronics* 35 (2024): 1745.

71. X. Gao, M. Zheng, X. Yan, J. Fu, M. Zhu, and Y. Hou, "The Alignment of BCZT Particles in PDMS Boosts the Sensitivity and Cycling Reliability of a Flexible Piezoelectric Touch Sensor," *Journal of Materials Chemistry C* 7 (2019): 961.

72. K. K. Sappati and S. Bhadra, "Flexible Piezoelectric 0-3 PZT-PDMS Thin Film for Tactile Sensing," *IEEE Sensors Journal* 20 (2020): 4610.

73. L. Zhen, L. Lu, Y. Yao, J. Liu, and B. Yang, "Flexible Inorganic Piezoelectric Functional Films and Their Applications," *Journal of Advanced Ceramics* 12 (2023): 433.

74. A. R. Jayakrishnan, A. Kumar, S. Druvakumar, et al., "Inorganic Ferroelectric Thin Films and Their Composites for Flexible Electronic and Energy Device Applications: Current Progress and Perspectives," *Journal of Materials Chemistry C* 11 (2023): 827.

75. S. Zhang and F. Li, "High Performance Ferroelectric Relaxor-PbTiO3 Single Crystals: Status and Perspective," *Journal of Applied Physics* 111 (2012): 031301.

76. X. Liu, S. Zhang, J. Luo, T. R. Shrout, and W. Cao, "Complete Set of Material Constants of Pb(In1/2Nb1/2)O3-Pb(Mg1/3Nb2/3)O3-PbTiO3 Single Crystal with Morphotropic Phase Boundary Composition," *Journal of Applied Physics* 106 (2009): 074112.

77. H. Wang, W. Shang, M. Ma, S. Xia, and Z. Li, "Growth and Enhanced Electrical Properties of PIN-PMN-PT Piezoelectric Single Crystal Grown by the Solid-State Crystal Growth Method," *Journal of the European Ceramic Society* 44 (2024): 858.

78. H. Guo, K. Song, Z. Li, S. Fan, and Z. Xu, "5′′ Diameter PIN-PMN-PT Crystal Growth by the Bridgman Method," *Journal of Advanced Dielectrics* 10 (2020): 2050001.

79. J. Zhang, B. Tan, X. Zhang, et al., "Atomically Thin Hexagonal Boron Nitride and Its Heterostructures," *Advanced Materials* 33 (2021): 2000769.

80. Y. Zhang, C. Ma, X. Lu, and M. Liu, "Recent Progress on Flexible Inorganic Single-Crystalline Functional Oxide Films for Advanced Electronics," *Materials Horizons* 6 (2019): 911.

81. Y. Xue, C. Zhou, X. Y. Zhang, and M. Chan, "A Flexible High Quality-Factor Bulk Acoustic Resonator Enabled with Transferred Single-Crystal Piezoelectric Thin Film for Sensing Applications," *Sensors and Actuators A: Physical* 326 (2021): 112721.

82. P.-K. Yang, S.-A. Chou, C.-H. Hsu, et al., "Tin Disulfide Piezoelectric Nanogenerators for Biomechanical Energy Harvesting and Intelligent Human-Robot Interface Applications," *Nano Energy* 75 (2020): 104879.

83. Y.-X. Zhou, Y.-T. Lin, S.-M. Huang, et al., "Tungsten Disulfide Nanosheets for Piezoelectric Nanogenerator and Human-Machine Interface Applications," *Nano Energy* 97 (2022): 107172.

84. E. Fukada, “History and Recent Progress in Piezoelectric Polymers,” *IEEE Transactions on Ultrasonics, Ferroelectrics, and Frequency Control* 47 (2000): 1277.

85. L. Dong, A. B. Closson, M. Oglesby, et al., “In Vivo Cardiac Power Generation Enabled by an Integrated Helical Piezoelectric Pacemaker Lead,” *Nano Energy* 66 (2019): 104085.

86. Z. Lu, C. Zhang, S. H. Kwon, Z. Jiang, and L. Dong, “Flexible Hybrid Piezoelectric-Electrostatic Device for Energy Harvesting and Sensing Applications,” *Advanced Materials Interfaces* 10 (2023): 2202173.

87. Y. Wang, M. Sun, S. H. Kwon, and L. Dong, “Advancements in Flexible Biomechanical Energy Harvesting for Smart Health Applications,” *Chemical Communications* 61 (2025): 2424.

88. L. Dong, C. Jin, A. B. Closson, et al., “Cardiac Energy Harvesting and Sensing Based on Piezoelectric and Triboelectric Designs,” *Nano Energy* 76 (2020): 105076.

89. S. Mohammadpourfazeli, S. Arash, A. Ansari, S. Yang, K. Mallick, and R. Bagherzadeh, “Future Prospects and Recent Developments of Polyvinylidene Fluoride (PVDF) Piezoelectric Polymer; Fabrication Methods, Structure, and Electro-Mechanical Properties,” *RSC Advances* 13 (2023): 370.

90. B. Mohammadi, A. A. Yousefi, and S. M. Bellah, “Effect of Tensile Strain Rate and Elongation on Crystalline Structure and Piezoelectric Properties of PVDF Thin Films,” *Polymer Testing* 26 (2007): 42.

91. V. K. Samoei, S. Maharjan, K. Sano, and A. H. Jayatissa, “Effect of Annealing on Graphene/PVDF Nanocomposites,” *ACS Omega* 8 (2023): 13876.

92. S. S. Dani, A. Tripathy, N. R. Alluri, S. Balasubramaniam, and A. Ramadoss, “A Critical Review: The Impact of Electrical Poling on the Longitudinal Piezoelectric Strain Coefficient,” *Materials Advances* 3 (2022): 8886.

93. L. Lu, W. Ding, J. Liu, and B. Yang, “Flexible PVDF Based Piezoelectric Nanogenerators,” *Nano Energy* 78 (2020): 105251.

94. M. Smith and S. Kar-Narayan, “Piezoelectric Polymers: Theory, Challenges and Opportunities,” *International Materials Reviews* 67 (2022): 65.

95. U. Pierre Claver and G. Zhao, “Recent Progress in Flexible Pressure Sensors Based Electronic Skin,” *Advanced Engineering Materials* 23 (2021): 2001187.

