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Electronic Skin: Opportunities and Challenges in Convergence with Machine Learning

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Keywords

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Abstract

Recent advancements in soft electronic skin (e-skin) have led to the development of human-like devices that reproduce the skin's functions and physical attributes. These devices are being explored for applications in robotic prostheses as well as for collecting biopotentials for disease diagnosis and treatment, as exemplified by biomedical e-skins. More recently, machine learning (ML) has been utilized to enhance device control accuracy and data processing efficiency. The convergence of e-skin technologies with ML is promoting their translation into clinical practice, especially in healthcare. This review highlights the latest developments in ML-reinforced e-skin devices for robotic prostheses and biomedical instrumentations. We first describe technological breakthroughs in state-of-the-art e-skin devices, emphasizing technologies that achieve skin-like properties. We then introduce ML methods adopted for control optimization and pattern recognition, followed by practical applications that converge the two technologies. Lastly, we briefly discuss the challenges this interdisciplinary research encounters in its clinical and industrial transition.

Contents

1. INTRODUCTION

Soft electronic skins (e-skins) are flexible and stretchable electronic devices designed to mimic the properties and functions of human skin. The initial concept of e-skins was introduced in the 1970s (1, 2), with the aim of replicating human skin's sensing capabilities by integrating electronic components with flexible materials. Their initial developments were constrained by the available materials and fabrication processes. However, the emergence of epidermal electronics (3) in the early 21st century established a foundation for advanced e-skins with a wide range of potential applications in robotics (4–6), prosthetics (7–9), wearable health monitoring and therapeutic devices (10–12), and human–machine interfaces (HMIs) (13–15). As such, e-skin devices can be broadly categorized into two types according to their intended uses: (*a*) artificial e-skins for robotics and prosthetics, which aim to replicate or restore the functions of human body parts; and (*b*) biomedical e-skins, which collect physiological data in real time for prevention and diagnosis of various diseases and provide immediate therapeutic interventions when possible (**Figure 1**).

Naturally, research efforts have been devoted to different directions for the two distinct types of e-skin devices. For instance, for artificial e-skins, the focus has been on precisely imitating the functions of human skin, such as sensing capabilities including but not limited to tactility (pressure and strain), temperature, vibrations, and humidity (16–18). Flexible and stretchable sensors, capable of multimodal sensing with high resolution and large-area coverage, have been extensively investigated. Robotic systems equipped with such artificial e-skins can obtain information about their surroundings to execute complicated tasks. Additionally, they can be biointegrated as prosthetic devices to restore human body functions such as somatosensation and vision (19–21). As this type of e-skin is not intended to be worn directly on human skin but instead is applied to robotic or prosthetic devices, the desired attributes of artificial e-skins include high toughness, self-healing capability, and robust adhesion to the applied devices. These characteristics are essential for longevity and consistent performance.

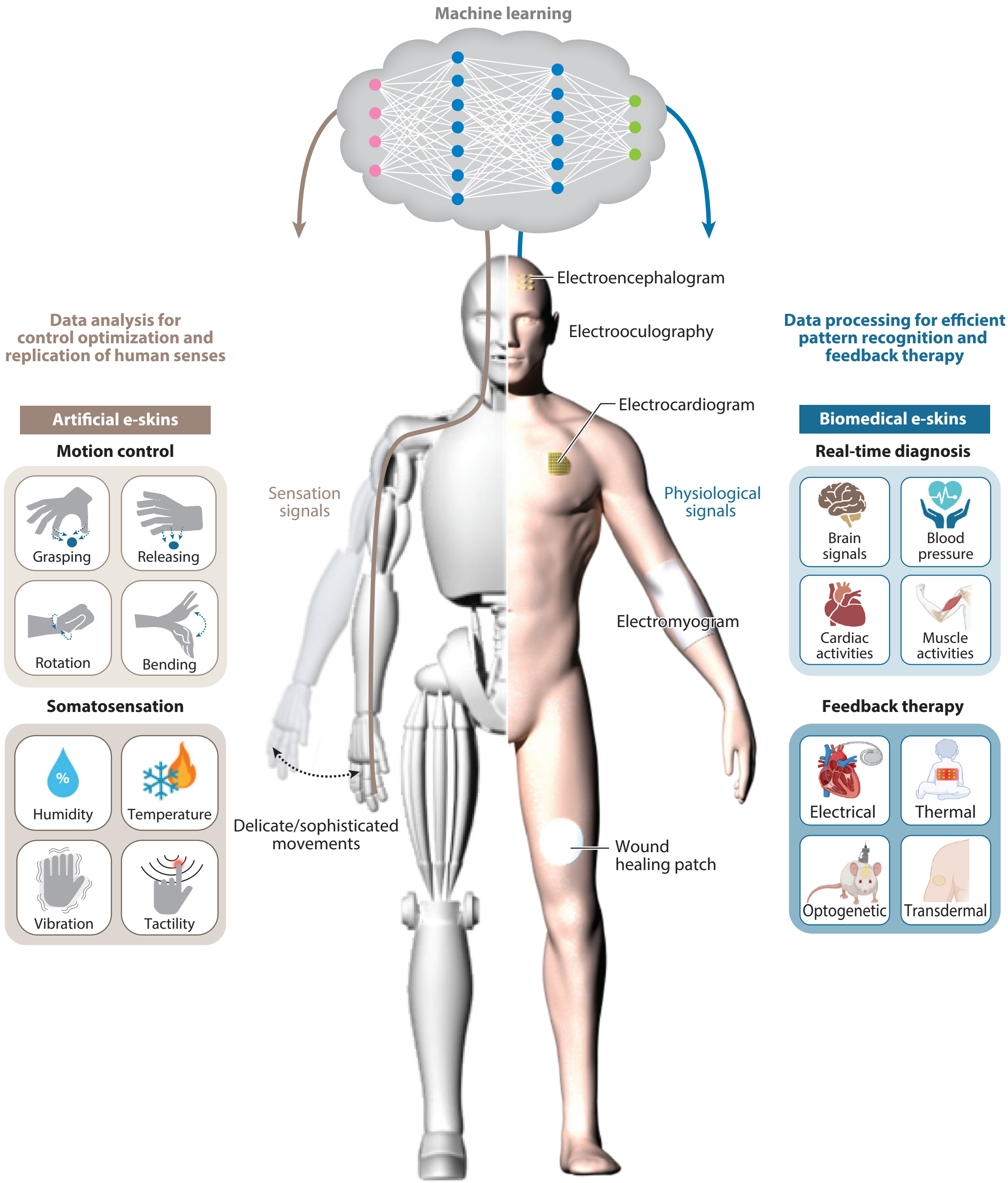


Figure 1

The convergence of machine learning with artificial soft electronic skins (e-skins) for robotics and prosthetics and with biomedical e-skins to conduct real-time physiological data-based disease diagnosis, prevention, and feedback therapy.

