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Artificial Intelligence-Powered Electronic Skin

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Abstract

Skin-interfaced electronics is gradually changing medical practices by enabling continuous and noninvasive tracking of physiological and biochemical information. With the rise of big data and digital medicine, next-generation electronic skin (e-skin) will be able to use artificial intelligence (AI) to optimize its design as well as uncover user-personalized health profiles. Recent multimodal e-skin platforms have already employed machine learning (ML) algorithms for autonomous data analytics. Unfortunately, there is a lack of appropriate AI protocols and guidelines for e-skin devices, resulting in overly complex models and non-reproducible conclusions for simple applications. This review aims to present AI technologies in e-skin hardware and assess their potential for new inspired integrated platform solutions. We outline recent breakthroughs in AI strategies and their applications in engineering e-skins as well as understanding health information collected by e-skins, highlighting the transformative deployment of AI in robotics, prosthetics, virtual reality, and personalized healthcare. We also discuss the challenges and prospects of AI-powered e-skins as well as predictions for the future trajectory of smart e-skins.

Keywords

electronic skin; artificial intelligence; human-machine interfaces; personalized healthcare; machine learning

1. Introduction

Electronic skin (e-skin) refers to integrated electronics that mimic and surpass the functionalities of human skin. Due to their flexible and conformable nature, e-skins may be placed on various robotic and human bodily locations for continuous biosignal monitoring, rivaling bulky medical equipment in the fields of robotics and prosthetics[1,2]. Engineered for self-contained operational frameworks, e-skins act as human-machine interfaces for smart bandages[3], wristbands[4], tattoo-like stickers[1], textiles[5], rings[6], face masks[7], as well as customized smart socks and shoes[8] for various applications. Compared with conventional rigid devices, soft e-skin patches seamlessly interface with the skin, achieving a conformal

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and stable contact that minimizes motion-induced artifacts and wearing discomfort[9]. The convenience and flexibility of applying these electronic patches to any target location, while continuously and noninvasively measuring multiplexed signals via mobile connectivity, has surpassed conventional point-of-care to become an ideal form of wearable systems. With the increasing demands for remote and at-home care, e-skins have been applied for personal fitness[4,10], virtual reality[11,12], telemedicine and early disease detection[13,14], as well as COVID-19 tracing and monitoring[15,16].

While emerging e-skin is revolutionizing robotics and medical practices by continuously monitoring multimodal data[17], data analysis is playing an increasingly important role for interpreting the large, complex biological profiles generated from various sensors. Conventional analysis of e-skin data largely relies on human supervision, where signal processing and data evaluation is time-consuming and interpreted from a restricted point of view[1,4,5]. There is an unmet demand between e-skin hardware and efficient data analysis solutions. Recent developments in deep learning have permitted the evaluation and even generation of big data for health applications[18]. Artificial intelligence (AI) can reveal medical insights that are challenging to acquire with traditional data-analytics while providing accurate predictions that can mimic or even surpass human expertise[19–21]. AI together with the rapidly growing interest in health monitoring and remote robotics have become the main catalyst pushing forward advanced e-skin innovations.

This review details the recent developments of e-skin technologies with a particular focus on AI (Fig. 1 and Table 1). We first present the general machine learning (ML) pipeline for e-skin applications, along with a summary of emerging sensors. We then discuss how machine intelligence could revolutionize the field of e-skin by optimizing manual designs and facilitating high-accuracy task assistance and decision-making. We then highlight use cases for AI-powered e-skins in human-machine interfaces (HMI) and personalized healthcare. Finally, we will discuss the challenges and prospects for e-skins in the era of AI and big data.

2. Emerging Sensor Landscape in E-skins for Data Acquisition

In a typical ML pipeline (Fig. 1), raw data collected from e-skins will first be preprocessed for feature extraction. Popular preprocessing techniques include filtering, smoothing, downsampling with a sliding window, dimensionality reduction, as well as baseline removal and normalization[22]. An ML algorithm is then selected for the specific objective (Table 1), which can be supervised or unsupervised, classification or regression, discriminative or generative[22]. During model selection, one needs to account for data availability[20]. While simple models may struggle to represent the expected trends, complex models on simple datasets may lead to non-reproducible conclusions, particularly in health applications when a small dataset may be specific to a particular demographic.

Training of an intelligent ML system requires a substantial amount of high-quality data. Unlike conventional clinical laboratory tests that are performed discretely and infrequently, emerging wearable sensors provide the ability for continuous acquisition of digitalized data with multiplexed sensors, allowing for more personalized care by analyzing deviations in individual baselines[23]. This approach greatly mitigates the biases from environmental factors such as diet, age, stress, and drug use, yielding a more appropriate and accurate medical diagnostic tool based on the individual rather than population-level statistics. Here we focus on the two primary sensing domains in e-skin platforms (Fig. 2), namely physical and biochemical sensors, highlighting their key usage and applications.

Strain and pressure sensing

A commonly integrated sensor, strain sensors track the resistance of electronic materials under deformations. These sensors enable the detection of large distortions from bodily motions[24] and small deviations for tactile perception[25]. As another motion sensing mechanism, pressure sensors utilize piezoresistive materials or capacitors with a pressure cavity. Similar to strain sensors, pressure sensors could be customized to perform pressure mapping[26,27], user interactive visualization[28,29], as well as tactile sensing[30,31].

To fully mimic skin sensations, strain and pressure sensors are often combined for haptic interfaces in HMI applications[11]. When placed near arteries, strain and pressure sensors can detect vital signs such as blood pressure and heart rate variability[32]. Recent studies have also utilized piezoelectric sensor arrays, which capture acoustic vibrations from tissue for blood pressure monitoring and imaging applications[33–35].

