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REVIEW

AI-powered electronic skin: from smart design to cognitive interaction

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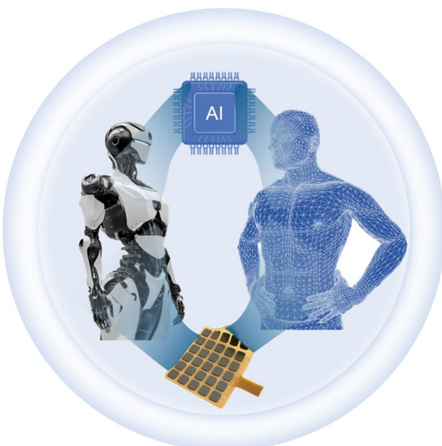
Abstract

Robotic electronic skin (e-skin) is inspired by human skin and endows robots with tactile perception, temperature detection, and environmental interaction capabilities. However, its development is hampered by prolonged design cycles, limited signal enhancement, and weak cognitive abilities. Given that the convergence of artificial intelligence (AI) with e-skin is fundamentally transforming this landscape, the present review highlights the pivotal contributions of AI across the entire development spectrum of robotic e-skin, including design optimization, signal processing, and cognitive enhancement. AI-driven design paradigms dramatically shorten development time and enable the discovery of optimal sensor materials and structures. In signal processing, AI algorithms notably improve the ability to decouple complex sensory data, enabling robust, multimodal, super-resolution sensing. AI endows e-skin with advanced cognitive capabilities, allowing it to interpret intricate tactile information and intelligently respond to external environments. By underscoring the potential of AI throughout the entire development pipeline, this review aims to drive the creation of e-skin with minimal hardware and maximal cognition and thus achieve revolutionary breakthroughs in cutting-edge fields such as human–robot interactions, precise robot control, and soft robotics for environmental exploration.

Graphical abstract



Keywords Robotics · Electronic skin · Artificial intelligence (AI) · Tactile perception

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1 Introduction

Human skin features a remarkably sophisticated sensory system that integrates numerous mechano- and thermoreceptors to achieve multimodal perception with exceptional precision [1–3]. The corresponding specialized cellular structures include Merkel cells for pressure sensing, Pacinian corpuscles for high-frequency vibration sensing, Ruffini endings for strain and shear sensing, and free nerve endings for temperature sensing [4–6]. These structures transduce mechanical and thermal stimuli into electrochemical signals, which undergo hierarchical processing in the peripheral and central nervous systems to enable the execution of complex tactile tasks ranging from delicate object manipulation and texture discrimination to affective touch and social interaction [2]. The ability of skin to dynamically adapt to varying stimuli while maintaining robustness against environmental noise and crossmodal interference remains the gold standard for artificial sensing systems.

Inspired by this biological paradigm, electronic skin (e-skin) has emerged as a transformative technology for robotic systems, aiming to replicate—and in some aspects surpass—the sensory capabilities of natural skin [7–18]. Recent advances in soft electronics, stretchable nanomaterials, and bioinspired sensor architectures allow robotic e-skin to detect a wide array of stimuli, including pressure, shear, temperature, humidity, and even chemical signatures [19–28]. Such progress unlocks unprecedented applications in human–robot collaboration [29–36], precise manipulation [37–42], soft robotics [43–47], and neuromorphic robotic sensing [48–52]. For example, e-skin-equipped robotic arms ensure safe physical interaction by halting motion upon collision detection, and tactile sensor-enabled grippers delicately handle fragile or deformable objects with slip prevention. Furthermore, the integration of e-skin in soft robotics enables adaptive interactions in unstructured environments, expanding the potential for autonomous operation in real-world scenarios.

Despite these breakthroughs, e-skin development remains challenging. Conventional design approaches heavily rely on empirical trial-and-error methods, resulting in prolonged optimization cycles for materials, microstructures, and transduction mechanisms [44, 53–55]. Additionally, environmental noise, sensor drift, and cross-sensitivity effects degrade signal reliability, while the intrinsic coupling of multimodal stimuli (e.g., tactile–thermal–humidity interference) complicates accurate decoding [56–59]. The scalability of high-density sensor arrays also poses wiring and signal processing challenges, limiting spatial resolution and system robustness [60–63]. Although human skin exhibits advanced cognitive functions, such as object shape, size, and texture recognition [64–68], existing e-skins exhibit poor intelligent perception performances under dynamic real-world conditions.

The convergence of artificial intelligence (AI) and e-skin technology is a promising strategy for overcoming these limitations. In particular, machine learning (ML) and deep learning (DL) models have unlocked new possibilities in optimizing material properties, improving sensor performance, and enabling advanced cognitive functions in e-skin. For instance, active learning, generative models, and explainable algorithms accelerate material discovery and structural design [69–76], while neural networks facilitate signal denoising, spatial resolution enhancement, and multimodal decoupling [77–81]. At the cognitive level, transformer architectures, meta-learning, and neuromorphic computing enable the development of e-skins capable of emotion recognition, predictive interaction, and adaptive decision-making [82–87], bridging the gap between artificial and biological tactile intelligence.

Unlike prior reviews, which primarily focus on material innovations, sensor hardware, or signal processing in isolation [88–95], this review provides a closed-loop analysis of how AI is reshaping the e-skin technology, emphasizing three key frontiers (Fig. 1): (1) design optimization, i.e., decoding material–structure–property relationships; (2) performance enhancement, i.e., achieving noise-resilient super-resolution multimodal decoupling; (3) cognitive perception, i.e., identifying object attributes and human emotions and executing dexterous control. In contrast to prior reviews, which often treat sensing hardware, signal processing, and cognition as separate domains, this work highlights the synergistic potential of AI-driven closed-loop e-skins. As AI continues to evolve alongside novel sensing materials and architectures, the e-skin technology is poised to achieve true biomimetic intelligence, blurring the boundaries between artificial and biological tactile perception.

2 Robotic e-skin and ML algorithms

2.1 Materials, fabrication, and sensing mechanisms for robotic e-skin

Drawing inspiration from the multifaceted sensory capabilities of human skin, e-skin represents notable progress in flexible sensing systems and features a multilayered architecture including a substrate layer for mechanical support, an electrode layer for signal transduction, and a sensitive layer for stimulus detection. The substrate layer, often fabricated from elastomers such as polydimethylsiloxane or ecoflex®, provides the necessary stretchability and durability, with some designs achieving large strain through advanced structural engineering (e.g., kirigami-inspired patterns) [103–111]. The electrode layer leverages conductive materials such as silver nanowires, graphene, or liquid metals, balancing high conductivity with mechanical flexibility [112–117]. The

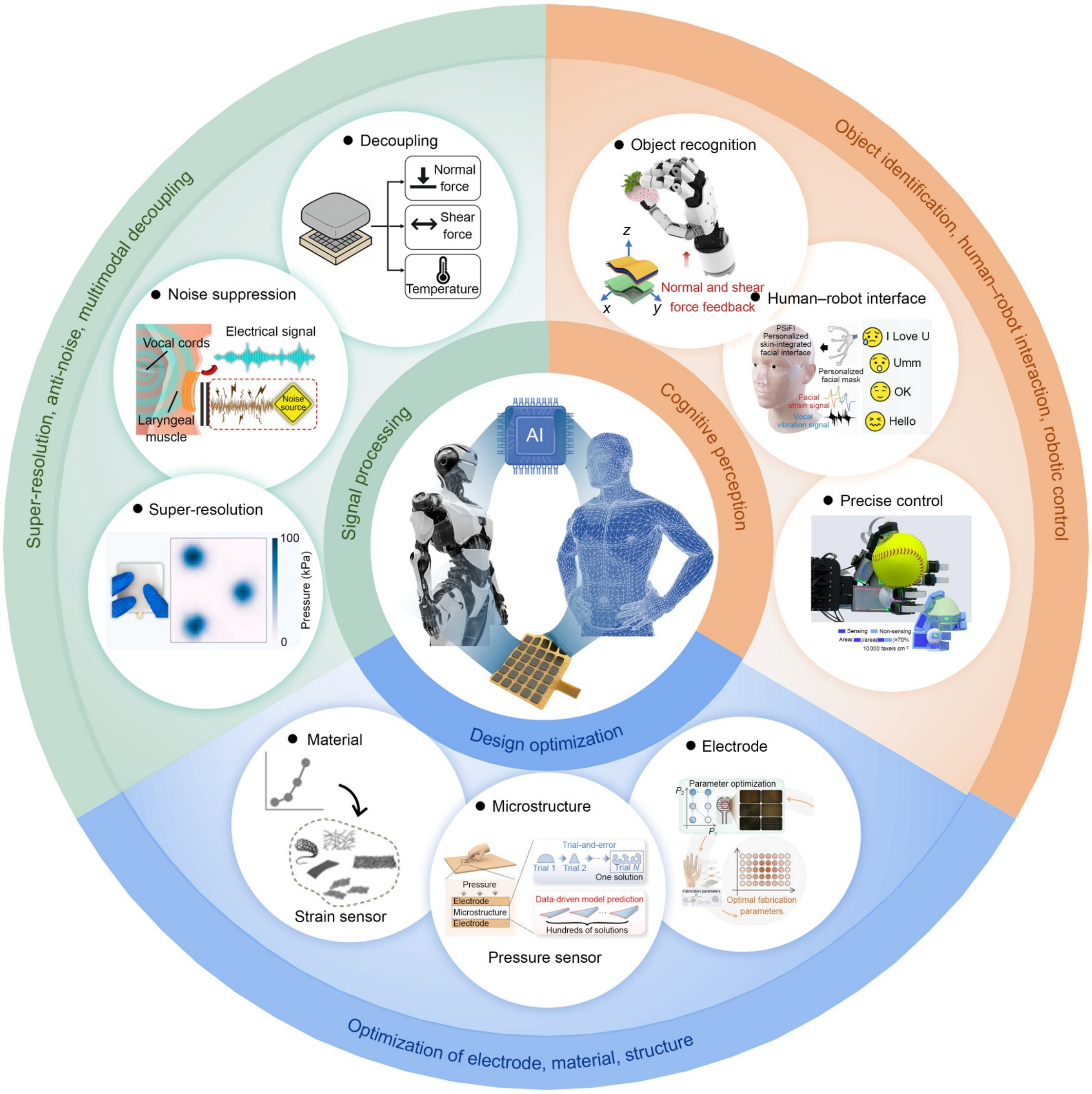

Fig. 1 AI-driven closed-loop development of robotic e-skins from design optimization and signal processing to robot cognition and control. Images representing “design optimization”: “material,” reproduced from [96], with permission from Springer Nature Limited; “microstructure,” reproduced from [97], licensed under CC BY-NC-ND 4.0; “electrode,” reproduced from [98], licensed under CC BY 4.0. Images representing “signal processing”: “super-resolution,” reproduced from [99], licensed under CC BY 4.0; “noise suppression,” reproduced from [100], licensed under CC BY-NC-ND 4.0. Images representing “cognitive perception”: “object recognition,” reproduced from [101], licensed under CC BY 4.0; “human–robot interface,” reproduced from [102], licensed under CC BY 4.0; “precise control,” reproduced from [83], licensed under CC BY-NC-ND 4.0

sensitive layer employs functional materials such as carbon nanotubes (CNTs), MXenes, or hydrogels selected because of their unique electromechanical properties, as exemplified by the high piezoresistivity of CNT composites or the strain-sensitive bandgap modulation of two-dimensional materials such as MoS_2 [118–125].