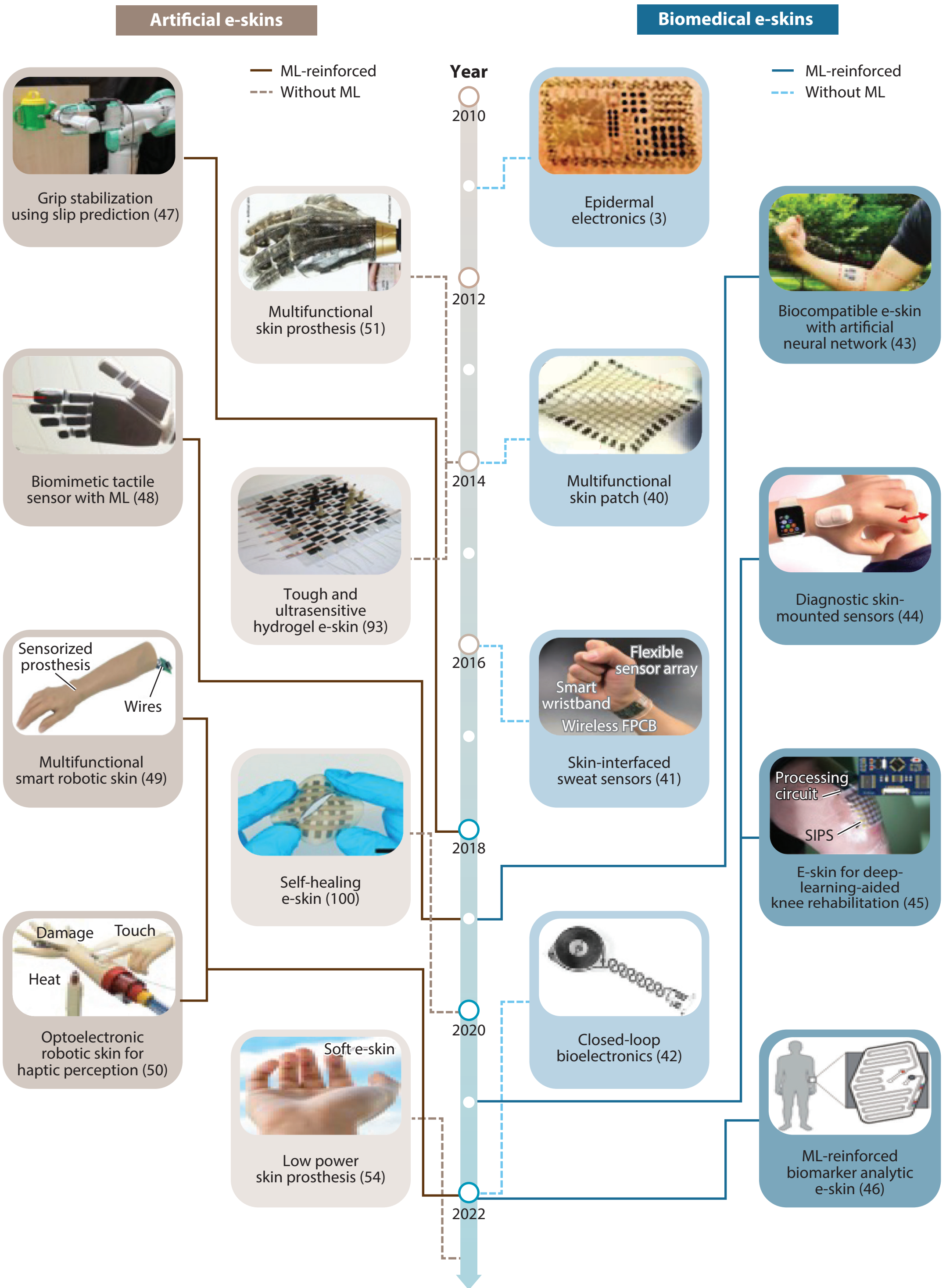
On the other hand, the primary objective of biomedical e-skins is to accurately collect the desired physiological data with high reliability. This can be achieved via conformal integration of the biomedical e-skins on human skin, by matching the elastic moduli of the two distinct materials (22–24). A cohesive fit of the electronics on human skin results in maximized sensing capabilities, as well as reduced side effects, which are crucial for the long-term application of biomedical e-skins for continuous health monitoring. In addition, biomedical e-skins are required to be biocompatible, and methods to overcome degradation in the biotic-abiotic interface due to secretions are highly desirable. Lastly, a low impedance is essential for the biomedical e-skin materials to ensure appropriate feedback treatment through the integrated soft actuators. Thus, significant research efforts have been directed toward developing high-performance sensors and actuators from materials with skin-like mechanical/physical properties (25–30). Advancements in these types of e-skin devices were mainly achieved through the synthesis of novel flexible and stretchable materials, complemented by device design and integration strategies in both hardware and software aspects.

Despite the progress in data collection technologies using both types of soft e-skin devices, the technology for translating massive data into meaningful and understandable information remains a significant challenge. This is mainly attributed to the difficulty of developing powerful data storage and processing units with skin-like properties, or in wearable formats. Furthermore, integrating multiple functional electronic devices into a single wearable platform is extremely challenging, as the materials and processing tools used for each might be incompatible. In this regard, artificial intelligence (AI) technologies have been recently highlighted as more convenient and effective solutions. Machine learning (ML), in particular, has been employed as a powerful tool for analyzing and processing data collected from e-skin devices and has proven effective in applications such as activity recognition (31, 32), gesture recognition (33, 34), and object detection (35, 36). ML algorithms have also been successfully paired with biomedical e-skin devices to verify normal/abnormal patterns in biomarkers with high accuracy (37–39). **Figure 2** illustrates a combined timeline of ML and soft e-skins, presenting their development and the recent emergence of ML-equipped e-skins (3, 40–54). The interdisciplinary research bridging soft e-skin devices and ML algorithms is expected to accelerate the translation of related technologies into clinical practices and industrial applications, benefitting both patients and customers.

In this review, we first summarize recent technological advances in soft e-skin devices, with a particular focus on the materials and device strategies for both artificial and biomedical e-skins. The desired features of the two different e-skins will be discussed, and examples of state-of-the-art e-skin applications that achieved such features will be introduced in detail. We then give a general introduction to the ML algorithms that can be used to reinforce the e-skins, with classifications of supervised, unsupervised, and reinforcement algorithms. A review of the specific algorithms used for control optimization and pattern recognition follows, and detailed examples of ML-reinforced e-skins are provided, emphasizing the performance improvement by ML-enabled data processing. Finally, in the conclusion, we briefly discuss the challenges faced by this interdisciplinary research and future prospects.

2. DESIGN RULES AND FABRICATION TECHNIQUES OF SOFT E-SKINS

A high mechanical compliance is required for both artificial and biomedical e-skin devices to ensure safer and more efficient human–machine interaction, as well as seamless interaction with the human body (55, 56). The functional electronic devices that constitute e-skins, such as sensors, actuators, data storage and transmission modules, and energy devices, should adapt to the body's



(*Caption appears on following page*)

Figure 2 (*Figure appears on preceding page*)

Timeline showing advancements in artificial and biomedical electronic skin (e-skin) technologies (*dashed lines*) along with their recent integration with machine learning (ML) for intelligent e-skins (*solid lines*). Abbreviations: FPCB, flexible printed circuit board; SIPS, stretchable iontronic pressure sensor. Images adapted with permission from Reference 3, copyright 2011 AAAS; Reference 40, copyright 2014 Springer Nature; Reference 41, copyright 2016 Springer Nature; Reference 42, copyright 2022 AAAS; Reference 43, copyright 2019 Wiley; Reference 44 (CC BY 4.0); Reference 45 (CC BY 4.0); Reference 46 (CC BY 4.0); Reference 47 (CC BY 4.0); Reference 48 (CC BY 4.0); Reference 49, copyright 2022 AAAS; Reference 50, copyright 2022 AAAS; Reference 51, copyright 2014 Springer Nature; Reference 54, copyright 2023 AAAS; Reference 93 (CC BY 4.0); and Reference 100 (CC BY 4.0).

dynamic shapes and movements without compromising their functionalities and performance. Early research in e-skins focused on imparting stretchability to individual devices, especially sensor devices, aiming for high sensitivity and durability over repeated use cycles (57–60). Among various strategies, structural engineering of device designs (61, 62) and the use of intrinsically stretchable materials as the fundamental building blocks for device fabrication (63, 64) have proven to be highly effective in simultaneously achieving high performance and high mechanical freedom. The former approach utilizes well-established yet rigid inorganic materials with crystallinity for their high performance, combined with geometrically engineered designs to achieve stretchability. Typical designs include prestrained buckled structures (65, 66), island-bridge configurations (67, 68), serpentine/honeycomb routing designs (69, 70), and kirigami-inspired stretchable designs (71, 72). Commonly, these devices employ rigid crystalline materials with nanoscale thickness to minimize flexural rigidity and improve mechanical performance. Since numerous comprehensive reviews are available detailing the mechanics and physics of these stretchable devices and their fabrication techniques (73–75), this review provides a concise overview, along with representative examples of e-skin applications.