Temperature monitoring

While elevated core body temperatures often result from infections and overheating, a decreased temperature can lead to faltered physiological systems and even organ failure. Although e-skin sensors are commonly applied to monitor skin surface temperature, arrays of sensors could be used in conjunction to minimize local deviations and display an accurate temperature profile[36]. Further studies have investigated correlating skin surface temperatures to core body profiles[37]. In addition, temperature data is of significance for calibrating biochemical sensors, as chemical reactions are sensitive to their operating temperature[38].

Electrophysiology

Electrophysiology refers to measuring the electrical activities of tissues and organs. Common skin-interfaced biopotential modalities involve electrocardiography (ECG)[39], electromyography (EMG)[40,41], and electroencephalography (EEG)[42,43]. These signals are measured by placing arrays of electrodes on the skin at different locations. E-skin-based electrophysiology sensors commonly show high performance due to the conformal contact between the soft e-skin and body with a low contact impedance.

Biochemical sensing

E-skin-based biochemical sensors have been widely applied to analyze molecular biomarkers (e.g., electrolytes[44], metabolites[4], amino acids[10], neurotransmitters[45], and proteins[46]) in human biofluids including sweat[4,10,13,47], saliva[48], and interstitial fluids[49]. Common biosensing signal transduction strategies include electrochemical and optical detection mechanisms[50]. These sensors can be applied for a wide range of biomedical applications including fitness tracking, metabolic monitoring[4], cystic fibrosis diagnosis[44], gout management[13], and stress assessment[51].

Substance monitoring

In addition to natural biofluid components, e-skins can also detect substances that are extrinsic to the normal metabolism such as drugs[52] (e.g., vancomycin[53] and levodopa[54,55]), alcohol[56,57], caffeine[58], and heavy metals[59]. By focusing on personalized pharmacokinetics instead of population studies, continuous therapeutic drug monitoring can improve treatment outcomes and reduce side effects through dosage adjustments, which are especially important for drugs with narrow therapeutic windows[52]. Moreover, e-skin sensors can serve as a rapid screening tool for drug abuse[60,61].

Gas sensors

Human breath contains rich molecular information and could provide a noninvasive health profile like biofluids. Many volatile organic compounds (VOCs) in the breath are diagnostic biomarkers for infectious, metabolic, and genetic diseases[62,63]; For example, breath carbon monoxide is linked to neonatal jaundice and breath ammonia and nitric oxide are connected to asthma[64]. Integrated sensor arrays known as electronic noses (e-noses) have been developed to detect humidity, VOCs and other gas components in exhaled breath and the surrounding environment[65]. Combined with ML, these sensors can distinguish complex chemical signatures[66,67], and have been employed for breath-based individual authentication[68], soil nitrogen assessment[69], and evaluating food freshness[70].

Environmental monitoring

Environmental risk factors, including chemical threats and pathogenic biohazards, pose a risk to both the human body and safe robotic operations. AI-powered e-skins have expanded their scope to encompass not only monitoring the human body but also the surrounding environment. During remote operations, e-skin systems can detect trace amounts of dangerous compounds and provide environmental feedback without human exposure[2]. A combination of biochemical sensors was integrated into an e-skin patch attached to a robotic arm that could detect hazardous materials including nitroaromatic explosives, pesticides, nerve agents, and infectious pathogens with autonomous ML-based decision-making algorithms[2].

3. AI-generated e-skin

Human skin possesses outstanding mechanical properties, including flexibility, stretchability, toughness, along with multifunctional sensing abilities. However, there are many unsolved material challenges to replicating key properties in artificial skin[71]. AI has been proposed to optimize materials discovery and sensor designs to autonomously redesign new e-skin patches[71,72]. AI can be integrated into the materials design process in three phases (Fig. 3). The first phase involves model prediction and patch design based on functional requirements: size, weight, lifetime, cost, and other material specifications; the second phase entails computational modeling and experimental validation; and lastly, the improvement of current databases and model accuracies based on the results.

Emerging materials and e-skin designs

The conventional selection of substrate materials typically involves natural materials such as cotton and silk, which are known for their biocompatibility, low-cost, and comfort. However, natural materials have inherent limitations in stretchability and tunability. Material scientists and chemists consequently synthesize soft materials based on a combination of manual designs, drawing inspiration from nature, and leveraging previous material examples as references[73–75]. Some material design strategies include ultrathin tattoo-like substrates[1], applying serpentine interconnects[76], and using nature-inspired skin adhesion to realize high fiducial signal collection[77]. Meanwhile, these materials and designs require extra validation to characterize their properties, and many synthetic processes involve toxic precursors and require careful biocompatibility tests.

With a diverse availability of material candidates, designing or selecting a material with desired properties for a specified task is becoming increasingly challenging[78]. ML provides an attractive pathway to explore new materials and identify promising candidates with targeted properties, including alloy materials[79], nanoparticle synthesis[80], and electronic materials[81]. To date, a number of publicly available databases have been launched for simulating functional materials and recipes[71]. Moreover, ML can also be used to optimize and explore material synthesis, such as extracting text from scientific literature and giving synthesis protocol suggestions[82,83].

AI can help select and optimize fabrication methods based on material characteristics. Additionally, ML is can assist in quality control during mass fabrication, such as with jet printing of electronic circuits[84]. In addition to materials and fabrication methods, ML is also capable of optimizing e-skin designs. For example, a ML-based circuit designer has enabled transistor sizing adjustments using graph convolutional neural networks[85]. While conventional e-skin designs from planar designs typically do not conform to curvy surfaces[86], ML can guide structural designs of e-skins by finding kirigami designs for 3D shape-adaptive e-skins and pixelated planar elastomeric membranes more efficiently than mechanical simulations[87,88].

As most data from material experiments are discrete and noisy with high variance, it is necessary to preprocess the data through interpolating missing data and rebalancing biased training sets[89,90]. Additionally, many material science fields are not data-rich, and anthropogenic biases in the limited dataset may hinder model generalization[90]. This can be particularly true for collecting data about novel materials for human subjects. It is anticipated that a more standardized materials dataset and pipeline will speed up materials development and discovery[72].