96. J. Qu, B. Mao, Z. Li, et al., “Recent Progress in Advanced Tactile Sensing Technologies for Soft Grippers,” *Advanced Functional Materials* 33 (2023): 2306249.

97. J. Zheng, Y. Chen, Z. Wu, Y. Wang, and L. Wang, “Integration of Flexible Touch Panels and Machine Learning: Applications and Techniques,” *Advanced Intelligent Systems* 6 (2023): 2300560.

98. Y. Wang, P. Zhu, M. Tan, M. Niu, S. Liang, and Y. Mao, “Recent Advances in Hydrogel-Based Self-Powered Artificial Skins for Human-Machine Interfaces,” *Advanced Intelligent Systems* 5 (2023): 2300162.

99. Z. Wang, C. Dong, X. Wang, et al., “Highly Sensitive Integrated Flexible Tactile Sensors with Piezoresistive Ge2Sb2Te5 Thin Films,” *npj Flexible Electronics* 2 (2018): 17.

100. J. Qu, G. Cui, Z. Li, et al., “Advanced Flexible Sensing Technologies for Soft Robots,” *Advanced Functional Materials* 34 (2024): 2401311.

101. Q. Shu, Y. Pang, Q. Li, et al., “Flexible Resistive Tactile Pressure Sensors,” *Journal of Materials Chemistry A* 12 (2024): 9296.

102. T. Liu, G.-Y. Gou, F. Gao, et al., “Multichannel Flexible Pulse Perception Array for Intelligent Disease Diagnosis System,” *ACS Nano* 17 (2023): 5673.

103. S. Pyo, J. Lee, K. Bae, S. Sim, and J. Kim, “Recent Progress in Flexible Tactile Sensors for Human-Interactive Systems: From Sensors to Advanced Applications,” *Advanced Materials* 33 (2021): e2005902.

104. R. Tchantchane, H. Zhou, S. Zhang, A. Dunn, E. Sariyildiz, and G. Alici, “Advancing Human-Machine Interface (HMI) through Development of a Conductive-Textile Based Capacitive Sensor,” *Advanced Materials Technologies* 10 (2024): 2401458.

105. J. Xu, J. Pan, T. Cui, S. Zhang, Y. Yang, and T. L. Ren, “Recent Progress of Tactile and Force Sensors for Human-Machine Interaction,” *Sensors (Basel)* 23 (2023): 1868.

106. J. H. Shin, J. Kwon, J. U. Kim, et al., “Wearable EEG Electronics for a Brain-AI Closed-Loop System to Enhance Autonomous Machine Decision-Making,” *npj Flexible Electronics* 6 (2022): 32.

107. M. Reis Carneiro, C. Majidi, and M. Tavakoli, “Multi-Electrode Printed Bioelectronic Patches for Long-Term Electrophysiological Monitoring,” *Advanced Functional Materials* 32 (2022): 2205956.

108. H. Lee, S. Lee, J. Kim, et al., “Stretchable Array Electromyography Sensor with Graph Neural Network for Static and Dynamic Gestures Recognition System,” *npj Flexible Electronics* 7 (2023): 20.

109. L. Yin, Y. Wang, J. Zhan, et al., “Chest-Scale Self-Compensated Epidermal Electronics for Standard 6-Precordial-Lead ECG,” *npj Flexible Electronics* 6 (2022): 29.

110. A. Khosla, P. Khandnor, and T. Chand, “A Comparative Analysis of Signal Processing and Classification Methods for Different Applications Based on EEG Signals,” *Biocybernetics and Biomedical Engineering* 40 (2020): 649.

111. V. L. Towle, J. Bolaños, D. Suarez, et al., “The Spatial Location of EEG Electrodes: Locating the Best-Fitting Sphere Relative to Cortical Anatomy,” *Electroencephalography and Clinical Neurophysiology* 86 (1993): 1.

112. T. Walczak and S. Chokroverty, “7 - Electroencephalography, Electromyography and Electrooculography: General Principles and Basic Technology,” in *Sleep Disorders Medicine*, ed. S. Chokroverty (Butterworth-Heinemann, 1994), 95.

113. D. Farina, D. F. Stegeman, and R. Merletti, “Biophysics of the Generation of EMG Signals,” in Surface Electromyography: Physiology, Engineering, and Applications (2016), 1, https://doi.org/10.1002/9781119082934.ch02.

114. Y. J. Hong, H. Jeong, K. W. Cho, N. Lu, and D.-H. Kim, “Wearable and Implantable Devices for Cardiovascular Healthcare: From Monitoring to Therapy Based on Flexible and Stretchable Electronics,” *Advanced Functional Materials* 29 (2019): 1808247.

115. P. Nagwade, S. Parandeh, and S. Lee, “Prospects of Soft Biopotential Interfaces for Wearable Human-Machine Interactive Devices and Applications,” *Soft Science* 3 (2023): 24.

116. L.-L. Li, G.-Z. Cao, H.-J. Liang, Y.-P. Zhang, and F. Cui, “Human Lower Limb Motion Intention Recognition for Exoskeletons: A Review,” *IEEE Sensors Journal* 23 (2023): 30007.

117. C. Metallo, R. D. White, and B. A. Trimmer, “Flexible Parylene-Based Microelectrode Arrays for High Resolution EMG Recordings in Freely Moving Small Animals,” *Journal of Neuroscience Methods* 195 (2011): 176.

118. Y. Zhang, K. Y. Li, C. Jin, et al., “Comparative Studies on the Implantation of Nano Platinum Black and Pure Platinum Electrodes in the Rabbit Orbicularis Oculi Muscle,” *Journal of Laryngology and Otology* 128 (2014): 679.

119. A. B. Nigusse, D. A. Mengistie, B. Malengier, G. B. Tseghai, and L. V. Langenhove, “Wearable Smart Textiles for Long-Term Electrocardiography Monitoring-A Review,” *Sensors (Basel)* 21 (2021): 4174.

120. I. Constant and N. Sabourdin, “The EEG Signal: A Window on the Cortical Brain Activity,”*Pediatric Anesthesia* 22 (2012): 539.

121. N. S. Amer and S. B. Belhaouari, “EEG Signal Processing for Medical Diagnosis, Healthcare, and Monitoring: A Comprehensive Review,” *IEEE Access* 11 (2023): 143116.