E-skin fabrication techniques have experienced remarkable progress due to the need for scalable high-resolution manufacturing. Traditional methods such as photolithography offer micron-scale precision but face challenges in cost and scalability for large-area applications [126, 127]. In contrast, additive manufacturing techniques such as three-dimensional (3D) printing, inkjet printing, or aerosol jet printing enable rapid prototyping with feature sizes below 30 μm [128–132]. Emerging approaches such as laser-induced graphene formation enable maskless single-step fabrication and the creation of porous graphene sensors directly on flexible substrates [133–136]. These advances have expanded the e-skin design space, allowing for customizable mechanical and electrical properties tailored to specific applications.

From a sensing perspective, robotic e-skin employs diverse transduction mechanisms, each with distinct advantages and limitations. Piezoresistive and capacitive sensors can detect both dynamic and static forces and thus find applications ranging from robotic grasping to health monitoring [137–142]. Piezo- and tribo-electric sensors are limited to dynamic force detection but offer the advantages of rapid-response time and self-powering capability, respectively [143–146]. Electromagnetic sensors stand out for their ability to decouple 3D forces, although the complexity of their design and integration remains a hurdle [147–149]. Chemical sensing e-skins are widely used in hazardous environments, industrial monitoring, and medical diagnostics, reducing human risk and improving efficiency [150–152]. However, challenges remain, including sensitivity to environmental interference and the need for periodic calibration.

2.2 ML algorithms for robotic e-skin

The integration of ML with e-skin transforms raw sensor data into actionable insights, enabling sophisticated perception and decision-making in robotic systems (Table 1). Traditional ML algorithms, including support vector machines (SVMs), multilayer perceptrons (MLPs), and random forests, have proven effective for processing low-dimensional tactile data, achieving high accuracy in tasks such as object classification and posture recognition [161, 162]. These methods are particularly valuable in scenarios where computational resources are limited, offering robust performance even with modest datasets. However, with the growing complexity of sensory data, which spans high-resolution pressure maps, time-varying strain signals, and multimodal inputs, DL approaches are becoming more crucial. Convolutional neural networks (CNNs) excel in interpreting spatial patterns and are ideal for analyzing pressure distributions across e-skin arrays, while recurrent neural networks (including long short-term memory (LSTM)) and transformers demonstrate superior performance in decoding temporal sequences such as vibrations or slip events during robotic manipulation. A critical challenge in ML-driven e-skin development is the scarcity of labeled training data due to the labor-intensive nature of tactile data collection. This problem can be addressed using techniques such as transfer learning, in which case models pretrained on large datasets are fine-tuned using limited e-skin-specific data to markedly reduce annotation efforts [159]. Self-supervised learning

Table 1 Representative studies integrating ML models and robotic skins

Category	Sensing mechanism	Learning parameters	Target performance	Core ML model	Ref.
ML for design optimization	Resistive	Strain signals of different fabrication recipes	Automatic design of strain sensor	Active learning	[96]
	Capacitive	Pressure signals of different microstructures	Inverse design of pressure sensor	Logistic regression analysis	[97]
	/	Inject printing parameters	Defect evaluation of printed electrodes	CNN	[153]
	Triboelectric	Tactile signals of different electrode layouts	Optimization of fabrication parameters	SVM	[98]
ML for signal processing	Magnetic	Tactile signals of different positions	Location resolution improvement	CNN	[154]
	Resistive	Tactile signals of different pressures and positions	Location-and-pressure resolution improvement	LSTM	[99]
	Triboelectric	Tactile signals of different positions	Location resolution improvement	GNN	[155]
	Moist-electric	Multimodal sensing signals	Multimodal decoupling	LSTM	[156]
	Piezo-thermic	Multimodal sensing signals	Six-axis force/torque decoupling	CNN	[157]
	Triboelectric	Sensing signals with noise	Robust acoustic signal recognition	CNN	[100]
ML for advanced cognitive perception	Triboelectric	Sensing signals of droplet flowing	Taste sensing	CNN	[158]
	Piezoelectric, piezoresistive	Sensing signals of softness and texture	Clinical feature identification and intelligent picking	CNN	[101]
	Triboelectric	Sensing signals of facial movements	Multimodal emotion encoding	CNN	[102]
	Resistive	Sensing signals of random hand motions	Recognition of different hand tasks	Transformer	[159]
	Capacitive	Sensing signals of deformation	Soft robotic proprioception	Transformer	[82]
	Vision	Tactile sensing signals	High-resolution robotic hands	Transformer	[83]
	Triboelectric	Tactile spike signals	Spike timing-based coding	Network of spiking neurons	[160]

ML: machine learning; CNN: convolutional neural network; SVM: support vector machine; LSTM: long short-term memory; GNN: graph neural network frameworks such as contrastive learning further mitigate data limitations by leveraging unlabeled sensor readings to pretrain feature extractors.

2.3 Integrated development of ML algorithms and robotic e-skin

The synergy between ML and robotic e-skin has evolved through distinct phases, reflecting broader trends in both fields (Fig. 2) [42, 82, 83, 97, 154, 157–159, 163–171]. Early research (around 2018) primarily focused on using classical ML algorithms such as SVMs to interpret strain sensor data for basic posture recognition [163, 164]. These foundational studies demonstrated the ability of ML to extract meaningful information from flexible-sensor data but were limited by model simplicity and low data dimensionality. As e-skin designs grew more sophisticated, incorporating higher sensor densities and multimodal capabilities, DL adoption became inevitable [12, 154, 168, 172]. MLPs and CNNs allow robots not only to detect contact but also infer object properties such as shape, texture, and stiffness, paving the way for more dexterous manipulation.

The recent years have witnessed the incorporation of advanced learning paradigms, as exemplified by the use of graph

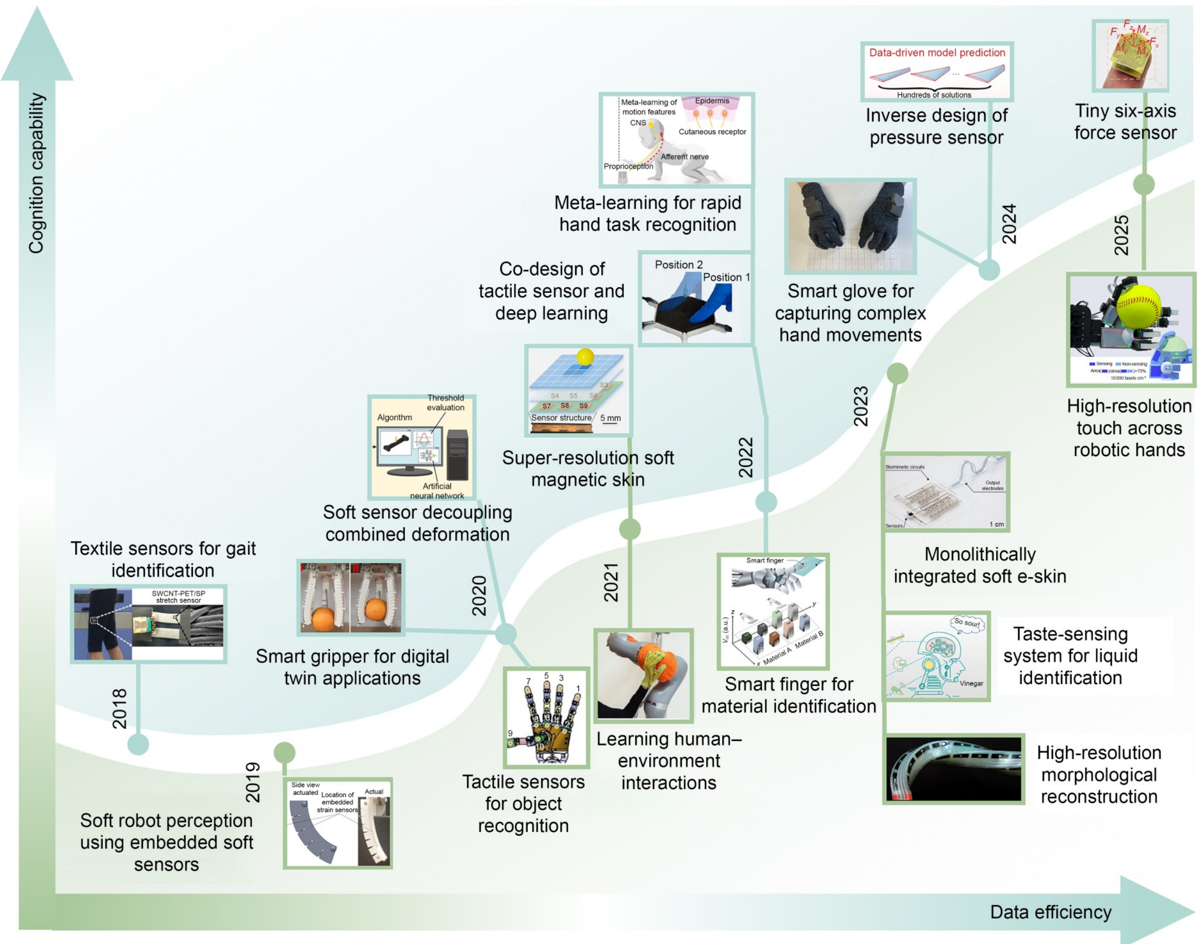

Fig. 2 Evolution of AI-driven robotic e-skins. Images: “textile sensors for gait identification,” reproduced from [163], licensed under CC BY 4.0; “soft robot perception using embedded soft sensors,” reproduced from [164], with permission from AAAS; “smart gripper for digital twin applications,” reproduced from [165], licensed under CC BY 4.0; “soft sensor decoupling combined deformation,” reproduced from [166], with permission from AAAS; “tactile sensors for object recognition,” reproduced from [42], with permission from AAAS; “learning human–environment interactions,” reproduced from [167], with permission from Springer Nature Limited; “super-resolution soft magnetic skin,” reproduced from [154], with permission from AAAS; “co-design of tactile sensor and deep learning,” reproduced from [168], licensed under CC BY 4.0; “meta-learning for rapid hand task recognition,” reproduced from [159], with permission from Springer Nature Limited; “smart finger for material identification,” reproduced from [169], licensed under CC BY-NC 4.0; “monolithically integrated soft e-skin,” reproduced from [170], with permission from AAAS; “taste-sensing system for liquid identification,” reproduced from [158], with permission from Springer Nature Limited; “high-resolution morphological reconstruction,” reproduced from [82], with permission from Springer Nature Limited; “smart glove for capturing complex hand movements,” reproduced from [171], with permission from Springer Nature Limited; “inverse design of pressure sensor,” reproduced from [97], licensed under CC BY-NC-ND 4.0; “tiny six-axis force sensor,” reproduced from [157], licensed under CC BY 4.0; “high-resolution touch across robotic hands,” reproduced from [83], licensed under CC BY-NC-ND 4.0

neural networks (GNNs) to model the spatial relationships between distributed sensors and by that of transformers to capture long-range dependencies in time-series data [83, 99]. These innovations have been complemented by the integration of neuromorphic computing, where spiking neural networks mimic the event-driven processing of biological sensory systems, drastically reducing power consumption [160]. The fusion of ML and e-skin technologies is poised to enter a new era characterized by edge AI [173, 174], where lightweight models are deployed directly on embedded processors within e-skin itself and enable real-time processing without reliance on external computing resources. Explainability is also emerging as a critical focus, with techniques such as Shapley additive explanations (SHAP) being employed to interpret model decisions. As these technologies mature, the boundary between artificial and biological sensory systems continues to blur, which highlights a future where robots perceive and interact with their environments as seamlessly as living organisms.