Ultrathin inorganic devices can achieve stretchability via buckled structures. This is done by attaching the device to prestrained elastomeric substrates and then releasing the strain. The degree of stretchability can be engineered by adjusting the prestretched strains of the supporting substrates. This strategy has been widely adopted for developing various functional e-skin devices, such as on-skin sensors for detecting diverse human activities (76, 77), photonic skins to monitor photoplethysmogram signals (78), and transparent humidity-sensing e-skin (79). For the island-bridge configurations, functional electronic devices are designed as separated island arrays, which are then connected by strain-tolerant interconnects. Applied strain is effectively dissipated through the stretched interconnects, leaving the functional devices on the rigid islands unaffected, which can thus be constructed from rigid crystalline materials for enhanced performance. Soft e-skin devices employing this island-bridge configuration have been deployed in biomedical patches for monitoring and therapy (11, 40), multifunctional e-skins for temperature display and strain sensing (80), and e-skins embedded with biomimetic mechanoreceptors (81).

Functional electronic devices can be fabricated on geometrically engineered supports that tolerate applied strains, such as bioinspired or serpentine structures. For instance, conductive electrodes combining patterned honeycomb and butterfly structures have demonstrated high mechanical stability across deformations and can be mounted on the skin for electrocardiogram recording (82). Fabrication of stretchable electrodes with serpentine designs has been also reported. The stretchable electrodes have been used as skin-mounted devices for articular thermotherapy or as epicardial devices to monitor cardiac activities and provide thermal therapy (83, 84). Similarly, by forming strategical openings (i.e., kirigami structures) in the elastic supports, the mechanical stress applied can be effectively alleviated through the torsional deformation of the kirigami structures. A recent report demonstrated the fabrication of multifunctional e-skin based on kirigami-structured liquid metal paper electrodes, which is capable of effectively monitoring various electrophysiological signals due to its robust mechanical properties (85).

Despite the high performance of e-skin devices based on rigid crystalline materials and stretchable device designs, various technical issues exist. First, the device density is restricted due to the use of stretchable interconnects or geometrical device designs, resulting in low spatiotemporal resolution. Complex device designs and fabrication methods lead to higher production costs, which are undesirable for mass production. Additionally, these functional electronic components struggle to recover from mechanical failures, making component replacement challenging and often unfeasible. Hence, developing e-skin devices with intrinsically soft materials has gained significant interest. Devices manufactured with these materials offer higher durability, resolution, affordability, and tunability of mechanical and physical properties. Intrinsically stretchable electronic materials can be readily synthesized by incorporating functional filler nanomaterials into elastomeric composites (86–88). Their electronic and mechanical properties can be tuned by varying the amount of filler materials. Generally, a higher quantity of functional fillers enhances electronic properties but diminishes their mechanical properties. Nevertheless, the performance of intrinsically stretchable devices remains generally inferior to the performance of those based on rigid crystalline materials. Moreover, most intrinsically stretchable functional materials are solution processed and are not compatible with the microfabrication tools currently used in the industry, posing significant limitations in fabrication fidelity. Consequently, investigation of novel fabrication techniques and materials technologies is required for advanced e-skin devices with intrinsic stretchable features. In the following sections, artificial e-skin devices and biomedical e-skin devices based on different stretchable device fabrication strategies are reviewed, focusing on the state-of-the-art technologies that grant them skin-like properties and functionalities.

2.1. Artificial E-Skins for Soft Robotics and Prostheses

The primary purpose of artificial e-skins, as highlighted earlier, is to mimic the functions of human skin. Achieving this necessitates understanding the intricate features of our skin: It not only acts as a protective barrier but also serves as a sophisticated sensory interface, enabling tactile sensations, temperature regulation, and even pain detection. To emulate these complex functionalities, artificial e-skins must incorporate a range of sensory, actuating, and protective devices. This ensures refined control when these skins are used in robotic devices. When integrated into prosthetics or incorporated into robots, such devices aim to restore, assist, or even replace certain human functionalities. Several characteristics are desirable to accomplish these goals. For prosthetics, such devices must integrate seamlessly with the human body to minimize the burden of discomfort, requiring high mechanical compliance (89). To this end, biomimetic e-skin devices should consist of sensor arrays with stretchable features and high spatiotemporal resolution across expansive areas. Additionally, they should support multimodal sensing, akin to various sensory receptors of human skin (**Figure 3*a***). These receptors detect and differentiate stimuli, such as humidity, temperature, vibration, and tactile information. Consequently, e-skin devices with multimodal sensing have become a focal point of research in recent years.

Jung et al. (90) reported the development of a flexible trimodal sensor adept at detecting pressure, temperature, and airflow. To closely mimic human skin's structure, varied sensors were vertically stacked in a multilayered formation without disturbing the electrical contacts. This was achieved by placing an insulating layer between the sensors, thereby minimizing interference and differentiating input response between the sensors. In another study by Lee et al. (91), the capability to discriminate materials and recognize texture was accomplished using fingerprint-inspired elastic designs made from composites of hybrid nanomaterials and elastomeric matrices. Their e-skin could successfully distinguish multiple stimuli combinations by utilizing different electrical properties of piezoelectricity, triboelectricity, and piezoresistivity. When the e-skin was applied

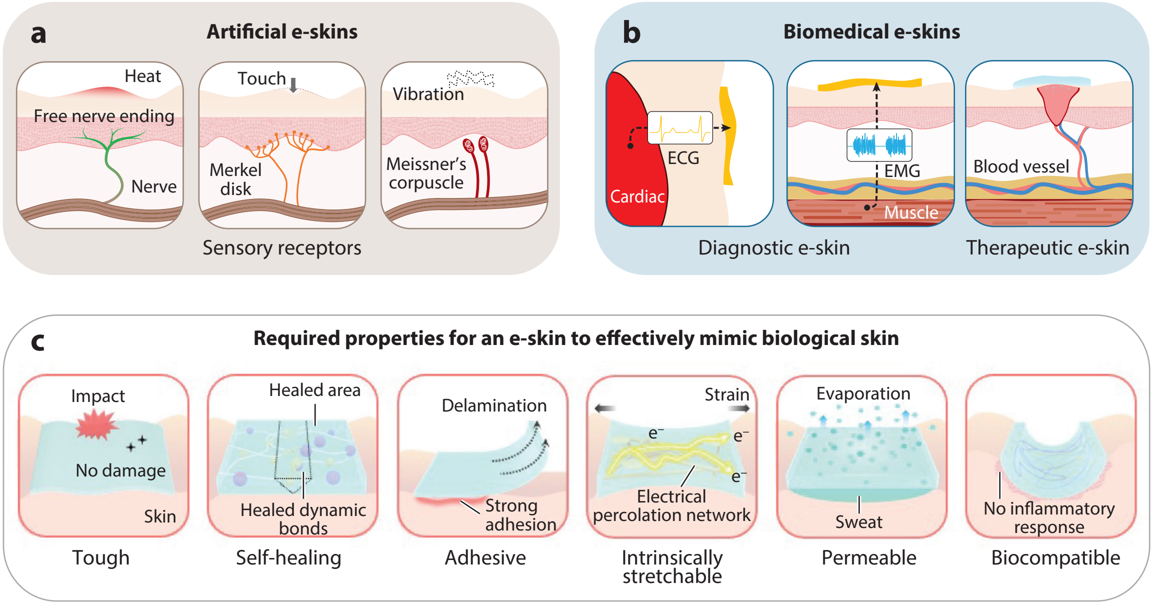


Figure 3

Requirements of electronic skin (e-skin) devices according to their types and purposes. (*a*) Mimicking sensory receptors of skin with artificial e-skins. (*b*) Real-time disease diagnosis and feedback therapy enabled by biomedical e-skins, including the capture of electrocardiogram (ECG) and electromyogram (EMG) signals. (*c*) Desirable physical properties of e-skins for sustainable operation with enhanced performance.

to a robotic hand, it exhibited capabilities similar to human tactile perception. Chen et al. (92), through a straightforward in situ reduction and solvent casting approach, fabricated e-skin sensors capable of detecting strain, temperature, and humidity. Uniformly dispersing nanoparticles and charged ions in an elastomeric matrix resulted in high stretchability (~600% strain) and optical transparency (transmittance of ~90%), which are ideal features for prosthetic devices.