122. H. Li, X. Li, and J. R. d. Millán, "Noninvasive EEG-Based Intelligent Mobile Robots: A Systematic Review," *IEEE Transactions on Automation Science and Engineering* 22 (2025): 6291.

123. A. Kilicarslan, S. Prasad, R. G. Grossman, and J. L. Contreras-Vidal, "High Accuracy Decoding of user Intentions using EEG to Control a Lower-body Exoskeleton," in 2013 35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC) (IEEE, 2013), 5606, https://doi.org/10.1109/EMBC.2013.6610821.

124. X. Wang, Y. Xiao, F. Deng, Y. Chen, and H. Zhang, "Eye-Movement-Controlled Wheelchair Based on Flexible Hydrogel Biosensor and WT-SVM," *Biosensors* 11 (2021): 198.

125. D. Yadav and K. Veer, "Recent Trends and Challenges of Surface Electromyography in Prosthetic Applications," *Biomedical Engineering Letters* 13 (2023): 353.

126. P. W. Sayyad, H. Al-Nashash, A. Al-Othman, and M. H. Al-Sayah, "Emerging Trends in System-Integrated Wearable Epidermal and Flexible Electrodes: Material Design and Applications in Physiological Monitoring," *IEEE Transactions on Components, Packaging and Manufacturing Technology* 15 (2025): 905.

127. A. Hofste, R. Soer, E. Salomons, et al., "Intramuscular EMG Versus Surface EMG of Lumbar Multifidus and Erector Spinae in Healthy Participants," *Spine* 45 (2020): E1319.

128. N. M. Hye, U. Hany, S. Chakravarty, L. Akter, and I. Ahmed, "Artificial Intelligence for sEMG-Based Muscular Movement Recognition for Hand Prosthesis," *IEEE Access* 11 (2023): 38850.

129. P. P. Vu, A. K. Vaskov, C. Lee, et al., "Long-Term Upper-Extremity Prosthetic Control Using Regenerative Peripheral Nerve Interfaces and Implanted EMG Electrodes," *Journal of Neural Engineering* 20 (2023): 026039.

130. S. Ramasamy and A. Balan, "Wearable Sensors for ECG Measurement: A Review," *Sensor Review* 38 (2018): 412.

131. M. Wasimuddin, K. Elleithy, A. S. Abuzneid, M. Faezipour, and O. Abuzaghleh, "Stages-Based ECG Signal Analysis From Traditional Signal Processing to Machine Learning Approaches: A Survey," *IEEE Access* 8 (2020): 177782.

132. T. Anbalagan, M. K. Nath, D. Vijayalakshmi, and A. Anbalagan, "Analysis of Various Techniques for ECG Signal in Healthcare, past, Present, and Future," *Biomedical Engineering Advances* 6 (2023): 100089.

133. A. Kalra, A. Lowe, and A. Al-Jumaily, "Critical Review of Electrocardiography Measurement Systems and Technology," *Measurement Science and Technology* 30 (2019): 012001.

134. P. Kamga, R. Mostafa, and S. Zafar, "The Use of Wearable ECG Devices in the Clinical Setting: A Review," *Current Emergency and Hospital Medicine Reports* 10 (2022): 67.

135. V. P. Rachim and W. Y. Chung, "Wearable Noncontact Armband for Mobile ECG Monitoring System," *IEEE Transactions on Biomedical Circuits and Systems* 10 (2016): 1112.

136. H. Zou, Q. Wu, L. Yang, Y. Zhu, and H. Wu, "Design and EMG-EEG Fusion-Based Admittance Control of a Hand Exoskeleton with Series Elatic Actuators," *IEEE Transactions on Medical Robotics and Bionics* 7 (2024): 347.

137. Y. Lu, D. Kong, G. Yang, et al., "Machine Learning-Enabled Tactile Sensor Design for Dynamic Touch Decoding," *Advanced Science* 10 (2023): 2303949.

138. E. Zhao, T. Wang, Y. Wang, et al., "Active Learning Assisted Piezoelectric Materials Synthesis on the Basis of Composite Decision-Making," *MedMat* 1 (2024): 95.

139. J. Shi, S. D. Ha, Y. Zhou, F. Schoofs, and S. Ramanathan, "A Correlated Nickelate Synaptic Transistor," *Nature Communications* 4 (2013): 2676.

140. X. Zhao, Z. Sun, and C. Lee, "Augmented Tactile Perception of Robotic Fingers Enabled by AI-Enhanced Triboelectric Multimodal Sensors," *Advanced Functional Materials* 34 (2024): 2409558.

141. Q. Mao, Z. Liao, J. Yuan, and R. Zhu, "Multimodal Tactile Sensing Fused with Vision for Dexterous Robotic Housekeeping," *Nature Communications* 15 (2024): 6871.

142. P. Wang, G. Wang, G. Sun, et al., "A Flexible-Integrated Multimodal Hydrogel-Based Sensing Patch," *Nano-Micro Letters* 17 (2025): 156.

143. C. Xie, H. Qiu, L. Liu, et al., "Machine Learning Approaches in Polymer Science: Progress and Fundamental for a New Paradigm," *SmartMat* 6 (2025): e1320.

144. L. Yang, H. Wang, D. Leng, S. Fang, Y. Yang, and Y. Du, "Machine Learning Applications in Nanomaterials: Recent Advances and Future Perspectives," *Chemical Engineering Journal* 500 (2024): 156687.

145. W. Li, T. Yang, C. Liu, et al., "Optimizing Piezoelectric Nanocomposites by High-Throughput Phase-Field Simulation and Machine Learning," *Advanced Science* 9 (2022): 2105550.

146. Z. Liu, M. Cai, S. Hong, et al., "Data-Driven Inverse Design of Flexible Pressure Sensors," *Proceedings of the National Academy of Sciences of the United States of America* 121 (2024): e2320222121.

147. H. Yang, J. Li, K. Z. Lim, et al., "Automatic Strain Sensor Design via Active Learning and Data Augmentation for Soft Machines," *Nature Machine Intelligence* 4 (2022): 84.

148. L. Deng, J. Zhang, Z. Yue, Z. Li, Y. Yuan, and H. Ding, "Active Learning-Aided Design of a Flexible Tactile Sensor Array for Recognizing Properties of Deformable Objects," *IEEE Transactions on Instrumentation and Measurement* 73 (2024): 1.