Signal processing and augmented sensor performance

While traditional intuition-driven sensors are based on situation-specific experimental trials and time-consuming numerical simulations, ML algorithms can search for optimal sensor architectures as a function of required material properties with an accelerated and efficient prediction time[66,91]. In addition to conventional task-specific and labor-intensive signal processing, ML is capable of fast, robust data analysis to provide transferrable frameworks under different initial conditions. For example, ML can perform signal denoising[92], multi-source separation[93], artefact identification and elimination[94]. Two crucial guidelines for e-skin sensors are sensitivity and selectivity to the target biomarker. Indistinctive signal-to-noise ratios and overlapping detection between targets and interferents are two main bottlenecks for applying sensors for trace-level molecular detections in complex biomatrices. Substrates with similar structures to the target in biofluids could lead to confounding results. ML has been illustrated to improve the specificity and sensing limit of detection in multimodal sensing[95]. Many biochemical sensors involve enzymes that have a narrow working range, while AI algorithms could surpass signal saturation and calibrate non-linear sensors in a dynamic testing environment[96].

Motion artifacts are another major source for background noise in e-skins. While extensive analog and digital signal processing techniques have been applied to reduce artifacts and improve data quality[39,97], they typically involve manual circuit designs and simulations, which entail high costs and are not easily expandable to different scenarios. ML can be used for precise data acquisition by compensating noise and defects in wearable sensors[98]. In addition, data acquisition hardware can be fundamentally redesigned for optimal sensing with an intelligent platform[67,99]. The improved sensing capabilities as well as compact systems will fundamentally enhance sensor performance through iterative analysis of data-driven sensing outcomes[91].

4. AI-powered e-skin for HMIs

HMIs enable the interaction between users and robotics, and have become crucial in remote robotic teleoperations. As the demand for precise and intuitive robotic control continues to grow, research has been turning its attention from conventional control theory towards a more immersive and interactive interfacing platform. The emerging AI-powered e-skins are creating new paradigms for robotic control and human commanded perception (Fig. 4)[100,101]. AI could quickly analyze multimodal data from e-skin patches and make autonomous decisions to manipulate robotics and provide human aid, which has already bridged the gap between human and machine interactions.

Tactile perception

Tactile perception decodes and transmits physical information to a computer system about hand movements, gestures, and force recognition[102]. The associated robotics can then accomplish tasks such as object grasping[103], shape detection[2], and object identification[104]. Haptic sensors are therefore widely adopted as a fundamental element for e-skin based HMI systems, which are usually built with arrays of strain and pressure sensors or electrophysiology electrodes such as surface EMG electrodes to capture complex hand movements[41,102,105,106], producing a large quantity of continuous data. Real-time haptic perception with the aid of AI has made tremendous progress in dynamic whole-body movements[106], gesture interpretation[107], tactile recognition[105,108], as well as object manipulation and detection[109].

Prosthetics and robotic feedback

Developing prostheses that rehabilitate motion for people with disabilities is a crucial goal in machine intelligence. Prosthetics typically involve a large sensing area with robotic feedback, where the e-skin extracts motion or audio data and ML algorithms analyze and control robotic operations accordingly. Strain and pressure sensors are fundamental components for actuators and grippers in robotics, enabling tactile feedback for enhanced functionality[105,110]. A variety of prosthetic solutions have been developed for different scenarios, including facial expressions[111], robotic control and feedback[2], translation of sign language into speech[112], personalized exoskeleton walking assistance[113], as well as providing steering and navigation assistance for people with impaired vision[114].

Smart robotic hands for prosthetics can also be applied for task assistance in healthy people. For example, a nanomesh-based e-skin integrated with meta-learning could assist rapid keyboard typing with a few-shot dataset[103]. Smart e-skin also has the potential for driving assistance by monitoring the driver’s state and preventing sleep deprivation-related accidents[115], which provides an alternative solution for vehicle automation.

Hearing aid and natural language processing (NLP)

Verbal communication with machines is another promising e-skin application that relies on AI, where a voice-user interface leveraging NLP is highly intuitive and convenient. Numerous studies have developed resonant acoustic sensors in e-skin for voice recognition[116], vocal fatigue quantification[117], and voice control of intelligent vehicles[118]. These sensors integrate resistive or piezoelectric membranes as sensing components[116,119,120], which converts human hearing range of around 20 Hz to 20 kHz. The customized frequency filtering can identify physical activities with different intrinsic frequency bands[119], or filter acoustic vibrations against human perspirations and background noise[121]. Voice sensors may also serve as a security device for biometric authentication[120].

Virtual and augmented reality

Virtual reality (VR) and augmented reality (AR) create a virtual environment where visual and auditory stimuli replicate sensations in the physical world[11]. E-skin provides an additional sensation of touch due to its unique skin interface[122]. For example, wireless actuators could be integrated in e-skins for programmed localized mechanical vibrations[11]. Such mechanical feedback can also form a closed-loop HMI system for motion capturing and vivid haptic feedback when interacting with virtual objects[123,124]. To further implement gesture controls for VR, a textile glove was developed with ML algorithms to classify hand patterns in various VR games[125]. AI could accelerate machine vision processing by utilizing a simple image sensor array matrix[126], empowering a high frame rate in VR visualizations. Additionally, some pioneering demonstrations have illustrated the potential of odor generators for olfactory VR applications[127].

5. AI-powered e-skin for healthcare and diagnostics

E-skin with arrays of integrated sensors can record the health profile of an individual in remote and community settings, detect aberrant physiology over time, and unveil health distributions at a population level. ML has aided diagnostics by identifying complex relationships between input physiological information and disease states[18,23,128]. There is a growing trend using AI-powered e-skins to address the growing demands in health monitoring and diagnosis (Fig. 5). Emerging AI has shown promising capabilities in approaching expert-level diagnosis, which could reduce the rate of misdiagnosis and create great clinical and market potential. For complex disease syndromes without established biomarkers, these ML algorithms could also facilitate our understanding in biomarker discovery, psychological predictions, and precision therapy.