In addition to multimodal sensing, artificial e-skins for robotic and prosthetic devices need to be resilient, resisting potential damages from diverse external inputs such as chemical, optical, physical, and thermal impacts (**Figure 3*c***). Such attributes are difficult and often contradictory to optimize, especially since e-skins are based on ultrathin and soft materials. In this regard, hydrogels have emerged as a promising material for robust e-skins due to their intrinsic properties resembling biological tissues, excellent mechanical characteristics, and functionalities (93, 94). Specifically, double-network hydrogels comprising two physically or chemically cross-linked polymers have been extensively investigated because of their high fracture energy and toughness while maintaining excellent stretchability. The porous nature of hydrogels offers tunable ion conductivity and mass transport capability, making them an ideal substrate for e-skin applications. Over the past few years, diverse investigations have been conducted to tailor the mechanical properties of hydrogels for e-skin devices with advanced functionalities.

Using a layer-by-layer polymerization process, Qu et al. (95) controlled the physical properties of a bilayer composite hydrogel to develop a stretchable and tough e-skin device capable of strain sensing. By controlling the polymer composition and polymerization conditions, they endowed each layer of hydrogel with distinguishable mechanical properties, achieving high stretchability of more than 3,600% and high toughness exceeding 200 kPa. Zhang et al. (96) developed an ultrathin yet highly durable conductive hydrogel film-based multifunctional e-skin device, which can sense motions and recognize the texture and roughness of objects via film casting and secondary hydration of conductive hydrogel. Their method utilized noncovalent synergistic effects, such as π-π stacking and hydrogen bonding. This resulted in a multitude of beneficial properties for e-skin applications, including high toughness (~3.5 MPa), swelling resistance, and antifriction properties. In more recent work, Chen et al. (97) reported a hydrogel-based e-skin manufactured via molecular self-assembly. This e-skin featured ultratough (~5.79 MPa), antibacterial, UV protective, and antiswelling properties, which were used as HMIs. They employed a physical cross-linking method termed salting-freezing-thawing to adjust the mechanical properties, suggesting a simple and effective strategy for optimizing e-skin devices.

Artificial e-skin devices that can replicate the self-healing properties of human skin are highly valuable. Self-healing not only extends the life span of devices but also substantially lessens replacement costs for damaged parts. For achieving toughness and self-healing properties concurrently, polymer elastic matrices are preferred due to their easy molecular design and functionalization. In particular, polyurethane (PU) stands out for its capacity to offer both these properties (98, 99). The inherent inhomogeneity in the microstructure of PU, arising from the thermodynamically incompatible hard and soft segments, grants it exceptional deformability and shape retention. This ensures high toughness and resistance to tearing compared with other elastomers. Dynamic and reversible covalent bonds further grant it self-healing capabilities. Consequently, recent research has focused on developing self-healing artificial e-skins with high toughness.

A remarkably tough (27.5 MJ/m^3) and stretchable (~300% tensile strain) e-skin was developed by Ying et al. (100). This PU-based matrix contained a polydisperse hard segment, a hydrophobic soft segment for water resistance, and a dynamic disulfide bond for self-healing. The self-healing capability was validated for pressure sensing, mechanical, and electrical properties, exhibiting almost full recovery after resting at room temperature for 6 h. In a different study, Xun et al. (101) demonstrated a self-powered e-skin founded on a bi-layered structure comprising a PU elastomer (PUE) for insulation and a conductive PUE for self-healing. A triboelectric-electrostatic induction effect between the PUE layers powered the e-skin, which had a toughness of ~2 MPa. Its mechanosensation abilities could be restored after fracture. Bai et al. (102) integrated optical sensors into an intelligent robotic system, using PU-based elastomers with dynamic aromatic disulfide bonds for self-healing. This e-skin, designed with mechanical contact-free optical waveguide sensors, was resilient to damage and adept at detecting and recovering from severe damage.

To ensure optimal performance, artificial e-skins must adhere firmly to the dynamic surfaces of robots or prosthetic devices. While complete contact with electronic devices is not always imperative for performance enhancement, the e-skins need to conform to the dynamic environments of their host structures for precise functionalities. Traditional chemical adhesives might degrade over time or be physically and chemically compromised by environmental conditions. A promising alternative is bioinspired adhesives, which excel in both wet and dry environments. Such structures, constructed from chemically inert materials, can serve as interfacial adhesive layers and as efficient tools for reversible adhesion without damaging either the target or themselves.

Drawing inspiration from the suction cups of octopuses, Baik et al. (103) devised a simple solution-based method to create patterned structures mimicking an octopus's architecture. With the base polymer's low air permeability, they enhanced suction behaviors and exhibited reversible and highly repeatable adhesion to various surfaces in both wet and dry conditions. This group further innovated by combining features of the octopus's sucker with a hierarchical microchannel network, as seen in tree frogs (104).

The recent developments in artificial e-skins covered in this section were aimed at mimicking the functionalities of real human skin, in terms of making them not only perceptible but also more durable. The technological advancements described in this section, along with continuous efforts in developing novel materials and device techniques for skin-like electronics, are expected to accelerate the growth of intelligent artificial e-skins for soft robotics and prosthetics.

2.2. Biomedical E-Skins for Diagnosis and Therapy

Whereas artificial e-skins primarily detect and distinguish external inputs, biomedical e-skins primarily sense inputs from their attachment point—human skin. These biomedical e-skins are designed to accurately capture various physiological signals from the human body (**Figure 3*b***), including but not limited to electroencephalogram, electrooculography, electrocardiogram (ECG), and electromyogram signals. The aim is to provide precise readings that enable timely therapeutic interventions upon users' decisions. Thus, these biomedical e-skins should incorporate soft actuators to immediately respond on demand and be connected to or integrated with soft-formed visual display modules that notify their users of irregular activities in real time (105).

The requirements and applications of artificial and biomedical e-skins differ, leading to variations in their desired physical properties. Biomedical e-skins need to collect high-fidelity biopotentials in real time, some of which originate epidermically or deep within the human body. Ensuring a high signal-to-noise ratio mandates a conformal integration of the devices onto the target points of human skin. This, in turn, requires the mechanical moduli between the device and the skin to be analogous (106, 107). Achieving such conformal contact is crucial not only for high sensitivity but also for establishing a robust interface that results in strong device adhesion on the skin with minimal adverse effects. Though previous approaches for stretchable device fabrication described earlier are applicable, each has its own benefits and drawbacks. For example, stretchable devices based on structural designs that incorporate high-performance crystalline materials possess a potential for mass production and exhibit superior electrical performance. However, the rigidity of the active materials employed can become stressed and may not recover from initial mechanical breakdowns. The inherent rigidity of these materials might deteriorate the biotic/abiotic interface over time, compromising the device's effectiveness despite the incorporated stretchable designs. Using such structures can also result in low spatiotemporal resolution due to a decreased density of the active devices.

In contrast, devices built from intrinsically stretchable materials exhibit superior durability and reliability, along with higher device densities (**Figure 3*c***). However, a primary concern is the low device performance of intrinsically stretchable conductors, semiconductors, and insulators. While significant progress has been achieved in the synthesis of intrinsically stretchable conductors and semiconductors with enhanced electrical properties (108, 109), finding suitable materials for intrinsically stretchable insulators remains a challenge. Specifically, most insulating materials currently adopted in intrinsically stretchable electronic/optoelectronic devices are polymers and elastomers, which are typically solution processed. This makes them incompatible with current vacuum-based microfabrication tools. These materials are often thick, which is particularly unfavorable for building transistors and circuits that require excellent gate controllability for low operation voltage and high speed. In addition, these insulators are vulnerable to various organic solvents, posing difficulties in the device fabrication process. Wang et al. (110) demonstrated that intrinsically stretchable transistors and sensor arrays with high spatiotemporal resolution and large area coverage can be fabricated using an azide-modified chemically durable elastomer as the dielectric material. Despite the innovation for scalable device fabrication, the use of a solution-processed elastomer as the dielectric material still could not address the high operation voltage issue, which is especially undesirable for biomedical e-skin applications. Recently, an intrinsically stretchable insulator that supports low-temperature vacuum deposition has been developed (111). This insulator provides excellent thickness controllability, large-area uniformity, improved gate controllability, and compatibility with conventional microfabrication techniques, and it retains good insulating performance even when stretched. These advances in intrinsically stretchable materials are expected to improve biomedical e-skins by not only ensuring higher performance but also facilitating multifunctionality through the integration of various functional devices onto a single platform.