149. F. Zhang, C. Li, Z. Li, L. Dong, and J. Zhao, "Recent Progress in Three-Terminal Artificial Synapses Based on 2D Materials: From Mechanisms to Applications," *Microsystems & Nanoengineering* 9 (2023): 16.

150. C. J. Wan, Y. H. Liu, P. Feng, et al., "Flexible Metal Oxide/Graphene Oxide Hybrid Neuromorphic Transistors on Flexible Conducting Graphene Substrates," *Advanced Materials* 28 (2016): 5878.

151. M. Jia, P. Guo, W. Wang, et al., "Tactile Tribotronic Reconfigurable p-n Junctions for Artificial Synapses," *Science Bulletin* 67 (2022): 803.

152. R. D. Nikam, M. Kwak, J. Lee, K. G. Rajput, W. Banerjee, and H. Hwang, "Near Ideal Synaptic Functionalities in Li Ion Synaptic Transistor Using Li3POxSex Electrolyte with High Ionic Conductivity," *Scientific Reports* 9 (2019): 18883.

153. M. J. Sultan, A. Bag, S. J. Hong, et al., "Tactile Sensory Synapse Based on Organic Electrochemical Transistors with Ionogel Triboelectric Layer," *Nano Energy* 131 (2024): 110202.

154. A. Shaheen, L. Ye, C. Karunaratne, and T. Seppänen, "Fully-Gated Denoising Auto-Encoder for Artifact Reduction in ECG Signals," *Sensors* 25 (2025): 801.

155. C. Yao, S. Liu, Z. Liu, et al., "Deep Learning-Enhanced Anti-Noise Triboelectric Acoustic Sensor for Human-Machine Collaboration in Noisy Environments," *Nature Communications* 16 (2025): 4276.

156. A. M. Moslhi, H. H. Aly, and M. ElMessiery, "The Impact of Feature Extraction on Classification Accuracy Examined by Employing a Signal Transformer to Classify Hand Gestures Using Surface Electromyography Signals," *Sensors* 24 (2024): 1259.

157. K. C. Liu, C. Y. Hsieh, H. Y. Huang, S. J. P. Hsu, and C. T. Chan, "An Analysis of Segmentation Approaches and Window Sizes in Wearable-Based Critical Fall Detection Systems With Machine Learning Models," *IEEE Sensors Journal* 20 (2020): 3303.

158. X. Wu, X. Luo, Z. Song, Y. Bai, B. Zhang, and G. Zhang, "Ultra-Robust and Sensitive Flexible Strain Sensor for Real-Time and Wearable Sign Language Translation," *Advanced Functional Materials* 33 (2023): 2303504.

159. D. Zhao, K. Zhang, Y. Meng, et al., "Untethered Triboelectric Patch for Wearable Smart Sensing and Energy Harvesting," *Nano Energy* 100 (2022): 107500.

160. Y. Yu, J. Li, S. A. Solomon, et al., "All-Printed Soft Human-Machine Interface for Robotic Physicochemical Sensing," *Science Robotics* 7 (2022): eabn0495.

161. Z. Wang, M. Bu, K. Xiu, et al., "A Flexible, Stretchable and Triboelectric Smart Sensor Based on Graphene Oxide and Polyacrylamide Hydrogel for High Precision Gait Recognition in Parkinsonian and Hemiplegic Patients," *Nano Energy* 104 (2022): 107978.

162. J. Xie, Y. Zhao, D. Zhu, et al., "A Machine Learning-Combined Flexible Sensor for Tactile Detection and Voice Recognition," *ACS Applied Materials & Interfaces* 15 (2023): 12551.

163. M. Wajahat, A. Z. Kouzani, S. Y. Khoo, and M. A. P. Mahmud, "Development of AI-Enabled Sign Language Predicting Glove Using 3-D Printed Triboelectric Sensors," *IEEE Journal on Flexible Electronics* 3 (2024): 266.

164. R. Katmah, A. Al Shehhi, H. F. Jelinek, A. A. Hulleck, and K. Khalaf, "A Systematic Review of Gait Analysis in the Context of Multimodal Sensing Fusion and AI," *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 31 (2023): 4189.

165. D. Lahat, T. Adali, and C. Jutten, "Multimodal Data Fusion: an Overview of Methods, Challenges, and Prospects," *Proceedings of the IEEE* 103 (2015): 1449.

166. T. Meng, X. Jing, Z. Yan, and W. Pedrycz, "A Survey on Machine Learning for Data Fusion," *Information Fusion* 57 (2020): 115.

167. Y. Celik, S. Stuart, W. L. Woo, E. Sejdic, and A. Godfrey, "Multi-Modal Gait: A Wearable, Algorithm and Data Fusion Approach for Clinical and Free-Living Assessment," *Information Fusion* 78 (2022): 57.

168. W. Qi, H. Su, K. Fan, et al., "Multimodal Data Fusion Framework Enhanced Robot-Assisted Minimally Invasive Surgery," *Transactions of the Institute of Measurement and Control* 44 (2021): 735.

169. C. L. Fall, F. Quevillon, M. Blouin, et al., "A Multimodal Adaptive Wireless Control Interface for People with Upper-Body Disabilities," *IEEE Transactions on Biomedical Circuits and Systems* 12 (2018): 564.

170. R. Tchantchane, H. Zhou, S. Zhang, and G. Alici, "A Review of Hand Gesture Recognition Systems Based on Noninvasive Wearable Sensors," *Advanced Intelligent Systems* 5 (2023): 2300207.

171. P. Kang, J. Li, S. Jiang, and P. Shull, "Reduce System Redundancy and Optimize Sensor Disposition for EMG-IMU Multi-Modal Fusion Human-Machine Interfaces with XAI," *IEEE Transactions on Instrumentation and Measurement* 92 (2022): 1.

172. S. Yu, Y. Xu, Z. Cao, et al., "Alterable Robotic Skin Using Material Gene Expression Modulation," *Advanced Functional Materials* 35 (2024): 2416984.

173. Y. Liu, J. Wang, T. Liu, et al., "Triboelectric Tactile Sensor for Pressure and Temperature Sensing in High-Temperature Applications," *Nature Communications* 16 (2025): 383.