Cardiovascular monitoring

Heart failure can worsen progressively over days while current telemedicine tools are not sufficient to detect acute exacerbations. AI-powered e-skins hold the promise of specialist-level diagnosis for cardiac contractile dysfunction or arrhythmias[129,130]. E-skins can integrate multiple modalities and facilitate the rapid evaluation of hemodynamic consequences of heart failure[131]. ML has been widely adapted for data analysis to extract cardiac parameters, such as blood pressure predictions[132,133] and left ventricular volume[34]. AI-based e-skin is anticipated to spot small and gradual cardiovascular changes over time and facilitate automatic diagnosis in a timely manner[131]. Such an approach will also alleviate the clinical load of physicians by reducing unnecessary hospital consultations.

Stress and mental health

Stress and mental health are significant problems for global health but their assessments rely heavily on subjective questionnaires. Pioneering studies for mental health predictions have been introduced including stress[134–136] and fatigue[137–139], but most studies still focus on commercial wearables such as watches which only monitor physical vital signs and are prone to motion artefacts. Several pioneering studies have demonstrated dynamic monitoring of the stress hormone cortisol using e-skin devices[51,140]. Next generation e-skins will combine physiological data with molecular signatures and perform multimodal data analysis[141]. By identifying previously unrecognized associations between health patterns and stress risk factors[142], smart multimodal e-skins with the aid of AI have the potential to model risk associations and unveil stress outcomes for mental health.

Biomarker discovery

The development of AI is driving advances in both medical diagnosis and fundamental studies. Given the quantity of data in clinical studies, ML could be a transformative technology for data-driven biomarker discovery[143]. ML-based algorithms perform automatic data analysis for biomarker prediction, including skin disease[144], dysphagia[145], seizure[146], and COVID-19[147], where multiparametric monitoring based on multimodal e-skin platforms can reveal correlations between sensors and target outputs[148]. For diseases such as Parkinson’s disease where no known effective biomarker is available, ML has the potential to unveil underlying correlations from the multi-dimensional data[14].

Personalized therapy

The development of drug and metabolic monitoring using e-skins has also aided in personalized therapy. AI-powered e-skins could benefit drug dosage personalization, where multimodal data coupled with ML models can be applied to evaluate pharmacokinetics and pharmacodynamics for personalized dosage[149,150]. Additionally, dynamic treatment of a disease affected by the individual's history and current course of action is well suited for the sequential decision-making used in reinforcement learning[151]. Prospective cohort studies involving physiological, metabolomic, environmental, and genomic data are anticipated to pave the way for the advancement of personalized therapy through the integration of AI-powered electronic skin.

6. Challenges and outlook

With the continued development and innovations in AI-powered e-skin, next generation e-skin is expected to aid prosthetics and the discovery of diseases, yet there remains several major bottlenecks including data acquisition and handling, data security, and data generalization.

Data handling in both quantity and quality has become a challenge for model deployment. AI-driven data analytics are typically data-hungry, and training models with high prediction accuracy depends on large amounts of high-quality labeled data. Mature models such as decision trees and support vector machines demonstrate great accuracy and reproducibility and find extensive applications, yet their reliance on structured and manually labeled data poses high acquisition costs. In contrast, unsupervised learning unveils hidden patterns in unlabeled data, albeit with reduced accuracy and constrained applicability. Recent advanced models such as transformers have shown success in language processing and generation, but these models are of high complexity and require pre-training over big data sources using resource-intensive computing, with the underlying mechanisms still insufficiently understood. The time-continuous datastream from e-skin sensors carrying large amounts of unlabeled and heterogeneous data poses high demand for data processing and system integration. This necessitates a fast and cost-effective system for collecting and transmitting data to cloud-computing-based e-skins, while high-performance computing and storage units with low latency are required for in-situ applications[23]. Despite the growth in AI-driven e-skins, comprehensive regulatory frameworks addressing data accessibility, ownership, and security are yet to be fully established. This is crucial as public perception of data privacy risks can directly influence the adoptability of wearable devices, while user acceptance to disclose their medical information is uncertain at present[152]. While latest ML algorithms such as GPT-4 models have been reshaping the world, the success of large language model (LLMs) stems from the enormous amount of publicly available Internet data, which may not apply to the privately restricted medical datasets. Accessing regulated medical records and data poses significant challenges as they are highly restricted and obtaining them entails stringent protocols and privacy considerations[153], and data differences may potentially result in divergence from training accuracy. The FDA has recently updated its guidelines for handling sensitive medical data after announcing a new Office of Digital Transformation in 2021. Data generalization originating from built-in bias is another issue that could harm marginalized groups of people, which warrants special consideration for adopting ML models in medical practice. AI models can often make mistakes, but it is unknown who or what will be held responsible for controversial behaviors and outcomes of AI systems. Although models will become more powerful and capable over time, to what extent people can trust the ML predictions is still unknown[153]. The ability of fact-checking versus proof-reading may be beyond the expertise of users without clinical expertise[20]. Studies on interpretation and explanation of AI may be a possible solution[154].