While establishing conformal contact between biomedical e-skin devices and human skin is critical for accurate sensing, other features, such as air permeability (also known as breathability) and biocompatibility, should also be considered for their long-term operation (**Figure 3*c***). Fortunately, a large portion of synthetic polymers, which are readily used as substrate materials, are known to be biocompatible (i.e., they do not negatively impact the human body). Nevertheless, the long-term application of e-skin devices to skin may cause skin inflammation, even if device materials are entirely biocompatible. This may occur when the e-skin devices prevent the skin's physiologic functions (such as "breathing"), or if skin by-products accumulate at the biotic/abiotic interface. Such reactions prevent precise cutaneous sensing over an extended period and cause delamination of the skin-mounted devices. Breathable e-skins can mitigate these issues, enhancing the comfort of long-term e-skin wearability. The substrate materials of e-skin devices dominantly affect the device's breathability. Traditional substrates, such as plastics or elastomers, are often impermeable. Consequently, strategies for imparting porosity and permeable features in these materials have been extensively researched.

Yeon et al. (112) designed sweat pore–inspired e-skins with perforation that performed reliable health monitoring over several weeks. These devices created hole patterns with fractal cuts to achieve two objectives: ensuring permeability by exposing the skin's sweat pores to the open air and enhancing mechanical reliability through auxetic kirigami patterns. The porosity-engineered e-skin devices exhibited ultraconformality and fitness for long-term physiological data collection, even under vigorous physical activities such as exercising at the gym. Elsewhere, Peng et al. (113) introduced breathable e-skins utilizing chitosan substrates—a natural polymer. Although chitosan is known for its simple processing and biocompatibility, it has limited water vapor penetration. Permeability was achieved by incorporating nontoxic plasticizers, resulting in the formation of microcrack structures in the chitosan membrane. These intentional microcracks provided channels for moisture flow between human skin and the external environment. Such breathable e-skins are expected to enhance long-term monitoring of physiological skin signals, ensuring a more comfortable and natural environment.

3. MACHINE LEARNING FOR ARTIFICIAL AND BIOMEDICAL E-SKINS

With the continual advancement of e-skin technology, capturing better conformality, resolution, and modality, both artificial and biomedical e-skins are now able to acquire and process data at an unprecedented scale. These data offer significant potential, from enhancing embodied intelligence in devices and robots (114, 115) to aiding medical diagnoses (116–118). Within this context, ML, a subset of AI, serves as a powerful tool for effectively organizing and extracting meaningful insights from voluminous data in an interpretable and practical manner (**Figure 4*a***). ML's iterative algorithmic procedures effectively extract intricate statistical connections within the input data. They also elucidate highly nonlinear relationships between acquired signals and desired outcomes. These characteristics are often prevalent in physiological signals and real-world interactions. Ultimately, ML constructs a comprehensive model capable of predicting outcomes for new inputs with precision and computational efficiency. ML encompasses three primary categories of algorithms, each serving distinct purposes: supervised learning, unsupervised learning, and reinforcement learning.

Supervised learning involves establishing relationships within labeled datasets, facilitating the prediction of output values based on given inputs. It is widely adopted in ML due to its predictive

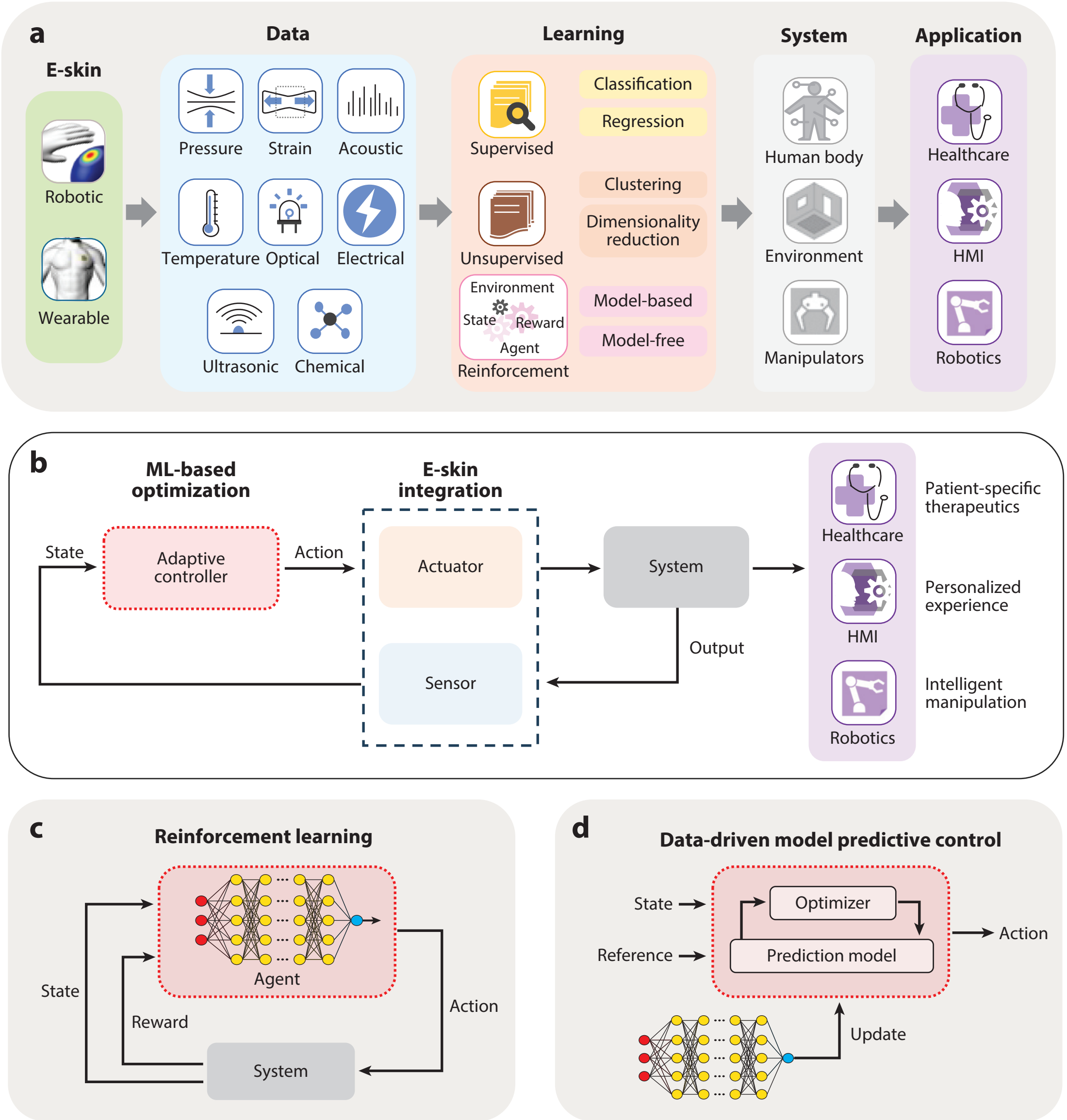


Figure 4

Integration scheme of electronic skins (e-skins) with machine learning (ML). (*a*) Flowchart for integrating e-skins, various sensing modalities, ML, deployable systems, and their applications in healthcare, human–machine interface (HMI), and robotics systems. (*b*) Closed-loop system consisting of an ML-reinforced controller; an ML-reinforced e-skin integrated actuator and sensor; and a system for healthcare, HMI, and robotics applications. (*c*) Diagram of a reinforcement learning system. (*d*) Diagram of a data-driven model predictive control system.

accuracy. In supervised learning, two common tasks are regression and classification, where continuous output values are predicted and inputs are categorized into discrete classes, respectively. Algorithms such as support vector machines (SVM) (119), k-nearest neighbors (kNN) (120), decision trees (DT) (121), and random forests (RF) (122) are often applied in classification tasks, while linear regression, Bayesian regression, DT, and RF are often applied in regression tasks. A major drawback of supervised learning is the necessity for labeled data, which can be expensive and time consuming to obtain and may potentially introduce biases and errors if not carefully curated.