3 AI-driven design and optimization of robotic e-skin

E-skin development faces intricate multidisciplinary challenges due to the highly nonlinear multiphysics coupling between material composition, microstructure, and sensing performance. Conventional design strategies relying on empirical trial-and-error approaches struggle to optimize competing performance metrics such as sensitivity, linearity, and detection range [53]. The heterogeneity of material systems (e.g., substrate, sensing, and electrode layers) constituting e-skin devices further complicates optimization [27]. Moreover, the scarcity of high-throughput experimental data and inconsistencies in reported fabrication processes hinder data-driven optimization, and multiphysics simulations remain computationally prohibitive [55, 162]. Collectively, these limitations impede breakthroughs in e-skin performance and scalability. AI is revolutionizing e-skin development by enabling the intelligent design and discovery of novel materials and microstructures, enhancing manufacturing through optimized processes and real-time quality control, and providing explainable insights that deepen our understanding of complex sensor behaviors.

3.1 Optimization of materials, structures, and fabrication parameters

ML has been successfully deployed to optimize functional composites such as flexible silver/polyamide acid systems [175], where MLPs predict electrical resistance based on ion concentration and exchange time (Fig. 3a). However, such models often focus on single performance metrics (e.g., initial resistance), neglecting the holistic optimization required for high-performance sensors. To address this problem, Yang et al. [96] developed an active learning framework augmented by synthetic data generation, accurately predicting strain-response curves for CNT/polyvinyl alcohol/MXene nanocomposites using only 125 experimental samples (Fig. 3b). This system enabled on-demand strain sensor design by automatically recommending optimal material compositions for user-specified sensitivity and detection ranges. The generality of this method was further demonstrated by the development of tailored MXene aerogels [176]. Additionally, the performance metrics in the above works, such as sensitivity and detection range, are clearly defined and enable direct comparison across different studies. When AI is used for optimization, these metrics can readily serve as model labels or objective functions. However, a major difficulty emerges for sensors where performance lacks a standardized benchmark, hindering the selection of appropriate labels for AI-driven design optimization. For example, when evaluating e-skins for proprioception, some works report simple pointwise or angular data [165, 177], whereas others provide complex geometric point cloud data [82]. To maximize the speed of AI-based e-skin performance enhancement, one should establish a robust common benchmark. Optimizing performance against this benchmark is the fastest and most effective way of accelerating e-skin development.

Beyond material composition, microstructure engineering plays a pivotal role in enhancing sensing performance. Traditional approaches, which iteratively test different geometries (e.g., pyramids [178], pillars [140], or sponges [179]), are inefficient and often fail to identify global optima. Liu et al. [97] pioneered a reverse-design strategy wherein reduced-order physical models constrained the design space and a jumping-selection algorithm rapidly identified optimal microstructures (Fig. 3c). This approach enabled the discovery of hundreds of architectures that maintained high linearity across a broad pressure range (0–300 kPa) and overcame the signal saturation problem plaguing conventional sensors (Fig. 3d). The development cycle for flexible pressure sensors was reduced from months to days by shifting from empirical optimization to AI-guided design.

The optimization of chemical e-skins is more complex than that of their physical counterparts, primarily because of the time-intensive simulation and fabrication processes involved in the former case. For sweat sensors, optimizing the selectivity of molecularly imprinted polymers (MIPs) is crucial; however, MIP synthesis is time-consuming, and the corresponding density functional theory simulations are computationally intensive. To address this problem, QuantumDock was introduced as an automated computational framework for universal MIP development (Figs. 4a and 4b) [180]. Leveraging quantum theory, QuantumDock probes molecular

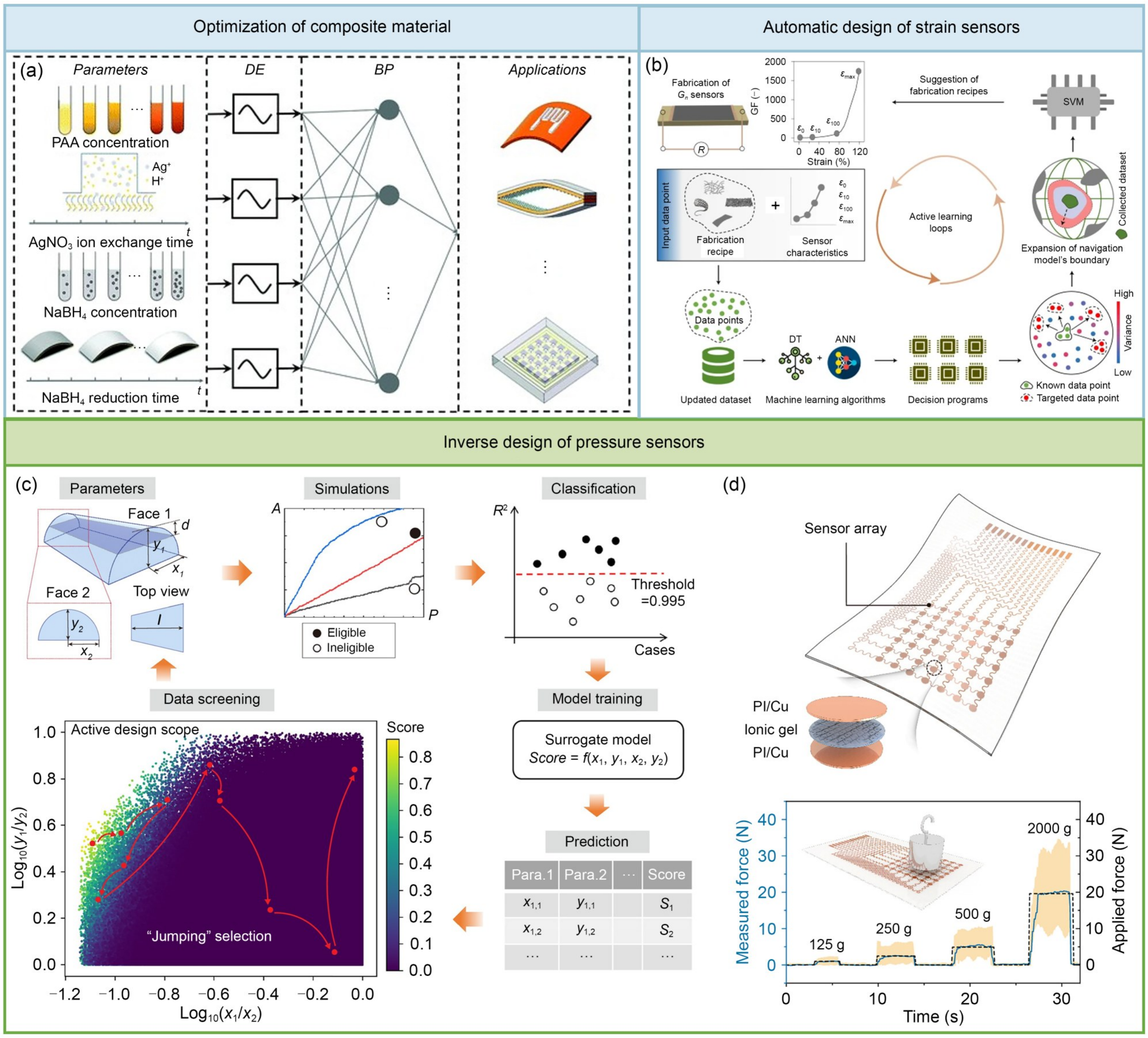

Fig. 3 AI-driven approaches optimizing robotic e-skin materials and structures. (a) ML-assisted optimization of electrical resistance in flexible silver/polyamide acid composites. Reproduced from [175], with permission from The Royal Society of Chemistry. (b) Visual data-augmented active learning framework enabling the on-demand design of strain sensors. Reproduced from [96], with permission from Springer Nature Limited. (c) Jumping-selection framework for the inverse design of pressure sensors. (d) Schematic of a pressure sensor array designed using the framework in (c) and sensor responses to different weights. Reproduced from [97], licensed under CC BY-NC-ND 4.0

interactions between monomers and target/interferent molecules. Its novelty lies in a molecular docking approach that identifies the most stable binding geometries and calculates a new selectivity metric, thereby accelerating the optimal selection of monomers and crosslinkers for MIP fabrication. Furthermore, a QuantumDock-optimized graphene-based wearable device enabling autonomous sweat induction, sampling, and sensing was developed.

Beyond the optimization of material properties and device structures, the precise control of fabrication parameters is equally critical for realizing high-performance e-skins, as it directly impacts device quality and functional integrity. For example, in the fabrication of inkjet-printed flexible circuits, which are commonly used in e-skin manufacturing, the morphology of the deposited ink and resulting interconnects between features must be precisely managed. Yao et al. [153] developed a dual-AI framework combining predictive and detective models: the former preoptimized printing parameters, achieving success rates of >80% prior to fabrication, while the latter performed real-time defect detection with an accuracy of 95.5% and a processing time per image of 4.6 ms (Figs. 4c and 4d). Such systems offer robust solutions for the high-throughput, high-quality manufacturing of flexible electronics.