From an e-skin perspective, another challenge is collecting high-quality biochemical data. Dealing with enormous amounts of rapidly fluctuating unlabeled data during continuous health monitoring may have adverse effects on model learning. Minimizing motion-induced artifacts from both the human and robotic bodies have required a strong interface and wearing comfort, and therefore poses need for strict materials properties, including biocompatibility, permeability, durability, mechanical strength, and conformability[9,22]. Biocompatible and non-toxic materials with strong, breathable and reversible skin adhesion are highly desirable for prolonged daily wearing, where the durability lifetime may depend on the specific use case[50]. Data accuracy can be improved by implementing multimodal sensing using one integrated platform to reduce defects from a single sensor[47]. Moreover, despite their high correlation with multiple potential diseases[155], many biochemical sensors struggle with low sensor stability, the necessity for frequent calibrations, and difficulty in detecting low-concentration biomarkers, which cannot provide as high-quality data as electrophysiological ones. Additionally, sensor embodiment and system integration is of concern when considering power sources, sensor arrays, signal processing and wireless data transmission[22]. Most integrated e-skins are powered through bulky rechargeable lithium-ion batteries; however, more research into wireless and low-power energy harvesting and storage is needed to develop fully flexible and sustainable e-skins[38,156]. These challenges have opened the door to exciting new opportunities in improving electronic sensors, optimizing patch designs, integrating cloud storage, protecting data privacy[157], and interpreting model accuracy[154]. The interdisciplinary collaborations among materials scientists, chemists, engineers, physicians, and data scientists are crucial to realize the full potential of the e-skin. The emergence of AI-powered e-skin marks a new era in the field of robotics and healthcare and is envisioned to transform the way human interacts with robotics and revolutionize medical diagnostics.

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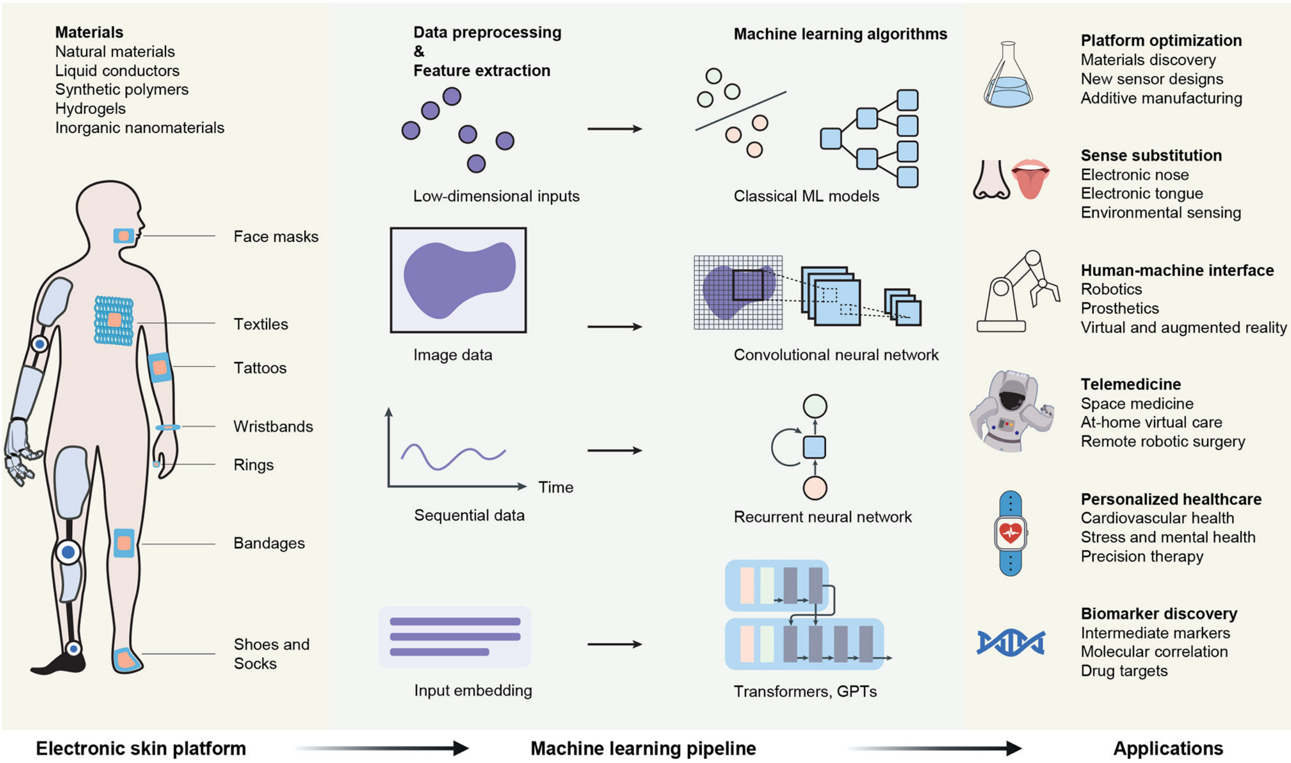

Figure 1.

Overview of AI-powered electronic skin (e-skin) and machine learning (ML) pipelines. E-skin provides access to human information or serves as an interface to robotics by continuous and noninvasive monitoring of multimodal physical and biochemical sensors. The data stream is constructed and transformed into a standard numerical format through data preprocessing and feature extraction. Based on the intrinsic data properties, different ML algorithms can be selected and trained, allowing for real-world applications. GPT, generative pre-trained transformer.