Unsupervised learning focuses on extracting valuable features from unlabeled datasets. Data clustering and dimensionality reduction are two common tasks in unsupervised learning. Algorithms such as k-means clustering (123) and hierarchical clustering (124) are commonly used for clustering tasks, while principal component analysis, singular value decomposition, and t-distributed stochastic neighbor embedding (125, 126) are commonly used for dimensionality reduction tasks. Unsupervised learning is suitable when exploring and discovering hidden patterns or structures within data and providing scalability to handle large datasets without the need for labeling. Nevertheless, evaluating the quality of results can be challenging in unsupervised learning due to the absence of clear objectives or metrics for validation. Moreover, as datasets grow larger, handling high-dimensional data becomes computationally expensive.

Reinforcement learning represents a distinct paradigm centered around the optimization of cumulative reward functions. In this approach, a reward function quantifies the success of each decision or action taken, and the algorithm refines its decision-making process through iterative optimization. Some examples of reinforcement learning methods include Markov-decision process (127), deep model predictive control (MPC) (128), Q-learning (129), state-action-reward-state-action (130), and deterministic policy gradient (DPG) (131). While inference follows the training in supervised learning and unsupervised learning, reinforcement learning continues to adapt in real time to enhance the model's performance. However, reinforcement learning often requires numerous interactions with the environment without explicit objectives, which can reduce sample efficiency and introduce high dimensionality, leading to computational challenges. Furthermore, in the field of reinforcement learning, where agents must navigate stochastic environments, it is crucial to meticulously design systems to manage probabilistic outcomes and reward functions. This approach aims not only to optimize agent behavior but also to uphold ethical and responsible agent conduct.

Recent advancements in sensing technology have combined e-skins and ML across a broad spectrum of applications. However, the integration of e-skins with ML-reinforced control policies remains relatively underexplored. As ML methods for control systems further mature, there is immense potential for leveraging them with ML-reinforced e-skins, creating a closed-loop system. Such a system could revolutionize patient-specific therapies in healthcare, presenting personalized interactions in HMIs and intelligent autonomous manipulations (**Figure 4*b***). For instance, DPG has been effectively employed in robotic insertion tasks, addressing tactile-based policy optimization problems (132) (**Figure 4*c***). In this work, the pipeline incorporates both simulated and real tactile sensor data as the observation input to a neural network policy, ultimately generating precise pose adjustments for subsequent steps. In applications of HMIs, data-driven deep MPC has been utilized for adaptive human model learning and inverse haptics optimization pipelines (133) (**Figure 4*d***). Here, the pipeline can generate personalized vibrotactile haptic instructions, ensuring the faithful reproduction of target tactile information while accommodating individual variabilities in tactile response. Despite notable advancements in robotics and HMIs, the application of ML-reinforced control policies in biomedical e-skin remains an unexplored and still challenging area to study. This is due to the highly stochastic and nonlinear nature of biological systems and the requirement for rigorous validation of control policies to ensure safety and responsibility. Further research and development in this area are essential to unlock the full potential of integrating ML-reinforced control policies with e-skins.

3.1. Machine Learning for Artificial E-Skins

Despite remarkable advancements in computer vision and ML technologies, achieving precise and dexterous interaction for robots and machines with objects and environments akin to human capabilities remains a formidable challenge. This challenge is particularly pronounced when dealing with visual information that is occluded or inherently complex. In response to these challenges, researchers have explored alternative sensing modalities, namely somatosensory perception, facilitated by the integration of artificial e-skin into robotics, prosthetics, and HMIs (134–136). The primary objective is to enable closed-loop control mechanisms guided by this sensory feedback.

Among these alternative sensing modalities, tactile sensing has received significant attention, as it allows for robots and machines with embodied AI agents to learn from their body interfaces. To impart this ability, artificial e-skin systems often adopt the form of 2D arrays of tactile sensing units. Interestingly, there are noteworthy parallels in the principles of shape perception between the tactile and visual domains. This similarity suggests that the processing of signals from arrays of tactile sensors can benefit from analogous techniques, where sets of sensor readings are encoded within their spatial relationships to effectively form an image-like representation. By associating sensor readings in an array of image classification tasks, artificial e-skin systems exhibit the capability to classify dynamic tactile information.

Barreiros et al. (137) reported on an elastomeric, optoelectronic robotic skin capable of sensing touch, temperature, and damage using a complementary metal-oxide semiconductor (CMOS) image sensor (**Figure 5*a***). This robotic skin incorporated layers of functional elastomers, such as thermochromic layers for temperature sensing and a stretchable optical fiber embedded layer that samples and projects light onto a CMOS image sensor. To address the intricacy of the interactions between light and materials such as reflection, refraction, transmission, coupling, and losses, various supervised learning frameworks were applied for feature extractions: SVM for touch location and gesture classification, linear regression for force sensing, and DT regressor for temperature sensing.

In addition to various supervised learning frameworks to analyze image-like representation, a convolutional neural network (CNN) stands out as the most prominent algorithm, as it enables human-level performance across a diverse range of visual tasks (138–140). In the domain of tactile sensing, CNN architecture takes the raw pixel data from the tactile sensors as inputs and learns to extract distinctive tactile features, ultimately inferring the nature of the object they interact with. In work by Park et al. (141), a biomimetic elastomeric robotic skin was developed, which was capable of sensing deep pressure that induced skin deformation, as well as various dynamic touch modalities (**Figure 5*b***). This robotic skin utilized conductive hydrogels and an array of electrodes to create electrical impedance tomography using CNN architecture to generate image reconstruction for various shape deformations from deep pressure. Moreover, the robotic skin employed an array of microphones to map the spatiotemporal pattern of the vibrations, which were then analyzed using CNN architecture to classify four touch modalities (pat, tickle, stroke, and wind blow). In the context of HMIs, Sundaram et al. (142) reported a tactile e-skin integrated into a glove that learns the signature of the human grasp with objects (**Figure 5*c***). Here, a hand-shaped 32×32 piezoresistive passive matrix array consisting of encapsulation layers, conductive threads, and force-sensitive film recorded a dataset of 135,198 tactile maps during interactions with 26 different objects. These recorded data were subsequently analyzed using CNN architecture for weighing and classifying objects with tactile information and studying cooperativity among different hand regions during manipulation.

When integrating artificial e-skins into real-world applications in robotics and HMIs, it becomes evident that the tasks encountered are extremely diverse and the signals generated are often