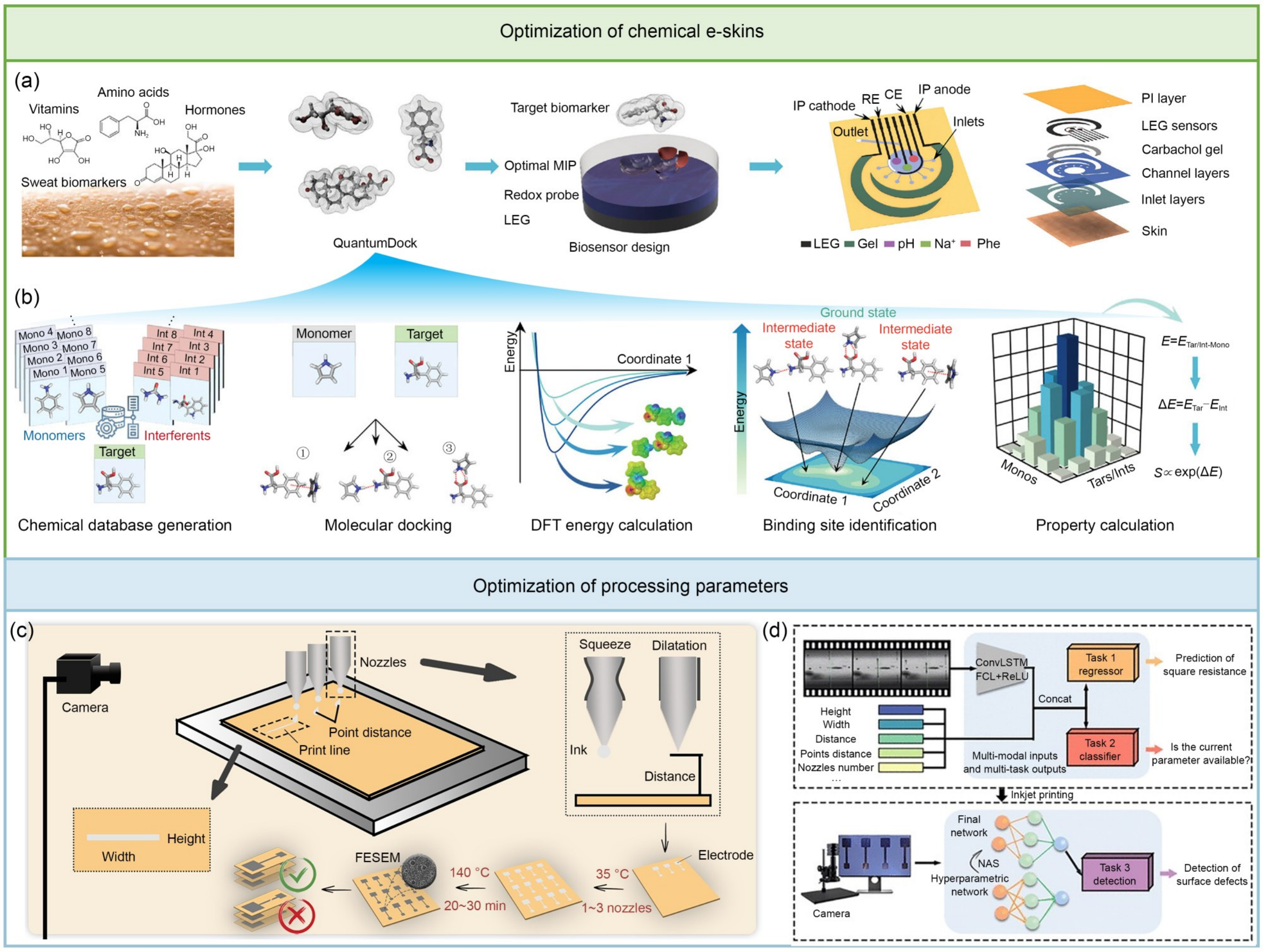

Fig. 4 AI-driven optimization of the chemical sensing layer and processing parameters of robotic e-skins. (a) QuantumDock-enabled molecularly imprinted polymer (MIP)-based wearable biosensor design and optimization for circulating biomarker monitoring. (b) General procedures of QuantumDock-based MIP design. Reproduced from [180], with permission from Wiley-VCH GmbH. (c) High-volume preparation of flexible electrodes based on inkjet printing. (d) Dual-AI framework for predicting success rates and detecting the defects of the electrodes in (c). Reproduced from [153], with permission from the American Chemical Society

3.2 Investigation of sensing mechanisms

Although explainable ML has been widely used in material optimization [181–183], its use in sensor systems, particularly for understanding and optimizing e-skin and multimodal sensing mechanisms, remains largely unexplored. Given the complex nonlinear interactions among sensor signals, traditional black-box DL models often lack transparency, which hinders error diagnosis and sensor design refinement. The incorporation of explainable learning techniques could bridge this gap, improving performance and providing mechanistic insights.

For example, a key challenge in triboelectric nanogenerator (TENG) design is the reliance on manual, time-consuming finite-element modeling or experimental iterations. To address this problem, an automated ML-based platform was developed, combining an MLP-based surrogate model for rapid and accurate performance prediction and a TreeSHAP interpretable ML model for global and local explanations [184]. This platform demonstrated broad adaptability across various TENG architectures, markedly accelerating design optimization while maintaining interpretability. By leveraging explainable ML, the framework not only predicted optimal designs but also elucidated the underlying physical relationships, supporting more efficient and sustainable energy solutions in mobile electronics.

Explainable learning has also been used to investigate relationships between material parameters and sensor characteristics. The impact of different fabrication variables (e.g., CNT loading, polyvinyl alcohol concentration, and layer thickness) on the strain sensitivity of graphene-based sensors was quantified using SHAP [96] and insights for design rules were uncovered; e.g., CNT loading was identified as the factor most strongly affecting the maximal working strain, and both CNT loading and sensing layer thickness had comparable effects. These insights, validated through microscopy characterization, highlighted how explainable ML can guide material and process optimization.

4 AI-driven signal processing of robotic e-skin

Despite remarkable progress in enhancing the sensitivity, dynamic range, and linearity of the individual sensing elements of robotic e-skin, system-level performance enhancement remains hindered by critical signal processing challenges. Complex and dynamic operational environments demand exceptional noise immunity, while nonlinear coupling among multimodal sensing signals compromises measurement accuracy. Additionally, the pursuit of high spatial resolution imposes stringent demands on sensor array design, fabrication, and reliability. The use of AI can address these limitations, elevating e-skin capabilities by enabling multimodal signal decoupling for precise, holistic perception based on complex inputs to ensure robust data accuracy through advanced noise suppression techniques and dramatically enhance tactile detail via spatial super-resolution.

4.1 Noise suppression

Noise suppression is critical for maintaining data accuracy. E-skins face noise from multiple sources, e.g., mechanical deformation, electromagnetic interference, and environmental fluctuations, which can distort sensor readings. For instance, bioinspired acoustic sensors often suffer from severe signal degradation in real-world environments due to ambient noise. AI-powered noise reduction techniques have emerged as a powerful solution for overcoming these challenges. For ear-proximal sensing applications, where background noise markedly interferes with signal clarity, Jung et al. developed a flexible piezoelectric acoustic sensor with a multiresonant bandpass structure (Fig. 5a) [185]. By integrating an attention-enhanced CNN, the system achieved a 96% speaker recognition rate in high-noise conditions (62% improvement over traditional microphones).

For throat-contact sensors, which bypass ambient noise by directly capturing vocal fold vibrations, the main challenge lies in preserving high-frequency speech components. Yao et al. [100] addressed this problem by designing a noise-resistant triboelectric acoustic sensor combined with a CNN-based speech reconstruction algorithm (Fig. 5b). This system demonstrated remarkable robustness, achieving a speech recognition accuracy of 99% even in extremely noisy environments, which is a crucial advancement for robotics operating in disaster zones or collaborative human–robot settings. To enable universal speech recognition in both quiet and noisy settings, a wearable graphene-based artificial throat has been developed [186]. Unlike bulky multichannel sensors, this device detected both acoustic signals and mechanical motions and could therefore capture low-frequency vocalizations while remaining noise-resistant, achieving a 99.05% accuracy in recognizing phonemes, tones, and words, along with a more than 90% accuracy in interpreting impaired speech from laryngectomy patients. The artificial throat could also synthesize speech in real time, thus holding promise for assistive technologies and human–machine interactions.

4.2 Multimodal signal decoupling

After the suppression of noise during signal processing, accurate multimodal decoupling becomes crucial to e-skin perception. However, the nonlinear coupling of response signals, compounded by environmental drift, renders conventional linear decoupling methods inadequate. ML offers a powerful solution by leveraging its intrinsic nonlinear modeling capacity to disentangle independent physical quantities from complex mixed signals. Keum et al. [187] integrated an MLP with a microporous ionic gel-based multimodal sensor, exploiting the synergistic effects of carbon black and the ionic gel to achieve dual-modal pressure–temperature sensing (Fig. 6a). DL-enabled decoupling allowed the precise discrimination of arbitrary mixed stimuli, with mean absolute errors being as low as 1.58% for pressure and 2.37% for temperature. To address the problem of increasing decoupling complexity with increasing sensing dimensionality, Yang et al. [156] devised a single-component graphene oxide-based multimodal sensor, employing a CNN for the synchronous monitoring and efficient decoupling of four coupled signals: temperature, humidity, pressure, and light intensity (Fig. 6b).

Another important trend is the development of sensors providing holistic touch awareness to enable the comprehensive perception of objects with a simple touch. In this case, the role of ML shifts to processing and interpreting complex feature sets from sensor outputs rather than simply separating scalar parameters. Guo et al. [188] devised transient-voltage and sustained-potential artificial neuron sensors enabling the synergistic sensing of vibration, material, texture, pressure, and temperature within a single unit. The development of multidimensional mechanoreceptors for omnidirectional force/torque sensing is crucial for achieving dexterous and precise human and robotic manipulation, but remains a major hardware challenge. A notable recent advance is the development of an ultralight (0.30 g), small (fingertip size), and flexible six-axis force/torque sensor [157] (Figs. 6c and 6d). Assisted by ML, this sensor accurately perceives six-dimensional force/torque by capturing the spatial strain field of an elastic piezo-thermic material. The integration of such sensors on fingertips can greatly enhance the dexterity of humans and robots in fine operations such as bottle cap opening.