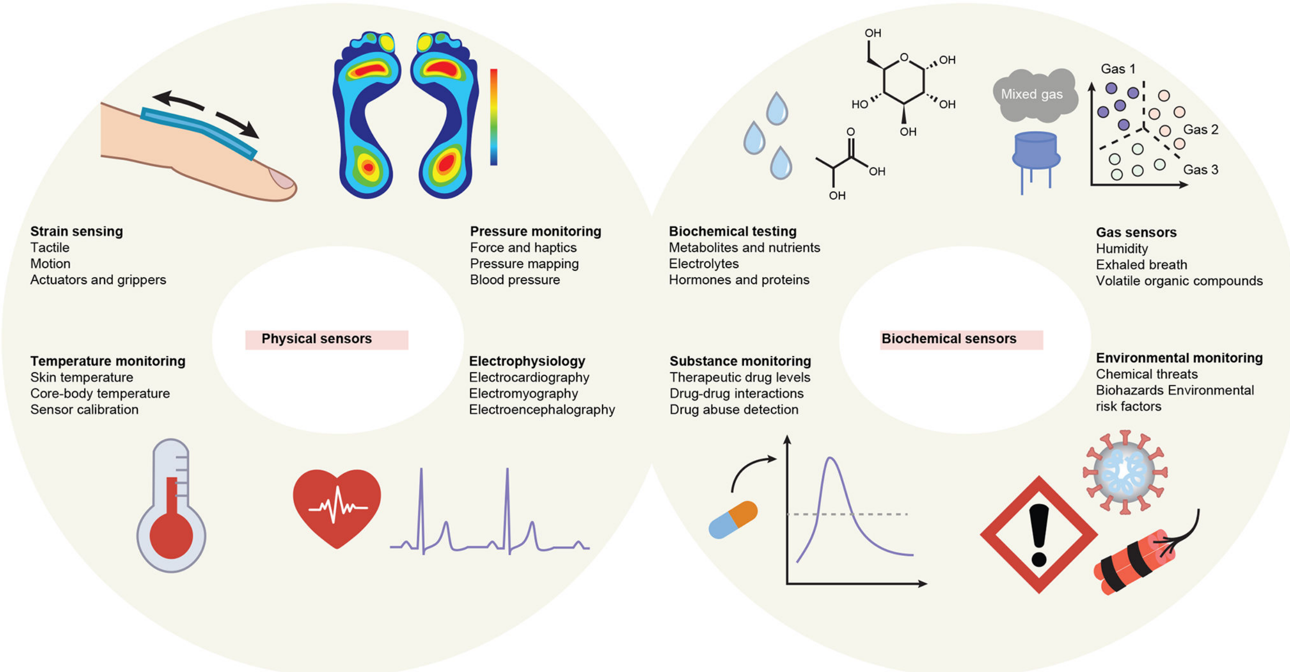

Figure 2.

Emerging sensors in e-skin for health monitoring and robotics. The combination of physical and biochemical sensors provides access to force sensing and mapping, electrophysiology, as well as biochemical substances in body fluids and surroundings.

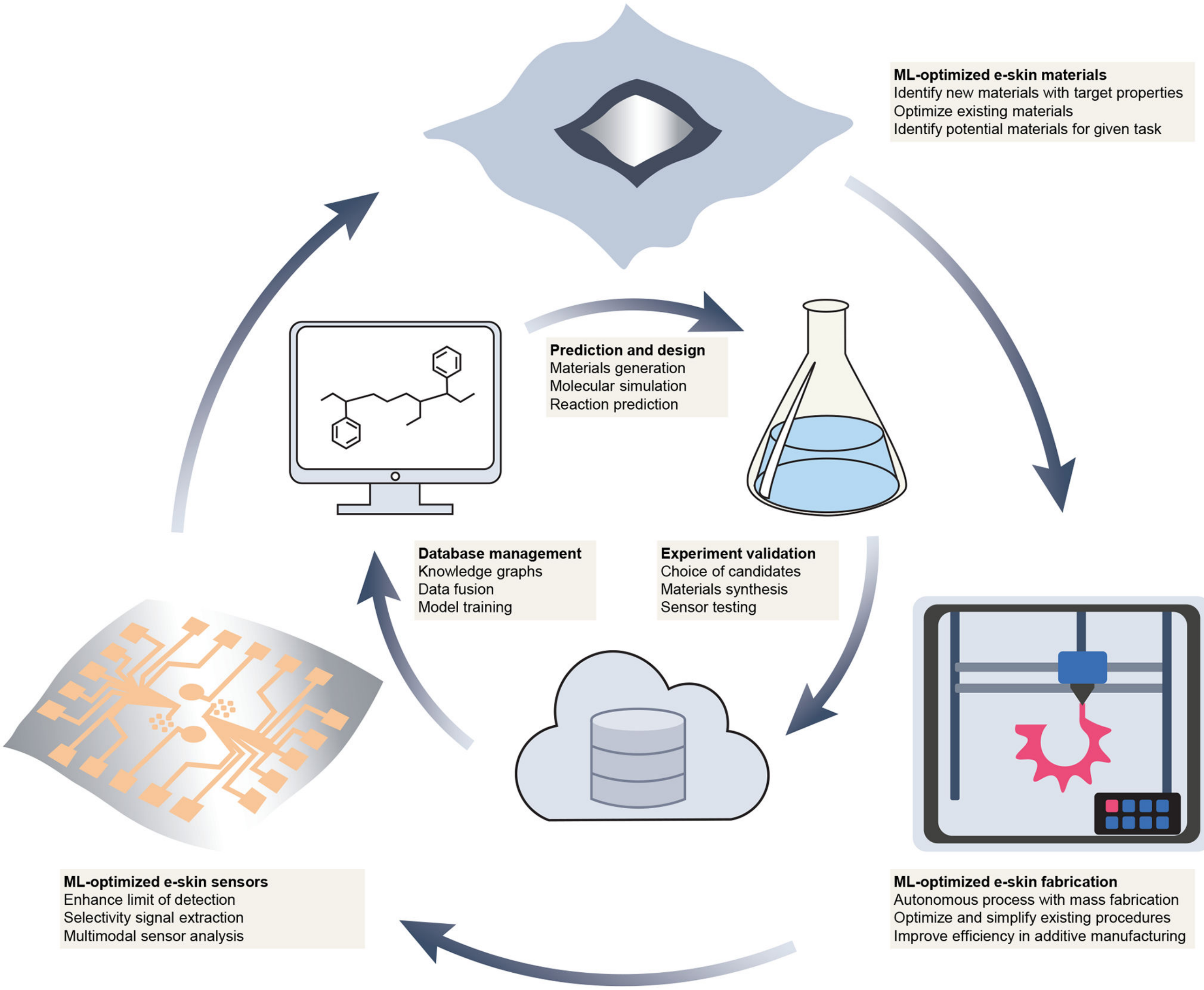

Figure 3.
ML optimizations for e-skin designs. AI algorithms serve as an alternative pathway to optimize and explore materials synthesis, facilitate automatic mass-fabrication, and optimize current sensor limits.