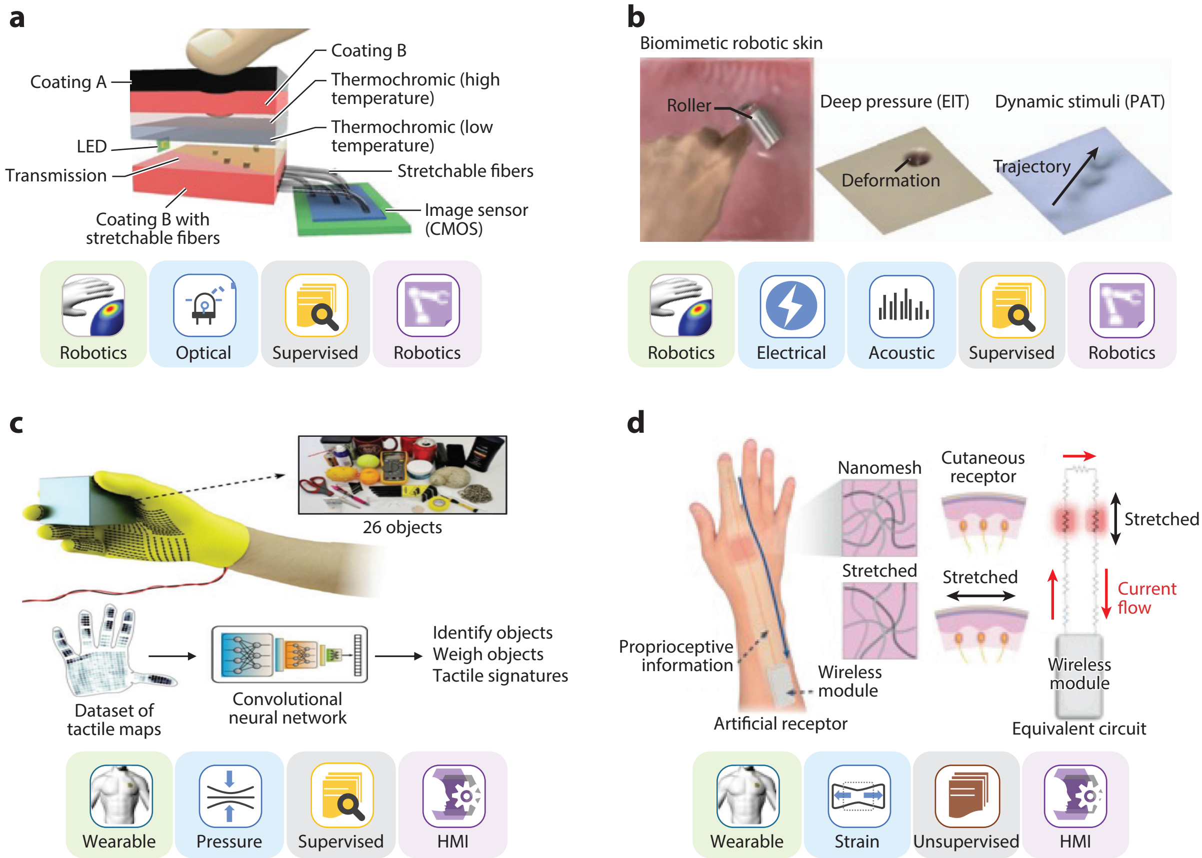


Figure 5

Diagrams and examples of ML-reinforced artificial e-skins. (*a*) An elastomeric, optoelectronic robotic skin for sensing touch, temperature, and cuts. (*b*) A biomimetic, elastomeric robotic skin capable of sensing pressure and light touch. (*c*) A piezoresistive e-skin sensing array integrated with a glove for exploring the tactile signatures of human grasps. (*d*) A sensory intelligent artificial e-skin system for learning and adapting to human tasks through biocompatible nanomesh cutaneous receptors. Abbreviations: CMOS, complementary metal-oxide semiconductor; e-skin, electronic skin; EIT, electrical impedance tomography; HMI, human–machine interface; LED, light-emitting diode; ML, machine learning; PAT, passive acoustic tomography. Panel *a* adapted with permission from Reference 137, copyright 2022 AAAS. Panel *b* adapted with permission from Reference 141, copyright 2022 AAAS. Panel *c* adapted with permission from Reference 142, copyright 2019 Springer Nature. Panel *d* adapted with permission from Reference 143, copyright 2023 Springer Nature.

subject to interpersonal and temporal variability. To address these variabilities, Kim et al. (143) introduced an innovative approach by incorporating unsupervised learning into their nanomesh artificial e-skin for recognizing and adapting to human hand tasks by measuring strain on the skin during such tasks (**Figure 5*d***). In this work, an unsupervised learning method known as the contrastive learning technique was applied to uncover the underlying structure of the data by instructing the model to discern similarities and differences between different examples. Through this application, a general latent multidimensional feature space (MFS) was generated, which allowed the system to identify a new user's hand gestures, even when these gestures exhibited signal patterns distinct from those found in the training data. This work also introduced a novel approach named TD-C learning, which leverages temporal features to create an MFS from unlabeled hand motion data by augmenting sensor signals on the basis of a sliding time window, encouraging the model to identify similarities between diverse hand motions according to their temporal characteristics.

The utilization of the ML advancements and seamlessly integrated artificial e-skin technologies outlined in this section represents a significant stride forward not only in enhancing the accuracy of dynamic signature sensing for robots, prosthetics, and human interfaces but also in promoting generalizability across a spectrum of tasks and users. As a result, these developments will promote the evolution of AI-powered intelligent machines tailored for specific applications.

3.2. Machine Learning for Biomedical E-Skins

Biomedical e-skin holds significant promise for a diverse range of functional applications, including continuous health monitoring and point-of-care therapy. However, realization of its potential faces significant challenges associated with the complexity of physiological signals, their multimodal characteristics, interindividual variability, and the transient nature of physiological systems. Recent research has made advancements in addressing these challenges through the integration of ML techniques. ML, with its capacity to analyze intricate and nonlinear data relationships, provides a robust solution for overcoming the aforementioned obstacles. In the context of ML approaches, unsupervised learning and reinforcement learning exhibit susceptibility to errors and demand substantial quantities of high-quality data. In laboratory settings, especially when dealing with emerging technologies still in the prototype phase, generating large-scale, high-quality, clinical data is often impractical (144). Consequently, supervised learning tends to be the preferred approach, since it involves clearly defined objectives.

One of the most frequently employed ML algorithms, not only in the domain of artificial e-skins but also in biomedical e-skins, is CNN via leveraging of its image processing capabilities. For example, Hu et al. (145) recently presented a skin-interfaced ultrasonic cardiac imager equipped with a piezoelectric transducer array (**Figure 6*a***). In this approach, preprocessed cardiac images serve as the training data for the fully convolutional network FCN-32 model, a specialized variant of CNN. This trained model autonomously and continuously analyzes unprocessed frame-by-frame cardiac images, predicting the volume of the left ventricle, a key metric used to calculate stroke volume, cardiac output, and ejection fractions. These parameters hold immense significance in critical care, cardiovascular disease management, and sports science, as they offer crucial insights into heart health and performance. In another work by Baker et al. (146), the authors introduced a skin-interfaced microfluidic system combined with image processing for sweat biomarker detection (**Figure 6*b***). In this setup, sweat undergoes chemical reactions within the wearable microfluidic system, resulting in color change. Scanning of the patch with a smartphone equipped with integrated image processing algorithms delivers real-time personalized hydration feedback. A CNN-based model processes the captured sweat patch image, identifying key features such as patch outlines, logo, and color swatches, and subsequently determines the volume and chloride concentration through image analysis.

When integrating CNN architecture into biomedical e-skin, another common approach is to segment continuous data into windows of defined widths. The CNN then processes these windows and classifies them according to labeled features. Kim et al. (147) demonstrated a skin-interfaced electronic device capable of capturing ambulatory physiological signals using this technique (**Figure 6*c***). Here, 12-lead ECG signals are captured with ECG front-end and nano-membrane electrodes, while motion activities are recorded with an inertial measurement unit. CNN-based models classify four types of physiological signals from the raw ECG, acceleration, and angular velocity data, including heart rate estimation, respiratory rate estimation, cardiac disease prediction, and motion activity classification. More recently, Jeong et al. (148) presented a closed-loop network of skin-interfaced wireless devices for monitoring vocal fatigue and ambulatory physiological