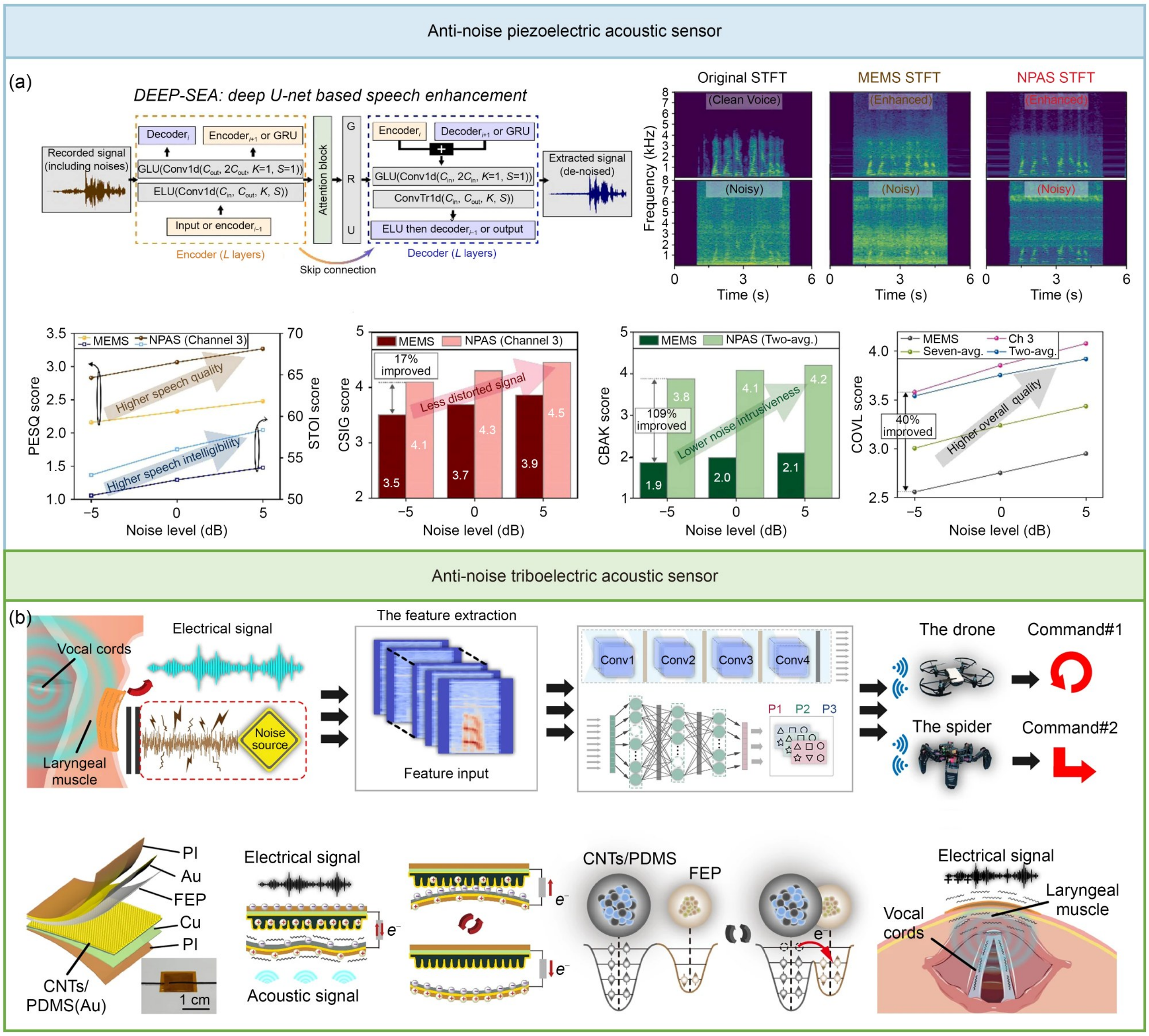

Fig. 5 AI-driven noise suppression in robotic e-skins. (a) Attention mechanism-enhanced CNN for noise-robust speech processing using flexible piezoelectric acoustic sensors. Reproduced from [185], with permission from Elsevier Ltd. (b) CNN-assisted anti-noise triboelectric acoustic sensor enabling reliable human–machine interactions in high-noise environments. Reproduced from [100], licensed under CC BY-NC-ND 4.0

After decoupling external physical parameters, e-skin perception in flexible systems must address a more challenging system-level problem, namely the simultaneous and accurate estimation of the external applied force (exteroception/tactile sensing) and the own shape change or deformation (proprioception) of the system. Owing to the inherent compliance of soft robots and wearable devices, these signals are heavily coupled, which renders conventional decoupling inadequate. Advanced ML architectures can be used to achieve this critical signal separation. In soft robotics, soft capacitive e-skin featuring a sparse electrode distribution and employing an MLP was used to separate tactile sensing from geometric deformation caused by internal actuation [189]. This DL approach achieved high accuracy (99.88%) in touch recognition, while a transformer-based architecture simultaneously tracked the deformation of the soft actuator, effectively solving the signal interference problem and endowing the soft system with both exteroceptive and proprioceptive capabilities. Furthermore, this data-driven philosophy was extended to area sensing: a single-layer hydrogel skin utilizing electrical impedance tomography (EIT) employed an information structuring strategy to manage highly coupled redundant sensory data and thus decouple and localize human touch (exteroception) while generating concurrent proprioceptive data across an entire hand-shaped surface [190]. This strategic focus on isolating body state from external contact is vital for the development of truly sentient and dexterous soft machines.

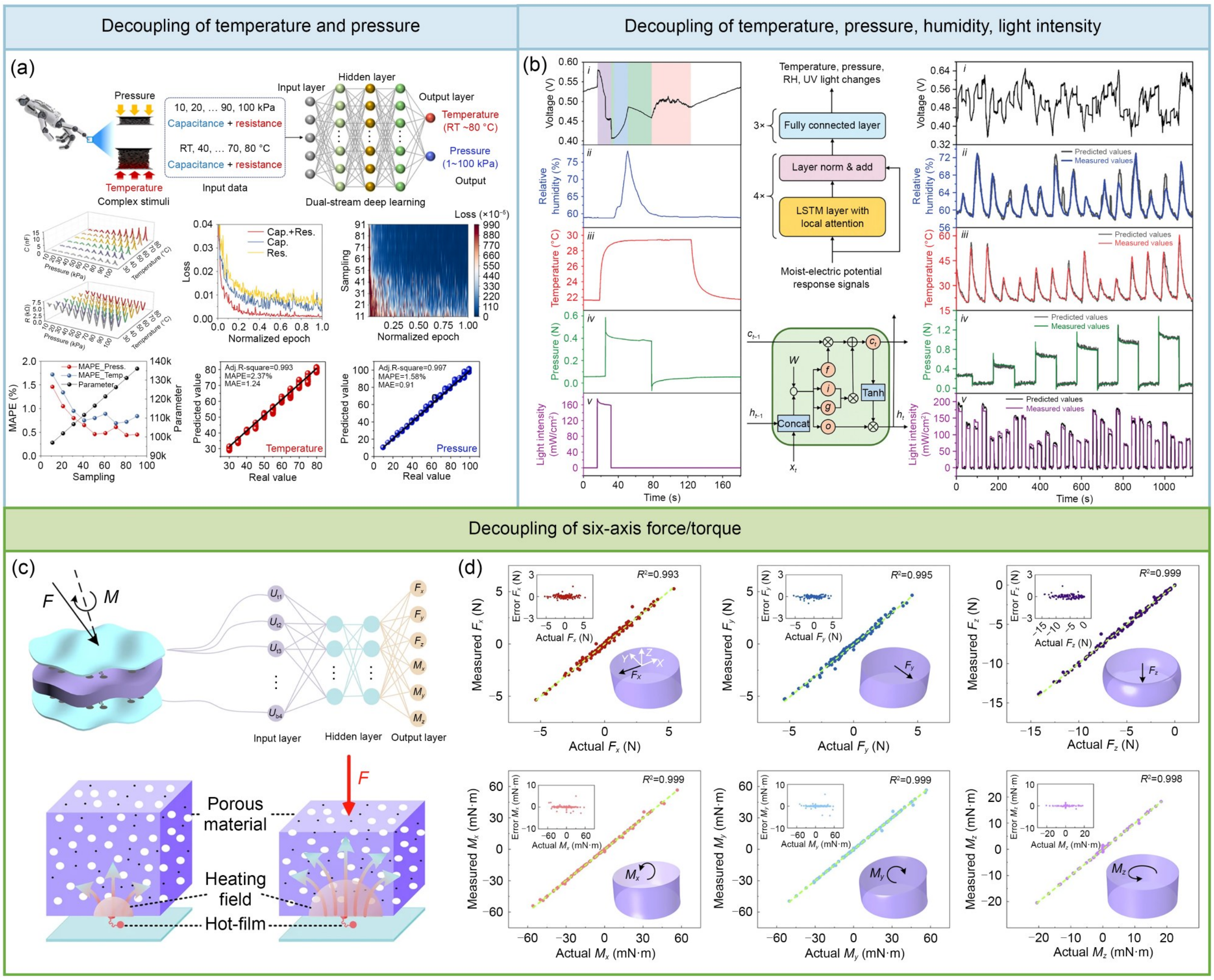

Fig. 6 AI-driven multimodal decoupling of robotic e-skins. (a) Decoupling of temperature and pressure based on a microporous ionic gel-based multimodal sensor. Reproduced from [187], with permission from Elsevier Ltd. (b) Decoupling of temperature, pressure, humidity, and light intensity based on a moist-electric-powered multimodal sensor. Reproduced from [156], with permission from Wiley-VCH GmbH. (c) Decoupling of six-axis force/torque based on an elastic piezo-thermic material. (d) Performance of the sensor in (c). Reproduced from [157], licensed under CC BY 4.0

4.3 Spatial super-resolution

Advanced human–robot interactions demand high spatial resolution to capture rich tactile information. Traditional approaches rely on high-density sensor arrays, which introduce manufacturing complexity and computational overhead. Inspired by biological neural processing, data-driven super-resolution techniques allow low-resolution hardware to surpass inherent physical limitations. Yan et al. [154] employed an MLP to enhance the resolution of a flexible magnetic e-skin 60-fold, although multichannel information utilization remained suboptimal (Fig. 7a). Kong et al. [99] optimized sensor array topology to improve sensing efficiency and introduced a tactile super-resolution neural network based on multisensor fusion, achieving 117-fold resolution enhancement (pressure inference error: 0.116 kPa; localization precision: 0.73 mm) (Fig. 7b). The model allowed zero-shot knowledge transfer from single- to multi-point contact scenarios. Training only required single-point contact data to achieve super-resolution sensing. This breakthrough enables applications in contour reconstruction, microkeyboards, and robotic embodied perception. For dynamic force detection, the same research group developed an adaptive spatiotemporal GNN with multistage attention, achieving a localization error of 1.3 mm (75-fold resolution enhancement) and dynamic response of 30 ms and thus enabling the resolution of subtle force interactions (Fig. 7c) [155]. To realize large-area super-resolution, this group introduced an array-free hardware architecture paired with a DL-driven large-area perception model, achieving the precise localization of external stimuli (radial error: 3.83 mm; angular precision: 3.79°; depth resolution: 0.31 mm) (Fig. 7d) [168] and thus