174. M. H. Abidi, "Multimodal Data-Based Human Motion Intention Prediction Using Adaptive Hybrid Deep Learning Network for Movement Challenged Person," *Scientific Reports* 14 (2024): 30633.

175. O. Ali, M. Saif-ur-Rehman, T. Glasmachers, I. Iossifidis, and C. Klaes, "ConTraNet: A Hybrid Network for Improving the Classification of EEG and EMG Signals with Limited Training Data," *Computers in Biology and Medicine* 168 (2024): 107649.

176. Y. Li, P. Zhang, C. Guo, et al., "A Tactile Glove Based on Capacitive Pressure Sensor Array for Object Shape Recognition," *IEEE Sensors Journal* 24 (2024): 39690.

177. Z. Wang, Z. Li, S. Sun, et al., "Electromechanics of Stretchable Hybrid Response Pressure Sensors Based on Porous Nanocomposites," *Journal of the Mechanics and Physics of Solids* 193 (2024): 105872.

178. K.-H. Ha, Z. Li, S. Kim, et al., "Stretchable Hybrid Response Pressure Sensors," *Matter* 7 (2024): 1895.

179. L. Huang, S. Wang, P. Zhang, K. Zhang, Y. Li, and Z. Chen, "A Flexible Pressure Sensor with Wide Detection Range Based on Capacitive-Piezoresistive Dual Mode Conversion for Human-Machine Interaction," *Advanced Materials Technologies* 9 (2024): 2301377.

180. S. Han, X. Zhi, Y. Xia, et al., "All Resistive Pressure-Temperature Bimodal Sensing E-Skin for Object Classification," *Small* 19 (2023): 2301593.

181. Y. Xia, X. Zhi, M. Guo, Y. Zhang, S. Ma, and X. Wang, "Multimodal, Ultrasensitive, and Biomimetic Electronic Skin Based on Gradient Micro-Frustum Ionogel for Imaginary Keyboard and Haptic Cognition," *Advanced Functional Materials* 35 (2025): 2414936.

182. C. Zhang, S. Liu, X. Huang, W. Guo, Y. Li, and H. Wu, "A Stretchable Dual-Mode Sensor Array for Multifunctional Robotic Electronic Skin," *Nano Energy* 62 (2019): 164.

183. M. Zandigohar, M. Han, M. Sharif, et al., "Multimodal Fusion of Emg and Vision for Human Grasp Intent Inference in Prosthetic Hand Control," *Frontiers in Robotics and AI* 11 (2024): 1312554.

184. S. Geng, S. Fan, H. Li, et al., "An Artificial Neuromuscular System for Bimodal Human-Machine Interaction," *Advanced Functional Materials* 33 (2023): 2302345.

185. S. Sundaram, P. Kellnhofer, Y. Li, J.-Y. Zhu, A. Torralba, and W. Matusik, "Learning the Signatures of the Human Grasp Using a Scalable Tactile Glove," *Nature* 569 (2019): 698.

186. X. Ma, E. Kim, J. Zhou, et al., "Self-Powered Smart Skins for Multimodal Tactile Perception Based on Triboelectric and Hygroelectric Working Principles," *Nano Energy* 113 (2023): 108589.

187. S. Li, M. Yang, Y. Wu, et al., "A Flexible Dual-Mode Sensor with Decoupled Strain and Temperature Sensing for Smart Robots," *Materials Horizons* 11 (2024): 6361.

188. L. E. Osborn, A. Dragomir, J. L. Betthauser, et al., "Prosthesis with Neuromorphic Multilayered E-Dermis Perceives Touch and Pain," *Science Robotics* 3 (2018): eaat3818.

189. A. J. Thurston, "Paré and Prosthetics: The Early History of Artificial Limbs," *ANZ Journal of Surgery* 77 (2007): 1114.

190. E. D. Engeberg, "A Physiological Basis for Control of a Prosthetic Hand," *Biomedical Signal Processing and Control* 8 (2013): 6.

191. G. D. F. Ulloa, N. Sreenivasan, P. Bifulco, M. Cesarelli, G. Gargiulo, and U. Gunawardana, "Cost Effective Electro—Resistive Band based myo Activated Prosthetic Upper Limb for Amputees in the Developing World," in 2017 IEEE Life Sciences Conference (LSC) (IEEE, 2017), 250, https://doi.org/10.1109/LSC.2017.8268190.

192. J. Fuentes-Gonzalez, A. Infante-Alarcón, V. Asanza, and F. R. Loayza, "A 3D-printed EEG Based Prosthetic Arm," in 2020 IEEE International Conference on E-health Networking, Application & Services (HEALTHCOM) (IEEE, 2020), 1, https://doi.org/10.1109/HEALTHCOM49281.2021.9399035.

193. M. Nowak, T. Eiband, E. R. Ramírez, and C. Castellini, "Action Interference in Simultaneous and Proportional Myocontrol: Comparing Force- and Electromyography," *Journal of Neural Engineering* 17 (2020): 026011.

194. M. A. Garenfeld, C. K. Mortensen, M. Strbac, J. L. Dideriksen, and S. Dosen, "Amplitude versus Spatially Modulated Electrotactile Feedback for Myoelectric Control of Two Degrees of Freedom," *Journal of Neural Engineering* 17 (2020): 046034.

195. R. P. Borase, D. K. Maghade, S. Y. Sondkar, and S. N. Pawar, "A Review of PID Control, Tuning Methods and Applications," *International Journal of Dynamics and Control* 9 (2021): 818.

196. X. G. Duan, Y. Zhang, and H. D. Year, "A Simple Control Method to Avoid Overshoot for Prosthetic Hand Control," in 2014 IEEE

International Conference on Information and Automation (ICIA) (IEEE, 2014), 736.

197. L. Gohain, K. Sarma, A. J. Kalita, N. M. Kakoty, and S. M. Hazarika, "EMG Controlled Adaptive Multi-Grasp Prosthetic Hand with an Android Interface," *International Journal of Intelligent Robotics and Applications* 6 (2022): 791, https://doi.org/10.1109/ICInfA.2014.6932749

198. R. Raj, R. Ramakrishna, and K. S. Sivanandan, "A Real Time Surface Electromyography Signal Driven Prosthetic Hand Model Using PID Controlled DC Motor," *Biomedical Engineering Letters* 6 (2016): 276.