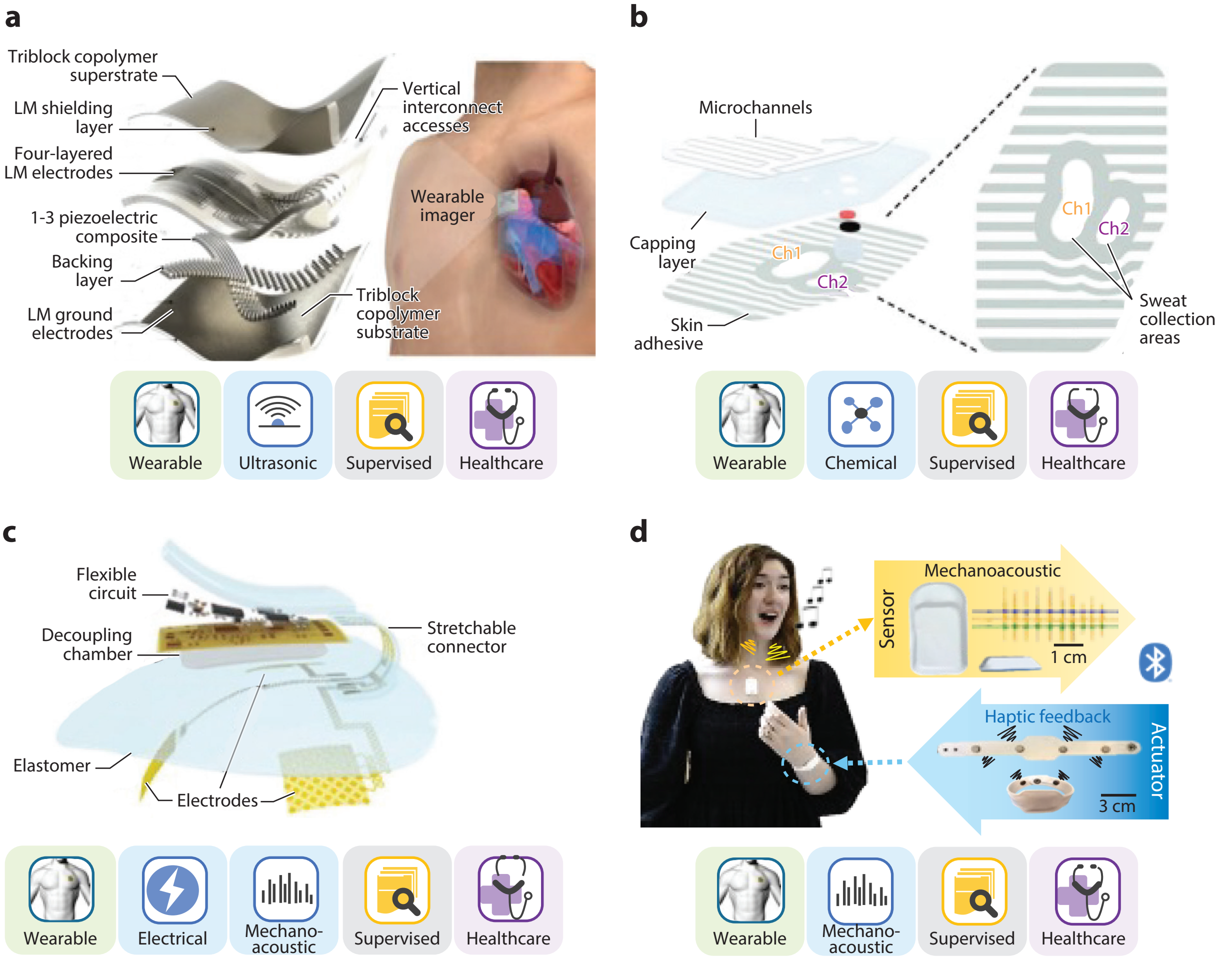


Figure 6

Diagrams and examples of machine learning (ML)-reinforced biomedical electronic skins (e-skins). (*a*) A skin-interfaced piezoelectric transducer array for cardiac imaging. (*b*) A skin-interfaced microfluidic sweat patch system for monitoring hydration. (*c*) A wireless, skin-interfaced electrocardiogram/respiration monitoring device. (*d*) A closed loop network of wireless, soft, skin-interfaced devices for monitoring vocal fatigue and providing haptic feedback. Abbreviation: LM, liquid metal. Panel *a* adapted from Reference 145 (CC BY 4.0). Panel *b* adapted from Reference 146 (CC BY 4.0). Panel *c* adapted from Reference 147 (CC BY 4.0). Panel *d* adapted from Reference 148 (CC BY 4.0).

signals, coupled with a haptic feedback wearable module (**Figure 6*d***). The skin-interfaced mechano-acoustic device is mounted on the upper chest for real-time data acquisition of signals such as vocal, cardiac, respiratory, and physical activities. Acquired time-series data are then transformed to spectrograms of singing and speaking. Taking spectrograms as input, the CNN model, trained with 2,500 1-s windows of singing and 2,500 1-s windows of speaking, classifies singing and speaking and generates daily vocal usage reports. To alleviate the computation load associated with continuous monitoring, a classical ML technique, kNN, was employed for mobile devices in real-time settings. The kNN-based image classification model distinguishes singing and speaking, allowing the calculation of energy doses for each 1-s window of data to monitor vocal fatigue and enable haptic feedback via a haptic wristband device on the basis of personalized thresholds.

The integration of ML algorithms into biomedical e-skins, as outlined in this section, continues to evolve, enabling the quantification of physiological signals that were previously challenging to capture. The ongoing advancements in utilizing supervised learning in continuous monitoring of various modalities of physiological signals offer the prospect of facilitating more accurate diagnosis and better-informed therapeutic decisions. In contrast, unsupervised learning and reinforcement learning within the context of biomedical e-skins remain underexplored areas. Nevertheless, enhancement of ML-reinforced biomedical e-skins by expanding generalizability and optimizing patient-specific feedback and therapy through unsupervised learning and reinforcement learning is an area promising remarkable opportunities in healthcare applications.

4. CONCLUSION AND PROSPECTS

Recent years have seen significant advancements in the technologies related to the materials and fabrication of e-skin devices. This progress is particularly noticeable in the enhancement of sensor sensitivities, improvement of mechanical durability, and realization of skin-like features. With the rapid evolution of AI technologies integrated into e-skins, such devices are expected to become smarter, more reliable, and more efficient—potentially ushering in a transformative phase in the soft robotic and medical domains. However, the current generation of AI-equipped e-skin devices are far from commercialization; the innovations, while promising and impressive, are not fully mature. The convergence of achievements from both fields presents challenges that demand meticulous attention.

The foremost challenge relates to data acquisition. Developing skin-like sensory arrays with high spatial resolution, temporal resolution, or data resolution remains difficult, directly affecting the quality and quantity of the data acquired. Multimodal sensing technologies also need refinement to enhance a robot's environmental awareness for artificial e-skin devices and promote user interactivity for biomedical e-skin devices. Beyond data acquisition, preprocessing remains essential: measurements from multiple devices must be synchronized and standardized, and statistical outliers and erroneous data must be eliminated. Once preprocessed, data become more amenable to analytics. Still, tools and methodologies available for this task are limited, primarily leaning on ML, which requires further optimization for real-world applications. Moreover, securing high-quality labels for the data proves to be time intensive, often necessitating expert input or user intervention.

Developing a high-bandwidth and energy-efficient data transmission solution is paramount. However, technologies that promise such benefits, particularly in stretchable and deformable formats, remain underexplored. Integrating these data transmission components with other multifunctional elements within the confined e-skin space is a complicated task, creating fabrication and material compatibility issues. Additionally, the rapid emergence of advanced connectivity technologies, such as 5G and its successors, is resulting in an exponential increase in the amount of data created. Managing the processing and storage demands of these data can be quite challenging, even after preprocessing. Relying solely on centralized cloud computing is not a viable option due to concerns about data processing latency and the substantial load it imposes on network resources. To alleviate latency issues, edge computing can come into play by relocating essential computations to the network's edge. However, challenges in developing compatible software and hardware for these edge devices remain, especially when aligning with the requirements of cloud computing.

The instrumentation of an intelligent e-skin system involves integrating multiple functional components, necessitating a substantial energy source. Conventional rigid and bulky batteries are not suitable for wearable applications. Potential alternatives include thin-film batteries that can be wirelessly charged or self-harnessing power modules designed in flexible formats. Given their prospective applications in robotic prostheses and biomedical e-skins, both power solutions require considerable innovation to ensure sustainable and long-term operation.

The last challenge centers around security and privacy issues, especially concerning biomedical e-skins. These devices have the capability to gather information on a user's physical activity, which may be deemed sensitive. Thus, safeguarding these data is undeniably vital. Currently, a comprehensive solution addressing the security and privacy risks of e-skin devices is absent, necessitating the need for further research and development efforts to enhance the security and privacy aspects of these wearable devices. Despite these challenges, the field of intelligent e-skins, applicable to both robotic and biomedical systems, is attracting considerable attention from both academia and industry. We anticipate significant societal benefits from a closer integration of such e-skins with our daily lives in the near future.

DISCLOSURE STATEMENT

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