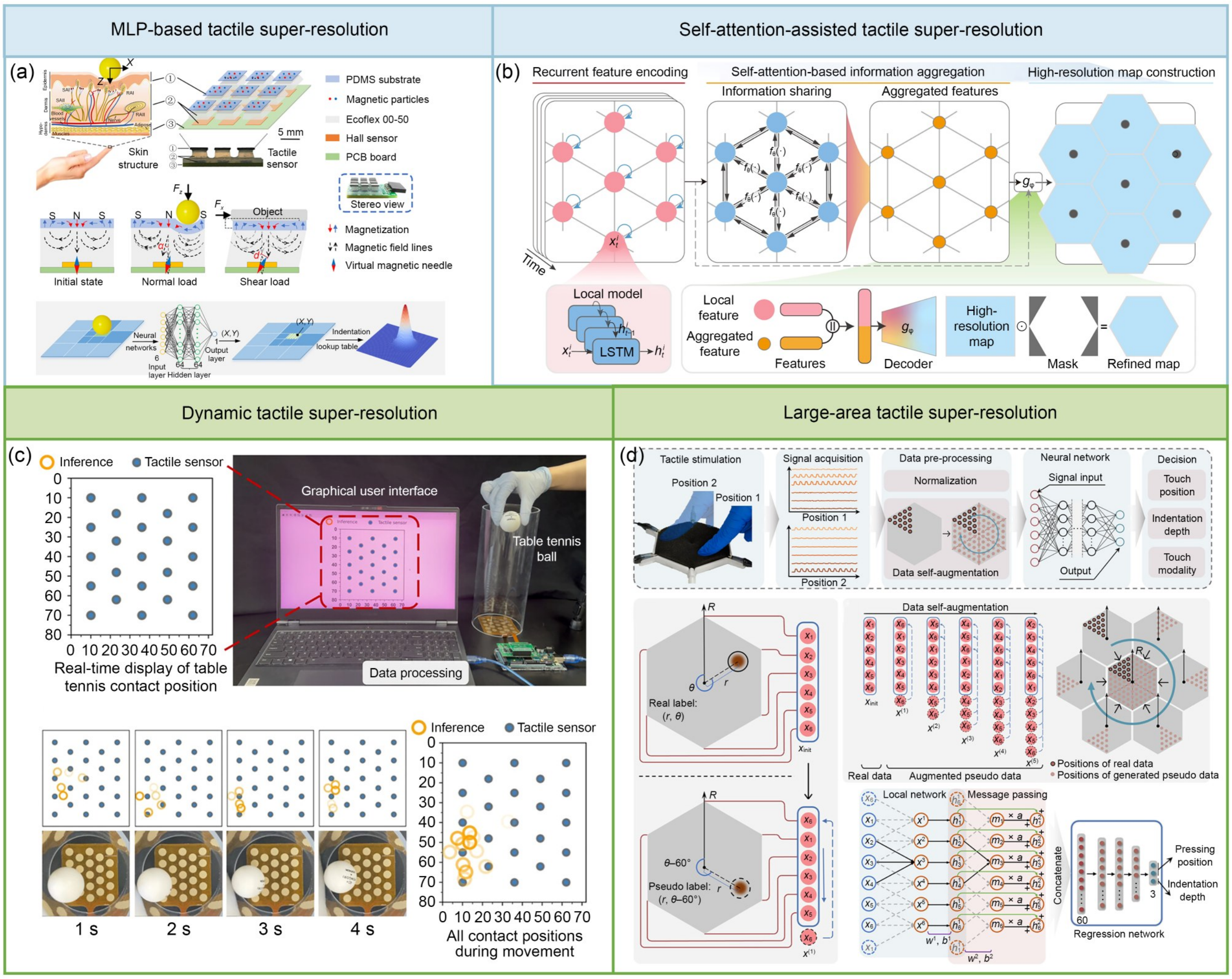

Fig. 7 AI-driven tactile super-resolution of robotic e-skins. (a) Soft magnetic skin for super-resolution tactile sensing with force self-decoupling. Reproduced from [154], with permission from AAAS. (b) End-to-end self-attention DL model enabling high-resolution multipoint tactile sensing. Reproduced from [99], licensed under CC BY 4.0. (c) Multistage attention-based adaptive graph neural network for rapid-response super-resolution tactile sensing. Reproduced from [155], licensed under CC BY 4.0. (d) Large-area super-resolution tactile sensing system combining deep neural networks with innovative data augmentation techniques. Reproduced from [168], licensed under CC BY 4.0

resolving the longstanding challenge of large-area high-resolution tactile sensing.

5 AI-driven cognitive perception of robotic e-skin

Having undergone systematic optimization and performance enhancement, e-skin exhibits remarkable multimodal and high-resolution sensing capabilities and robustness. However, further integration of advanced information fusion algorithms and DL technologies is required to achieve more advanced intelligent sensing functions, including the precise discrimination of object texture features, material hardness, and even human emotional states, as well as complex tasks such as precise manipulation. Progress in this direction will propel e-skin from basic sensing to an intelligent cognitive system.

5.1 Tactile sensing and object recognition

5.1.1 Tactile object attribute recognition

The accurate recognition of object attributes by robots is a key technical prerequisite of achieving adaptive grasping and fine manipulation. In terms of mechanical property recognition, Qiu et al. [101] developed a multidimensional stimulation capture system based on a bimodal tactile sensor (Fig. 8a). By synchronously quantifying the softness and texture features of objects, the authors achieved the high-precision recognition of pig mucosal features with an accuracy of 98.44%, providing a reliable technical solution for tissue palpation. He et al. [191] further expanded the

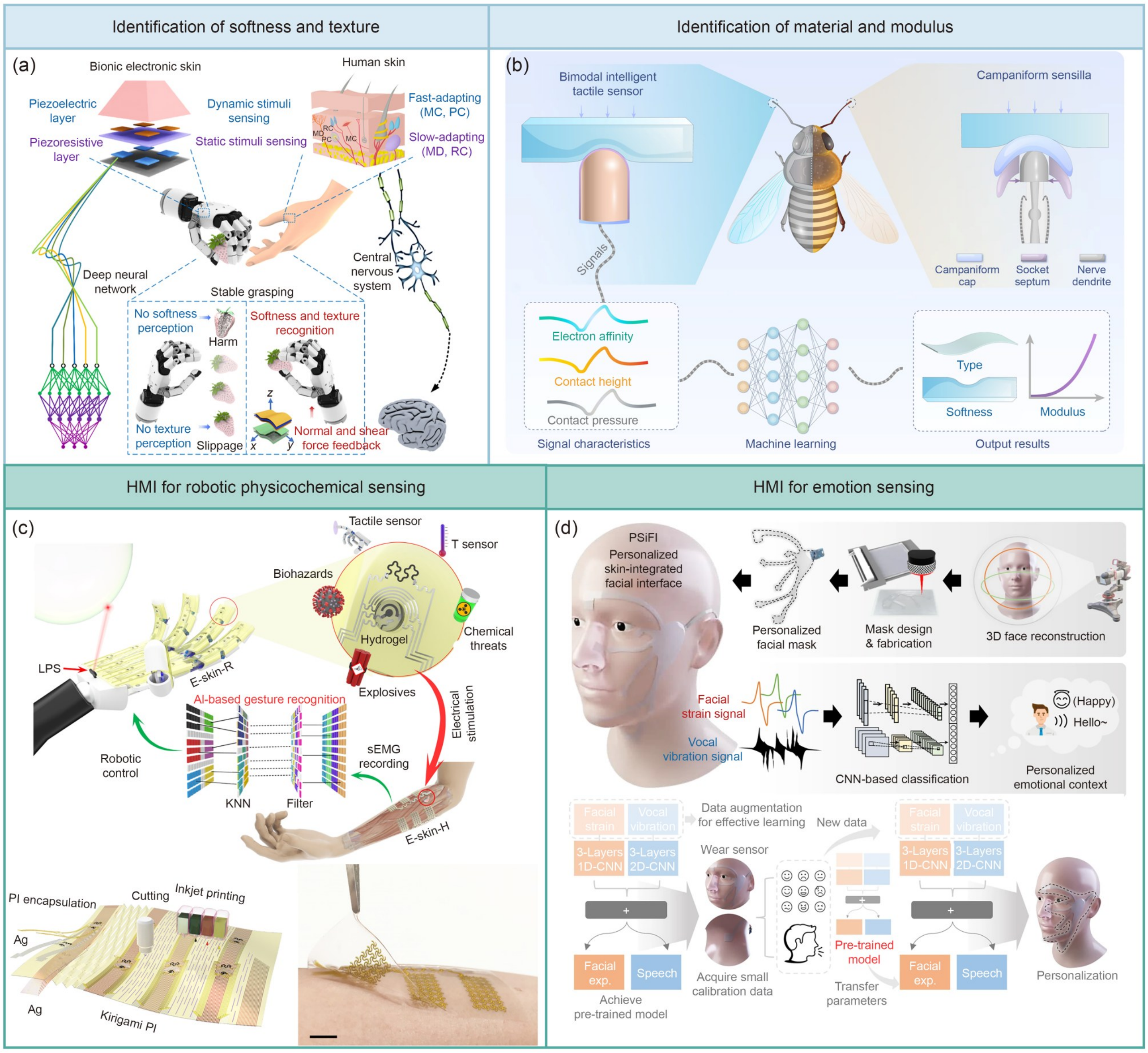

Fig. 8 AI-enhanced robotic e-skins for object attribute recognition and human–robot interactions. (a) CNN-assisted bimodal haptic sensors enabling quantitative softness and texture analysis for robotic clinical diagnostics. Reproduced from [101], licensed under CC BY 4.0. (b) Intelligent triboelectric tactile sensor array capable of simultaneous softness, elastic modulus, and material type discrimination. Reproduced from [191], licensed under CC BY 4.0. (c) ML-assisted all-printed soft HMI for robotic physicochemical sensing. Reproduced from [196], with permission from AAAS. (d) Multimodal emotion recognition system integrating facial expression analysis, vibration sensing, and CNN processing. Reproduced from [102], licensed under CC BY 4.0

dimensions of tactile perception, proposing a hemispherical intelligent tactile sensor array based on the triboelectric effect (Fig. 8b). This array utilized the triboelectric fingerprints generated upon material contact and employed a *k*-nearest neighbors algorithm to achieve an accurate material type recognition rate of 99.4% and a softness recognition rate of 100%.

The perception of object deformability is crucial for unstructured interactions, requiring both kinesthetic (movement) and cutaneous (skin) cues. A tactile sensor integrating the capabilities of slow-adapting mechanoreceptors within a soft medium has been developed [192], achieving the self-decoupled sensing of local pressure and strain, enabling the accurate and self-adaptive measurement of material softness, and even accommodating variations in thickness and applied forces. When combined with kinesthetic cues from a robot, such sensors can enhance tactile expression by synergizing deformation attributes such as material softness and compliance, ultimately facilitating robotic decision-making and dexterous manipulation.

Beyond the identification of solid objects, mimicking the processing ability of gustatory organs to perceive liquid substances is crucial for improving the sensing ability of robots. A self-powered droplet sensing system based on dynamic changes in droplet morphology and the contact electrification effect has been developed [158]. Using a DL model to learn triboelectric fingerprint signals, the system achieved a liquid recognition accuracy of >90% (which increased to 96.0% when these signals were combined with visual features), offering an innovative solution for food safety monitoring.

5.1.2 Noncontact object attribute recognition

Noncontact object identification helps reduce object damage and improve recognition efficiency. Du et al. [193] developed a teleperception multireceptor e-skin that relied on the structured doping of inorganic nanoparticles to enhance the local electric field. LSTM-based adaptive pulse identification was adopted to achieve a material identification accuracy of 99.56% and high processing speeds. In addition, the authors demonstrated the feasibility of using a two-dimensional sensor matrix to integrate real object scan data into a CNN and thus accurately discriminate the shapes and materials of 3D objects.

Noncontact object identification is hindered by the difficulty in integrating complex circuitry and enabling wireless functionality in compact devices. A recent innovation involves the fabrication of a biomimetic, ultrasensitive, and multifunctional wireless radiofrequency tactile sensor [194] comprising a porous polyaniline–polydimethylsiloxane sponge, pressure electrodes, and a communication coil. This sensor achieved exceptional spatial perception through the electromagnetic field at its surface. A noncontact intelligent material cognition system was established by integrating the sensor with ML models, achieving a recognition accuracy of 100% for eight materials.