199. Q. Chen, "Design of Human-Computer Interaction Gesture Recognition System Based on a Flexible Biosensor," *International Journal of Computational Intelligence Systems* 17 (2024): 180.

200. A. Dellacasa Bellingegni, E. Gruppioni, G. Colazzo, et al., "NLR, MLP, SVM, and LDA: A Comparative Analysis on EMG Data From People with Trans-Radial Amputation," *Journal of NeuroEngineering and Rehabilitation* 14 (2017): 82.

201. A. Marinelli, N. Boccardo, M. Semprini, et al., "Miniature EMG Sensors for Prosthetic Applications," in 2021 10th International IEEE/EMBS Conference on Neural Engineering (NER) (IEEE, 2021), 1022, https://doi.org/10.1109/NER49283.2021.9441111.

202. H. Zhou, C. Tawk, and G. Alici, "A Multipurpose Human-Machine Interface via 3D-Printed Pressure-Based Force Myography," *IEEE Transactions on Industrial Informatics* 20 (2024): 8838.

203. Y. Li, L. Yang, S. Deng, et al., "A Machine Learning-Assisted Multifunctional Tactile Sensor for Smart Prosthetics," *InfoMat* 5 (2023): e12463.

204. L. Z. Hong, A. Zourmand, J. V. Patricks, and G. T. Thing, "EEG-based Brain Wave Controlled Intelligent Prosthetic Arm," in 2020 IEEE 8th Conference on Systems, Process and Control (ICSPC) (IEEE, 2020), 52, https://doi.org/10.1109/ICSPC50992.2020.9305784.

205. A. Marinelli, M. Canepa, D. Di Domenico, et al., "A Comparative Optimization Procedure to Evaluate Pattern Recognition Algorithms on Hannes Prosthesis," *Neurocomputing* 569 (2024): 127123.

206. J. Zbinden, J. Molin, and M. Ortiz-Catalan, "Deep Learning for Enhanced Prosthetic Control: Real-Time Motor Intent Decoding for Simultaneous Control of Artificial Limbs," *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 32 (2024): 1177.

207. S. Duan, Q. Shi, and J. Wu, "Multimodal Sensors and ML-Based Data Fusion for Advanced Robots," *Advanced Intelligent Systems* 4 (2022): 2200213.

208. H. Zhou and G. Alici, "Non-Invasive Human-Machine Interface (HMI) Systems With Hybrid On-Body Sensors for Controlling Upper-Limb Prosthesis: A Review," *IEEE Sensors Journal* 22 (2022): 10292.

209. H. Shim, S. Jang, J. G. Jang, et al., "Fully Rubbery Synaptic Transistors Made Out of All-Organic Materials for Elastic Neurological Electronic Skin," *Nano Research* 15 (2022): 758.

210. Y. Qi, J. Tang, S. Fan, C. An, E. Wu, and J. liu, "Dual Interactive Mode Human-Machine Interfaces Based on Triboelectric Nanogenerator and IGZO/In2O3 Heterojunction Synaptic Transistor," *Small Methods* 8 (2024): 2301698.

211. Y.-J. Park, Y. G. Ro, Y.-E. Shin, et al., "Multi-Layered Triboelectric Nanogenerators with Controllable Multiple Spikes for Low-Power Artificial Synaptic Devices," *Advanced Science* 10 (2023): 2304598.

212. M. Zhu, Z. Sun, T. Chen, and C. Lee, "Low Cost Exoskeleton Manipulator Using Bidirectional Triboelectric Sensors Enhanced Multiple Degree of Freedom Sensory System," *Nature Communications* 12 (2021): 2692.

213. X. Zhao, R. Liu, T. Ma, H. Li, and Q. Song, "*Real-time Gait Phase Estimation Based on Multi-source Flexible Sensors Fusion*," in Proceedings of the 2023 3rd International Conference on Robotics and Control Engineering (Association for Computing Machinery (ACM), 2023), 113, https://doi.org/10.1145/3598151.3598223.

214. E. Hays, J. Slayton, G. Tejeda-Godinez, E. Carney, K. Cruz, and T. Exley, "A Review of Rehabilitative and Assistive Technologies for Upper-Body Exoskeletal Devices," *Actuators* 12 (2023): 178.

215. J. Lee, K. Kwon, I. Soltis, et al., "Intelligent Upper-Limb Exoskeleton Integrated with Soft Bioelectronics and Deep Learning for Intention-Driven Augmentation," *npj Flexible Electronics* 8 (2024): 11.

216. N. Kladovasilakis, I. Kostavelis, P. Sideridis, et al., "A Novel Soft Robotic Exoskeleton System for Hand Rehabilitation and Assistance Purposes," *Applied Sciences* 13 (2023): 553.

217. B. Hu, J. Xue, D. Jiang, et al., "Wearable Exoskeleton System for Energy Harvesting and Angle Sensing Based on a Piezoelectric Cantilever Generator Array," *ACS Applied Materials & Interfaces* 14 (2022): 36622.

218. M. Sun, S. Cui, Z. Wang, et al., "A Laser-Engraved Wearable Gait Recognition Sensor System for Exoskeleton Robots," *Microsystems & Nanoengineering* 10 (2024): 50.

219. H. Kim, J. Lee, U. Heo, et al., "Skin Preparation-Free, Stretchable Microneedle Adhesive Patches for Reliable Electrophysiological Sensing and Exoskeleton Robot Control," *Science Advances* 10 (2024): eadk5260.

220. X. Chen, L. Gong, L. Wei, et al., "A Wearable Hand Rehabilitation System With Soft Gloves," *IEEE Transactions on Industrial Informatics* 17 (2021): 943.

221. N. Paredes-Acuña, N. Berberich, E. Dean-León, and G. Cheng, "Tactile-Based Assistive Method to Support Physical Therapy Routines in a Lightweight Upper-Limb Exoskeleton," *IEEE Transactions on Medical Robotics and Bionics* 4 (2022): 541.

222. D. Bhatia, K.-S. Lee, M. U. K. Niazi, and H.-S. Park, "Triboelectric Nanogenerator Integrated Origami Gravity Support Device for Shoulder Rehabilitation Using Exercise Gaming," *Nano Energy* 97 (2022): 107179.