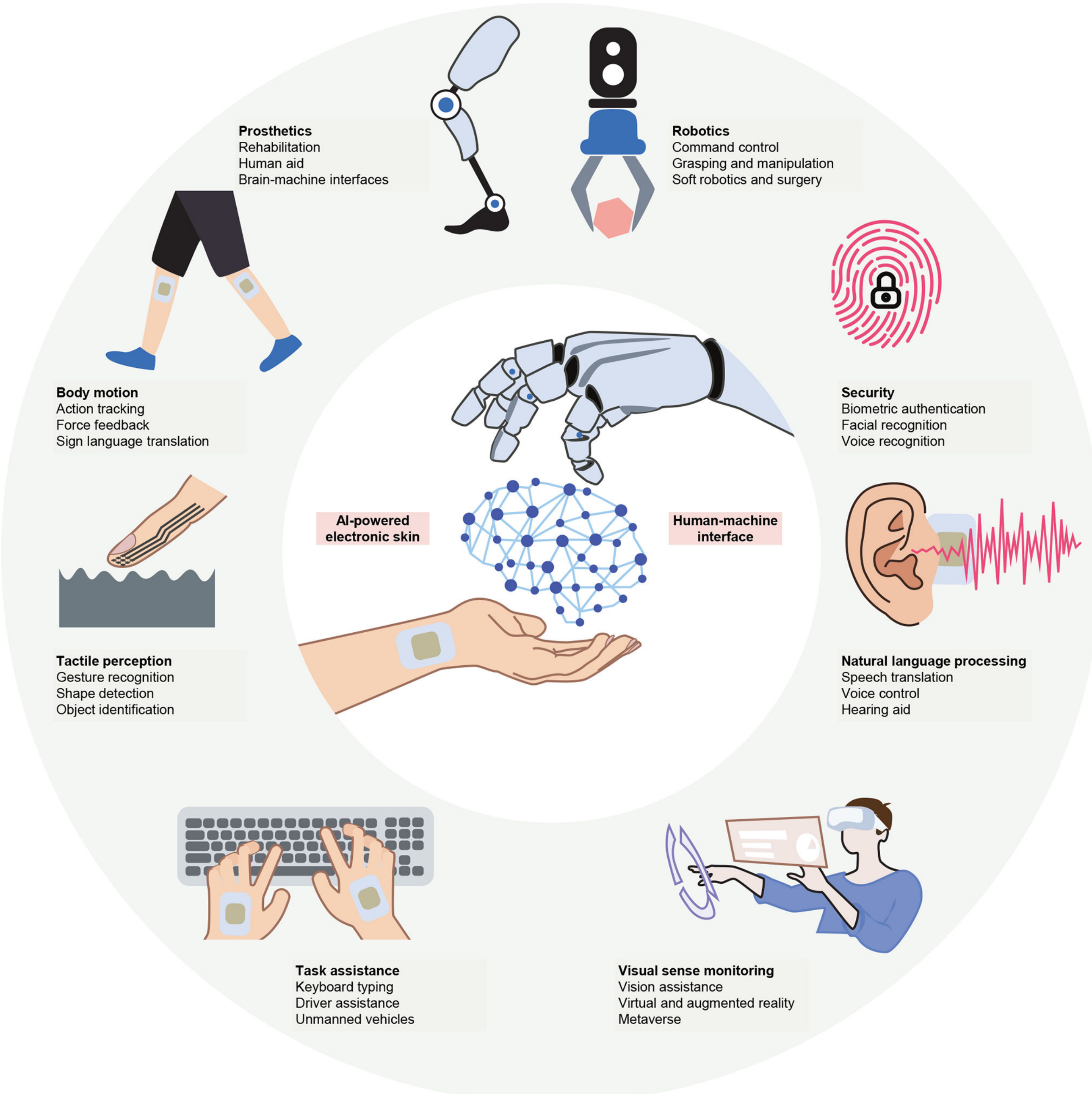

Figure 4.
AI-powered e-skin for human-machine interfaces (HMI). ML bridges the gap between humans and machines through task assistance, robotic control, and virtual reality.