5.2 Human–robot interactions

5.2.1 Gesture and motion recognition

Human–machine interfaces (HMIs) are crucial for seamless communication between humans and robots. Touchless HMIs combining high hand dexterity with enhanced hygiene standards have found numerous medical applications, particularly during the COVID-19 pandemic, as they effectively minimize viral transmission risks. A recent breakthrough in this field involves the development of an intelligent noncontact gesture recognition system integrating a triboelectric touchless sensor with an advanced DL technology [195]. This sensor demonstrated remarkable performance, recognizing 16 gesture types with an average accuracy of 96.5%. The practical utility of this system was validated through its implementation in controlling robotic throat swab collection procedures using completely contact-free operation.

Beyond hand gestures, broader human–robot interactions have been explored. A textile-based tactile learning platform using digitally machine-knitted piezoresistive fibers to create wearable, unobtrusive, and scalable sensory interfaces was reported [42]. A self-supervised learning paradigm was developed to provide robust sensing capabilities, normalize sensing responses, compensate for variations, and fix malfunctioning sensors. This calibration process notably improved the correlation between tactile responses and reference readings. 3D conformal sensing textiles can serve as tactile robotic e-skins providing real-time tactile feedback for dexterous manipulation and human–robot interactions, especially under limited-vision conditions.

Integrating chemical sensors with physical ones is a new frontier in multimodal perception for autonomous robotic decision-making. An AI-powered multimodal robotic sensing system with all-printed mass-producible soft e-skin interfaces has been introduced (Fig. 8c) [196]. It relies on scalable inkjet printing with custom-developed nanomaterial inks to manufacture flexible physicochemical sensor arrays for electrophysiological signal recording, tactile perception, and the robotic sensing of hazardous materials. This system allows robots to decode surface electromyography signals for remote control and perform in situ threat compound detection in extreme environments while providing user-interactive tactile and threat alarm feedback, thus finding diverse applications in environmental protection and public health.

5.2.2 Emotion recognition

Recognizing human affect is becoming increasingly important for enhancing HMIs. A multimodal human emotion recognition system efficiently utilizing comprehensive emotional information by sensing and combining verbal and nonverbal expression data was developed (Fig. 8d) [102]. This system incorporated a self-powered, stretchable, and transparent personalized skin-integrated facial interface relying on a bidirectional triboelectric strain and vibration sensor. By combining the facial interface with a CNN transfer learning algorithm, high-precision emotion recognition was achieved even for people wearing masks.

5.2.3 Responsive tactile feedback

Beyond sensing human input, e-skins can provide responsive tactile feedback, which is crucial for immersive experiences and skill transfer. A textile-based wearable HMI with integrated tactile sensors and vibrotactile haptic actuators was developed using digital embroidery [197]. The customizable, scalable, and modular glove could record, reproduce, and transfer tactile interactions. User studies investigate how people perceive sensations, and ML pipelines adaptively model individual user reactions to haptic sensations, optimizing feedback parameters. This enables adaptive tactile interaction transfer for applications such as alleviating tactile occlusion, guiding people to perform physical tasks, and enabling responsive robot teleoperation.

5.3 Robotic control and decision-making

5.3.1 Dexterous manipulation and adaptive grasping

Dexterous manipulation requires robots to effectively engage with their environment and interpret physical interactions, particularly through touch. Force-sensing capabilities are essential for robotic manipulation systems. Although traditional wrist-mounted force/torque sensors are heavy and expensive, novel vision-based contact force estimators leverage the deformations of compliant hands upon contact. Zhu et al. [198] developed a vision-based force estimator that predicted contact forces by analyzing deformations in a compliant robotic hand, offering a cost-effective alternative to traditional force sensors. The system used wrist-mounted cameras to observe elastic hand deformation and was enhanced by vision foundation models to handle occlusions and background noise. Although slower and less precise than commercial sensors, the optimized-design system minimized friction and hysteresis, achieving errors of 0.2–0.4 N and demonstrating robustness in real-world manipulation tasks despite challenging conditions.

Developing robotic hands that adapt to real-world dynamics remains a fundamental challenge in robotics and machine intelligence. Despite notable advances in replicating human-hand kinematics and control algorithms, robotic systems struggle to match human capabilities in dynamic environments, primarily because of inadequate tactile feedback. Zhao et al. [83] developed a bioinspired robotic hand, using optimized anthropomorphic structural design to overcome the traditional challenges of integrating high-resolution tactile sensors (spatial resolution: 0.1 mm) while maintaining a full range of motion (Fig. 9a). When combined with a transformer algorithm, this system outperformed control groups that did not rely on tactile sensing in dynamic grasping experiments involving 600 real-world objects (Fig. 9b). This result demonstrates the importance of rich tactile embodiment for developing advanced robotic intelligence and achieving human-level dexterity.

The perception of object slip is indispensable for dexterous and reliable grasping and helps avoid crushing fragile objects or dropping slippery ones. A flexible tactile sensor utilizing thin-film thermistors was developed to implement multimodal perceptions of pressure, temperature, matter thermal properties, texture, and, crucially, slippage [199], enabling ultrasensitive and ultrafast slip sensing. When combined with a robotic tactile–visual fusion architecture, the multimodal sensation enabled intelligent grasping strategies with rapid slip feedback control and tactile–visual fusion recognition, ensuring dexterous robotic grasping and the accurate recognition of daily objects even in challenging tasks (e.g., grabbing a paper cup containing a liquid).

5.3.2 Proprioception and environmental awareness

Soft robots with infinite degrees of freedom have difficulty in knowing their exact 3D geometry (proprioception). An intelligent stretchable capacitive e-skin was developed to endow soft robots with high proprioceptive geometry resolution and thus overcome this limitation (Fig. 9c) [82]. This e-skin could finely capture a wide range of complex 3D deformations across the entire soft body through multiposition capacitance measurements, providing signals that could be directly translated to high-density point clouds portraying the complete geometry via transformer architectures and thus enabling millimeter-scale, local, and global geometry reconstruction. Such systems can help solve fundamental problems in soft robotics, such as precise closed-loop control and digital twin modeling.

EIT-based tactile sensors are highly suitable for soft robots because of their low cost and excellent scalability. However, robot self-deformation can severely interfere with tactile signals. To solve this problem, Dong et al. [200] proposed an ML-assisted method. Instead of trying to avoid deformation, the authors actively captured deformation information and input it into a DL model along with EIT data. This model could intelligently separate deformation from true tactile sensation and thereby precisely reconstruct external contact information. In simulations and real experiments, this method demonstrated an extremely high accuracy, ensuring that soft robots could maintain reliable tactile interactions even during severe deformation.

Beyond exhibiting self-awareness, robots need to actively perceive and interact with their environment. A bioinspired multitasking electronic brush featuring bundled whisker-like structures and powered by reservoir computing was developed to mimic the functionality of biological whiskers [201]. This brush integrated pressure sensors for motion, speed, force, slip, and target surface monitoring, enabling long-term low-pressure detection. A reservoir computing algorithm extracted multiple brush motion parameters, including slip. As a proof of concept, the electronic brush was shown to detect the motion trajectory of handwriting, which highlights its potential for nuanced environmental interaction.

Another important feature is the ability to recognize curved surfaces, given their prevalence in daily life. A triboelectric multimodal tactile sensor simultaneously recognizing material, curvature, and pressure was developed [202]. By attaching the sensor to robotic fingertips and leveraging DL analytics, the authors showed that quantitative curvature

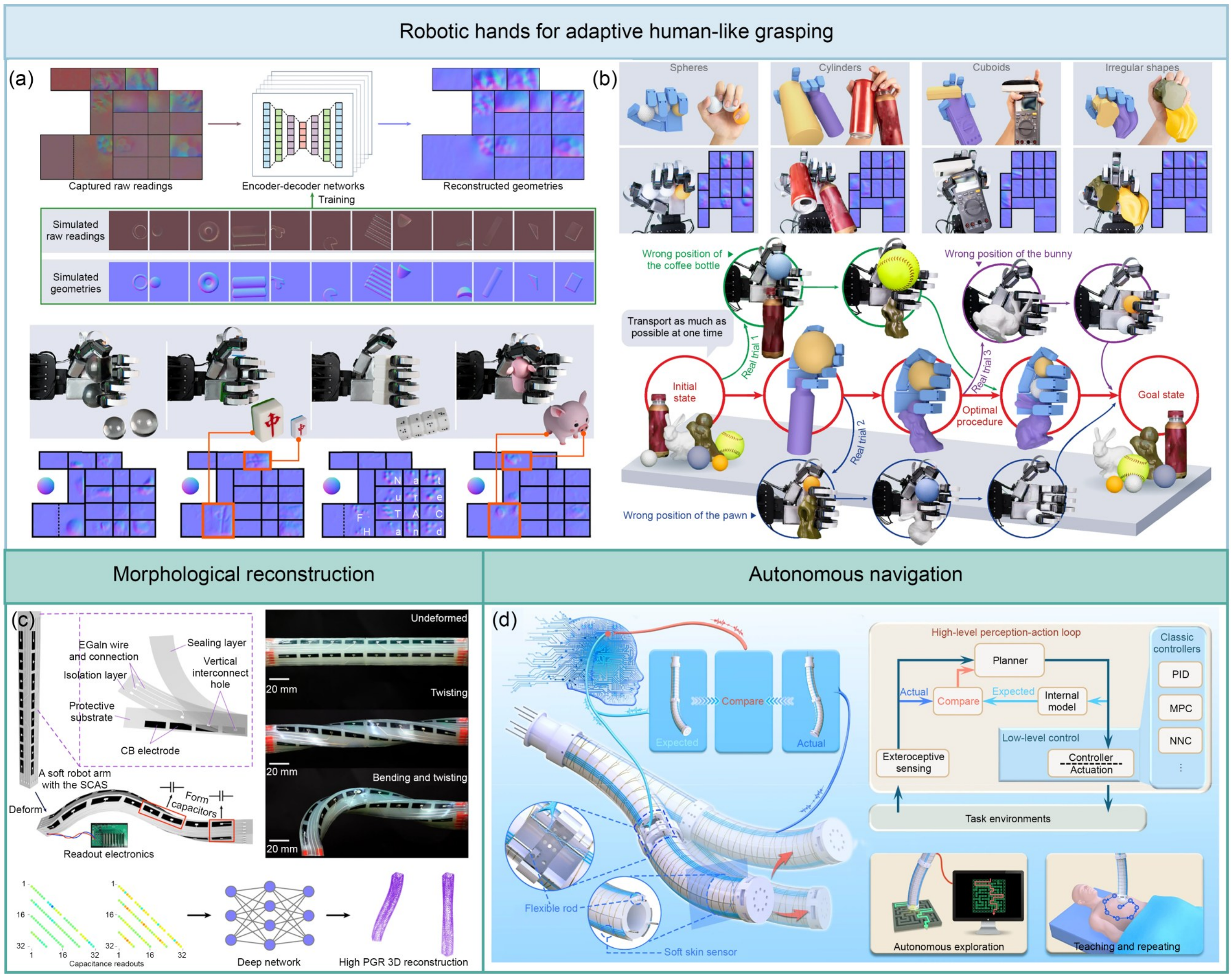

Fig. 9 AI-enhanced robotic e-skins for robotic control and decision-making. (a) Transformer-enabled high-resolution touch across robotic hands. (b) Adaptive human-like grasping based on the intelligent robotic hands in (a). Reproduced from [83], licensed under CC BY-NC-ND 4.0. (c) Learning-enhanced e-skin for tactile sensing on a deformable surface based on electrical impedance tomography. Reproduced from [82], with permission from Springer Nature Limited. (d) Transformer-empowered stretchable capacitive e-skin providing soft robots with high-fidelity proprioceptive feedback. Reproduced from [203], licensed under CC BY-NC-ND 4.0

measurement provided precise insights into the detailed geometric characteristics of objects, achieving the highly accurate automatic recognition of grasped objects and demonstrating the potential of their system for wide-ranging applications in a future robotized intelligent society.