223. C.-T. Pan, C.-C. Chang, Y.-S. Yang, C.-K. Yen, Y.-H. Kao, and Y.-L. Shiue, "Development of MMG Sensors Using PVDF Piezoelectric Electrospinning for Lower Limb Rehabilitation Exoskeleton," *Sensors and Actuators A: Physical* 301 (2020): 111708.

224. W. Li, Y. Ma, K. Shao, et al., "The Human-Machine Interface Design Based on sEMG and Motor Imagery EEG for Lower Limb Exoskeleton Assistance System," *IEEE Transactions on Instrumentation and Measurement* 73 (2024): 1.

225. D. Gomez-Vargas, F. Ballen-Moreno, C. Rodriguez-Guerrero, M. Munera, and C. A. Cifuentes, "Experimental Characterization of the T-FLEX Ankle Exoskeleton for Gait Assistance," *Mechatronics* 78 (2021): 102608.

226. M. C. Lee, C. H. Chuang, D. H. Lee, C. T. Pan, and K. M. Li, "Application of a Tactile Sensor for the Gait Phase Classification for an Exoskeleton," *IEEE Sensors Journal* 22 (2022): 11940.

227. B. Zhang, S. Wang, and M. Zhou, "A Novel Control for Gait Assistance and Resistance with a Robotic Hip Exoskeleton using Compact Soft Force Sensors," in 2021 IEEE/ASME International Conference on Advanced Intelligent Mechatronics (AIM) (2021), 923, https://doi.org/10.1109/AIM46487.2021.9517371.

228. S. Qiu, Z. Pei, C. Wang, and Z. Tang, "Systematic Review on Wearable Lower Extremity Robotic Exoskeletons for Assisted Locomotion," *Journal of Bionic Engineering* 20 (2023): 436.

229. J. Lee, K. Kwon, and W.-H. Yeo, "Recent Advances in Wearable Exoskeletons for Human Strength Augmentation," *Flexible and Printed Electronics* 7 (2022): 023002.

230. Y. G. Kim, M. Xiloyannis, D. Accoto, and L. Masia, "Development of a Soft Exosuit for Industrial Applications," in 2018 7th IEEE International

Conference on Biomedical Robotics and Biomechatronics (Biorob) (IEEE, 2018), 324.

231. Y. Yao, D. Shao, M. Tarabini, S. A. Moezi, K. Li, and P. Saccomandi, "Advancements in Sensor Technologies and Control Strategies for Lower-Limb Rehabilitation Exoskeletons: A Comprehensive Review," *Micromachines* 15 (2024): 489.

232. X. Hu, Z. Ma, F. Zhao, and S. Guo, "Recent Advances in Self-Powered Wearable Flexible Sensors for Human Gaits Analysis," *Nanomaterials* 14 (2024): 1173.

233. S. Neťuková, M. Bejtic, C. Malá, et al., "Lower Limb Exoskeleton Sensors: State-of-the-Art," *Sensors* 22 (2022): 9091.

234. C. Chen, W. Li, H. Wang, X. Mu, W. Guo, and X. Wu, "A Wearable Flexible Exoskeleton for Upper Limb Assistance," in 2023 IEEE International Conference on Real-time Computing and Robotics (RCAR) (IEEE, 2023), 560, https://doi.org/10.1109/RCAR58764.2023.10249746.

235. T. Ridremont, I. Singh, B. Bruzek, et al., "Pneumatically Actuated Soft Robotic Hand and Wrist Exoskeleton for Motion Assistance in Rehabilitation," *Actuators* 13 (2024): 180.

236. D. George, S. Kawamura, Y. Zheng, and Y. Hayashi, "Design and Validation of a High DOF Origami Inspired Soft Actuated Assistive Exoskeleton Arm and Spine," *IEEE Transactions on Medical Robotics and Bionics* 5 (2023): 1045.

237. Z. Zhao, X. Hou, D. Shan, H. Liu, H. Liu, and L. Hao, "Application of Fuzzy Adaptive Impedance Control Based on Backstepping Method for PAM Elbow Exoskeleton in Rehabilitation," *Polymers* 16 (2024): 3533.

238. S. Dinesh, U. K. Sahu, D. Sahu, S. K. Dash, and U. K. Yadav, "Review on Sensors and Components Used in Robotic Surgery: Recent Advances and New Challenges," *IEEE Access* 11 (2023): 140722.

239. Y. Qiu, A. Ashok, C. C. Nguyen, Y. Yamauchi, T. N. Do, and H. P. Phan, "Integrated Sensors for Soft Medical Robotics," *Small* 20 (2024): e2308805.

240. T.-V. Nguyen, R. Tanii, T. Takahata, and I. Shimoyama, "Development of a Single-Chip Elasticity Sensor Using MEMS-Based Piezoresistive Cantilevers with Different Tactile Properties," *Sensors and Actuators A: Physical* 285 (2019): 362.

241. C. Hou, K. Wang, F. Wang, et al., "A Highly Integrated 3D MEMS Force Sensing Module With Variable Sensitivity for Robotic-Assisted Minimally Invasive Surgery," *Advanced Functional Materials* 33 (2023): 2302812.

242. C. Zhang, Z. Jiang, M. Sun, R. Augustin-Lawson, S. H. Kwon, and L. Dong, "Nature-Inspired Helical Piezoelectric Hydrogels for Energy Harvesting and Self-Powered Human-Machine Interfaces," *Nano Energy* 136 (2025): 110755.

243. K. L. Mendez, C. E. Varela, J. Bonnemain, et al., "SmartSleeve: A Sutureless, Soft Robotic Epicardial Device that Enables Switchable on-Off Drug Delivery in Response to Epicardial ECG Sensing," *Device* 2 (2024): 100419.

244. C. D'Ambrosia, E. Aronoff-Spencer, E. Y. Huang, et al., "The Neurophysiology of Intraoperative Error: An EEG Study of Trainee Surgeons during Robotic-Assisted Surgery Simulations," *Frontiers in Neuroergonomics* 3 (2023): 1052411.

245. Q. Li, G. Gu, L. Wang, R. Song, and L. Qi, "Using EMG Signals to Assess Proximity of Instruments to Nerve Roots during Robot-Assisted Spinal Surgery," *The International Journal of Medical Robotics and Computer Assisted Surgery* 18 (2022): e2408.