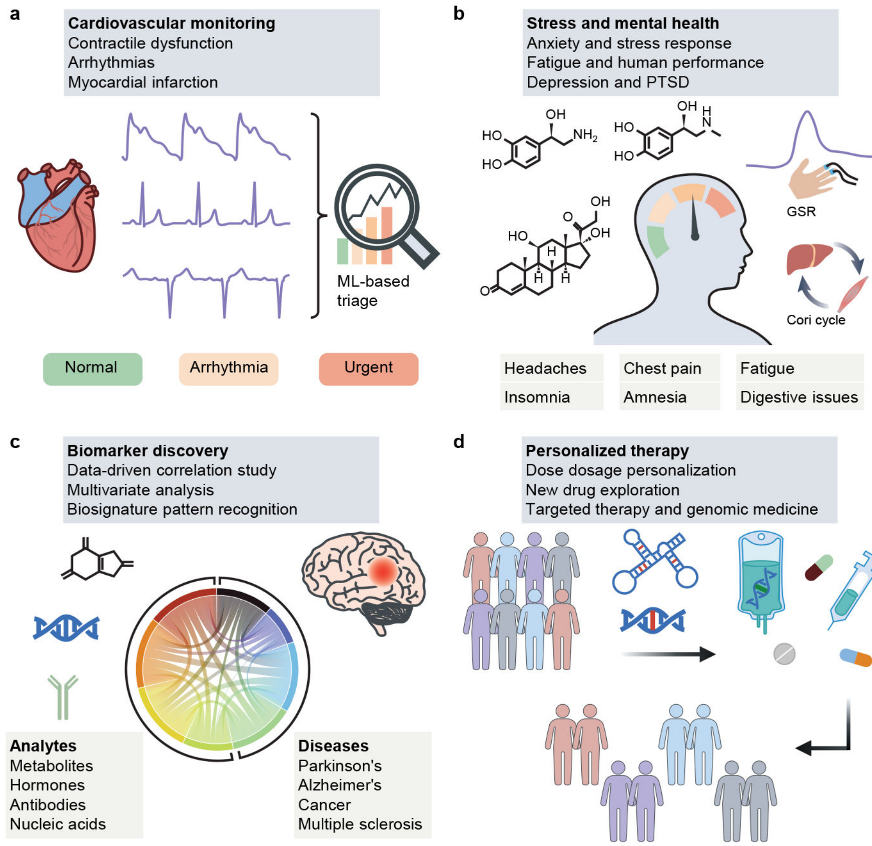

Figure 5.

AI-powered e-skins for personalized healthcare and predictive disease diagnostics. **a**, Cardiovascular health can be investigated through continuous monitoring of one's cardiac activities (ECG, pulse waveforms, etc.) with e-skins. Integrating autonomous analysis through AI algorithms creates further potential for screening urgent conditions such as arrythmias. **b**, The application of AI-powered e-skin can extend to mental health which is a complex event that involves behavioral and physiological responses, metabolic changes, and fluctuations in a number of stress hormones. PTSD, post-traumatic stress disorder. **c**, Biomarker discovery through AI algorithms will further aid in finding new missing information potential links between measured sensor data and health status of individuals. **d**, Personalized therapy can be achieved by measuring individual's genetic and metabolic status using e-skins to develop highly targeted medicine for medical treatment.

Table 1.

Representative studies that used ML-powered electronic skin for tasks.

Category	E-skin platform	Targeted parameters	ML models	Learning objectives	Ref	Year
ML for e-skin design	Soft membrane	Shape	NN	3D shapes	88	2022
	Graphene on polyimide	Electrical conductivity	DT	Jet printing design	84	2022
	Graphene kirigami	Stretchability	NN	Kirigami design	87	2018
ML for sensor enhancement	E-nose	VOC gas	RF	Multi-gas classification	66	2022
	Stretchable synaptic patch	Neuromorphic computing	NN	Handwritten digits (MNIST)	99	2022
	Field-effect transistors	Hg^{2+} sensors	Linear regression	Hg^{2+} sensor calibration	96	2021
	Colorimetric strips	Amine gas	CNN	Food freshness	70	2020
ML for HMI	Substrate-less nanomesh	Strain at finger joint	Transformer	Hand tasks	103	2023
	Graphene artificial throat	Strain from throat	CNN	Basic speech elements	121	2023
	Stretchable patch	Strain from throat	NN	Throat activities	119	2023
	Stretchable patch	Force reception using fibre Bragg grating transducers	CNN	Tactile force mapping	158	2022
	Smart finger	Triboelectric output on different surfaces	LDA	Materials	109	2022
	Stretchable magnetic patch	Force reception using Hall effect in magnetic film	NN	Tactile sensing with force self-decoupling	159	2021
	Flexible patch	EMG mapping on forearm	Hyperdimensional computing	Hand gestures	102	2021
	Textiles	Strain on different parts of body	CNN	Whole-body poses	106	2021
	Ultrathin flexible patch	Phonetic spectrum from piezoelectric acoustics	Gaussian mixture model	Biometric authentication	120	2021
	Stretchable patch	Strain at finger joint, hand gesture images	NN for sensor, CNN for image	Hand gestures	107	2020
	Stretchable patch	Strain at finger joints	SVM	Sign-to-speech translation	112	2020
	Flexible patch	Thermal conductivity, contact pressure and temperature	NN	Objects	104	2020
	Stretchable patch	Strain mapping on face	kNN	Facial kinematics	111	2020
	Textile glove	Full-hand strain distribution	CNN	Tactile signatures of hand grasp	105	2019
	Stretchable patch	EEG	CNN	EEG frequency	43	2019
ML for healthcare	Stretchable cardiac imager	Ultrasound image of heart	CNN	Left ventricular volume	34	2023
	Stretchable patch	Vocal intensity and energy dose	CNN	Vocal fatigue	117	2023

Category	E-skin platform	Targeted parameters	ML models	Learning objectives	Ref	Year
	Microfluidic skin patch	Heart rate, alcohol	Linear regression	Behavior impairment	[57]	2023
	Graphene tattoos	Pulse on wrist	AdaBoost	Systolic and diastolic pressure	[133]	2022
	Radio sensor	Night nocturnal breathing signals	NN	Parkinson's disease	[14]	2022
	Commercial EEG helmet	EEG	CNN	Drowsiness	[139]	2021
	Textiles	Pulse on wrist	NN	Systolic and diastolic pressure	[132]	2021
	Smart bandage	Vital signs from throat	CNN	Cough-like events for COVID-19	[147]	2021
	Epidermal electronic tattoos	ECG, respiration and GSR	DT	Fatigue	[137]	2020
	Textiles	Strain on leg	RF	Running fatigue	[138]	2020
	Commercial leads	ECG	CNN	Stress	[136]	2018
	Commercial wrist watch	Vital signs on wrist	SVM	Stress	[135]	2017
	Commercial wrist watch and straps	Vital signs on wrist	Logistic regression	Stress	[134]	2012

NN, neural networks. CNN, convolutional neural networks. DT, decision tree. RF, random forest. SVM, support vector machine. LDA, linear discriminant analysis. kNN, k-nearest neighbors. MNIST, Modified National Institute of Standards and Technology database.