246. A. Talasaz, "Deep Learning for Tumor Localization with Depth Estimation: A Minimally Invasive Robotics-Assisted Approach," in 2024 IEEE Conference on Artificial Intelligence (CAI) (IEEE, 2024), 438, https://doi.org/10.1109/CAI59869.2024.00087.

247. Y. Hong, Y. Zhang, C. Zhu, and F. Ju, "*A Robotic Endoscopic Injection Needle with Integrated Tactile Sensor for Intraoperative Autonomous Tumor Localization*," in Intelligent Robotics and Applications: 14th International Conference (Springer International Publishing, 2021), 165, https://doi.org/10.1007/978-3-030-89134-3_16.

248. Y. Sun, H. Li, C. Hou, et al., "*A Triboelectric Tactile Perception Ring for Continuum Robot Collision-Aware*," in 2021 21st International Conference on Solid-State Sensors, Actuators and Microsystems (Transducers) (2021), 329.

249. H. Oh, G.-C. Yi, M. Yip, and S. A. Dayeh, "Scalable Tactile Sensor Arrays on Flexible Substrates with High Spatiotemporal Resolution Enabling Slip and Grip for Closed-Loop Robotics," *Science Advances* 6 (2020): eabd7795.

250. C. Hou, J. Geng, Y. Sun, et al., "*A Sensorised Forcep Based on Piezoresistive Force Sensor for Robotic-Assisted Minimally Invasive Surgery*," in 2021 IEEE 16th International Conference on Nano/Micro Engineered and Molecular Systems (NEMS) (IEEE, 2021), 60, https://doi.org/10.1109/NEMS51815.2021.9451326.

251. A. Arshad, M. M. Saleem, M. I. Tiwana, H. ur Rahman, S. Iqbal, and R. Cheung, "A High Sensitivity and Multi-Axis Fringing Electric Field Based Capacitive Tactile Force Sensor for Robot Assisted Surgery," *Sensors and Actuators A: Physical* 354 (2023): 114272.

252. S. Hussain, M. M. Saleem, M. Rehan, H. Elahi, and M. I. Tiwana, "A High Sensitivity, Low Cost and Fully Decoupled Multi-Axis Capacitive Tactile Force Sensor for Robotic Surgical Systems," *PLoS One* 19 (2024): e0313737.

253. D. A. Aubeeluck, C. Forbrigger, S. Mohseni Taromsari, T. Chen, E. Diller, and H. E. Naguib, "Screen-Printed Capacitive Tactile Sensor for Monitoring Tool-Tissue Interactions and Grasping Performances of a Surgical Magnetic Microgripper," *ACS Applied Electronic Materials* 6 (2024): 6365.

254. P. Puneetha, S. P. R. Mallem, S. C. Park, et al., "Ultra-Flexible Graphene/Nylon/PDMS Coaxial Fiber-Shaped Multifunctional Sensor," *Nano Research* 16 (2023): 5541.

255. V. Arabagi, O. Felfoul, A. H. Gosline, R. J. Wood, and P. E. Dupont, "Biocompatible Pressure Sensing Skins for Minimally Invasive Surgical Instruments," *IEEE Sensors Journal* 16 (2016): 1294.

256. C. Yang, S. Chang, P. Liang, Z. Li, and C. Y. Su, "Teleoperated robot writing using EMG signals," in 2025 IEEE International Conference on Information and Automation (IEEE, 2015), 2264, https://doi.org/10.1109/ICInfA.2015.7279663.

257. K. Yang, T. B. Meier, H. Zhou, G. S. Fischer, and C. J. Nycz, "A sEMG Proportional Control for the Gripper of Patient Side Manipulator in da Vinci Surgical System," in 2022 44th Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC) (IEEE, 2022), 4843, https://doi.org/10.1109/EMBC48229.2022.9871664.

258. J. Yang, J. A. Barragan, J. M. Farrow, C. P. Sundaram, J. P. Wachs, and D. Yu, "An Adaptive Human-Robotic Interaction Architecture for Augmenting Surgery Performance Using Real-Time Workload Sensing-Demonstration of a Semi-Autonomous Suction Tool," *Human Factors* 66 (2024): 1081.

259. J. A. Barragan, J. Yang, D. Yu, and J. P. Wachs, "A Neurotechnological Aid for Semi-Autonomous Suction in Robotic-Assisted Surgery," *Scientific Reports* 12 (2022): 4504.

260. L. Cheng and M. Tavakoli, "Neural Network-Based Physiological Organ Motion Prediction and Robot Impedance Control for Teleoperated Beating-Heart Surgery," *Biomedical Signal Processing and Control* 66 (2021): 102423.

261. S. Niu, K. Jin, Z. Hu, C. Zhang, D. Zhao, and Y. Xing, "Ergonomic Evaluation between Laparoscopic and Robotic Surgery Based on EMG," in 2020 IEEE International Conference on Mechatronics and Automation (ICMA) (IEEE, 2020), 1756, https://doi.org/10.1109/ICMA49215.2020.9233756.

262. S. B. Shafiei, S. Shadpour, J. L. Mohler, et al., “Surgical Skill Level Classification Model Development Using EEG and Eye-Gaze Data and Machine Learning Algorithms,” *Journal of Robotic Surgery* 17 (2023): 2963.

263. M. J. Pérez-Salazar, D. Caballero, J. A. Sánchez-Margallo, and F. M. Sánchez-Margallo, “Comparative Study of Ergonomics in Conventional and Robotic-Assisted Laparoscopic Surgery,” *Sensors* 24 (2024): 3840.

264. J. Hislop, O. Tirosh, J. McCormick, R. Nagarajah, C. Hensman, and M. Isaksson, “Muscle Activation during Traditional Laparoscopic Surgery Compared with Robot-Assisted Laparoscopic Surgery: A Meta-Analysis,” *Surgical Endoscopy* 34 (2020): 31.

265. V. Ivanova, A. Boneva, S. Ivanov, and P. Vasilev, “A Wireless Device to Modular Robotized Instrument for Health Information,” *Computer Science & Engineering: An International Journal (CSEIJ)* 13 (2023): 21, https://doi.org/10.5121/cseij.2023.13203.