5.3.3 Autonomous decision-making

The ultimate goal of integrating e-skins with robotics is autonomous decision-making. A high-level perceptual model akin to the human brain is essential for guiding robotic control in perception-intensive interactive tasks. For soft robots, researchers proposed an expected–actual perception–action loop allowing sensorized soft continuum robots to rapidly and robustly detect contact and distinguish deformation sources through real-time shape matching [203] (Fig. 9d). This approach allowed a soft arm to accurately perceive contact direction even in interactive environments without vision, enabling autonomous navigation in scenarios such as learning by touching walls and teaching and repeating the desired configurations of position and force through human interaction.

Autonomous decision-making also extends to complex environmental monitoring. An AI-powered multimodal robotic sensing system with all-printed soft e-skin was used for in situ threat compound detection in extreme or contaminated environments [196]. This system decoded surface electromyography signals for remote robotic control and provided user-interactive tactile and threat alarm feedback, showing potential for a wide range of applications, including tracking the source of hazardous compound traces through autonomous and intelligent decision-making algorithms on platforms such as intelligent robotic boats.

5.4 Biomimetic prosthetic limbs

AI-enabled e-skin has demonstrated remarkable capabilities in robotic systems and transformative potential in prosthetic applications, where restoring both motor and sensory functions is paramount [204–206]. The integration of intelligent e-skin technologies with advanced prosthetics marks notable progress in recreating the multifaceted capabilities of the human hand, not just in terms of mechanical dexterity but also in restoring the rich sensory feedback essential for natural interaction. The remarkable dexterity of the human hand stems from its hybrid structure, combining rigid skeletal support with soft, compliant tissues. Recent advances in prosthetic hands have sought to replicate this duality by integrating rigid endoskeletons with soft robotic joints and thus enable both strength and adaptability in object manipulation. A key innovation in this domain is the incorporation of neuromorphic tactile sensing layers (inspired by human skin mechanoreceptors), which allow the prosthetic hand to classify objects with high accuracy (99.69%) based on texture, weight, and compliance [207] (Figs. 10a and 10b). Such hybrid designs, controlled via electromyography, outperform purely rigid or soft alternatives, bridging the gap between robotic functionality and biological versatility.

Beyond tactile feedback, the restoration of thermal perception is critical for amputees to regain a true sense of embodiment with their prosthetic limbs. Noninvasive wearable devices can evoke stable and natural thermal sensations by stimulating specific regions of the residual limb, effectively mapping temperature cues to the amputee’s phantom hand [208] (Fig. 10c). Powered by AI models, this approach allows users to discriminate between different thermal

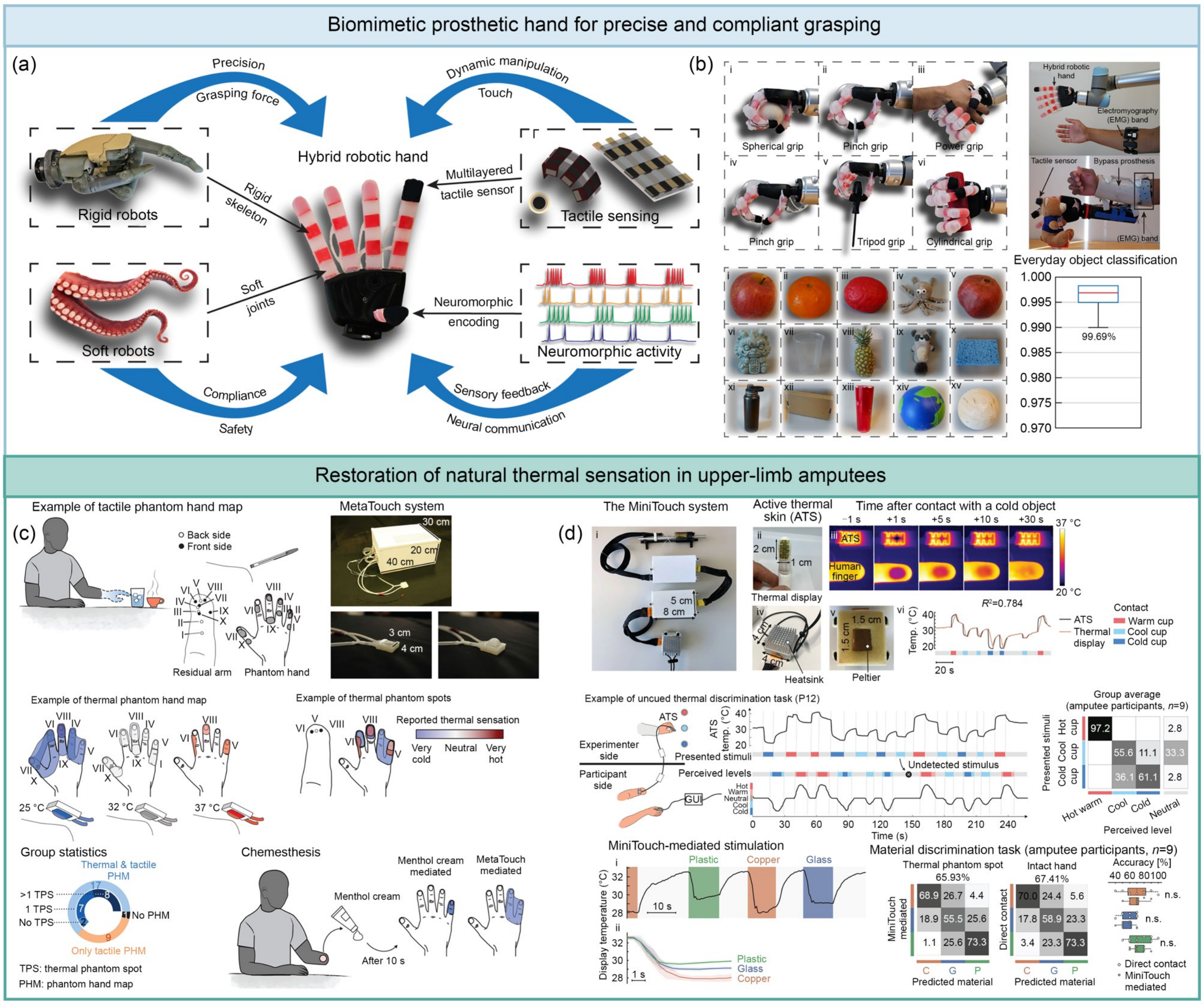

Fig. 10 Biomimetic prosthetic limb. (a) Biomimetic prosthetic hand with neuromorphic tactile sensing inspired by the human hand. (b) Grasping and object identification capabilities based on the biomimetic prosthetic hand in (a). Reproduced from [207], licensed under CC BY 4.0. (c) Tactile and thermal phantom hand maps. (d) Thermal feedback in sensory perception tasks based on the hand maps in (c). Reproduced from [208], with permission from AAAS

stimuli, markedly improving their interaction with the environment and overall quality of life (Fig. 10d). While tactile sensors enable precise grip adjustment, thermal feedback adds another layer of sensory richness, making prostheses feel more like a natural extension of the body.

Despite advances in hardware and sensing, intuitive control remains a major hurdle in prosthetic usability. Traditional myoelectric systems relying on muscle signals often result in limited and unnatural movements. A breakthrough solution lies in decoding spinal motoneuron synergies, which capture the body's inherent movement patterns more accurately than surface electromyography [209]. The alignment of prosthetic hand control with these neural synergies helps users achieve fluid coordinated motions and reach >90% of the mechanical workspace of the hand with an 82.5% success rate in posture matching, markedly outperforming muscle-based methods. This approach, combined with soft robotic actuation, enables the execution of complex tasks (e.g., in-hand manipulation) previously unattainable with conventional prostheses. Together, biomimetic design, multisensory feedback, and neural control form a cohesive framework for next-generation prosthetics (with AI-driven adaptation further refining functionality), bringing us closer to truly lifelike artificial limbs.

5.5 In-sensor computing

Covering an entire robot with e-skin is a critical step in achieving advanced physical interactions but it introduces a severe data processing challenge. In traditional models, thousands of sensors distributed throughout the body transmit raw data through complex wired networks to a central processing unit for analysis. This centralized processing approach leads to high latency, high power consumption, and system redundancy in high-density sensing scenarios, impeding the development of intelligent and responsive tactile systems. Two promising methods of addressing these challenges have emerged, namely (i) in-sensor information processing and decoding and (ii) neuromorphic e-skin, aiming to integrate computation directly within the sensor or mimic biological neural functionalities, respectively, and thus paving the way for more efficient, intelligent, and bioinspired e-skins.

5.5.1 In-sensor information processing and decoding

In-sensor information processing and decoding strategies aim to radically reduce data transmission in large-scale sensing networks. This approach optimizes energy efficiency, real-time performance, and scalability through three key methods. First, data are strictly limited at the source through hardware simplification. Second, edge computing shifts processing and AI inference locally, ensuring that only key information or condensed results are transmitted. Third, event-driven sensing leverages temporal efficiency, with data transmission triggered only when a significant event or change is detected.

In terms of hardware simplification, Heo et al. demonstrated how combining DL techniques with simple strain sensors provided robust tactile perception [210]. This streamlined methodology optimizes existing sensor arrays without the need for intricate material combinations or interconnections. Advanced decoding algorithms extract high-dimensional information from simple hardware, thereby reducing the inherent complexity of data preprocessing and transmission at the source (Figs. 11a and 11b). Dong et al. [211] proposed a data-efficient tactile sensing method based on EIT. Unlike traditional point-by-point measurements, the EIT protocol infers tactile distribution by globally measuring currents and voltages. This architecture-level innovation translates complex tactile information into more manageable electrical signal patterns, leading to highly data-efficient perception. Another strategy focuses on an efficient data compression scheme utilizing run-length coding for e-skin output [212]. By integrating this compression logic directly into the sensing path and efficiently compressing the learned sensor output before transmission, the system substantially reduces bandwidth and power consumption.

Beyond hardware design, data transmission can be notably reduced using edge computing. Capacitive pressure sensor arrays have moved beyond merely outputting raw capacitance changes and currently leverage multiple connected sensor networks to perform in situ analog multiplication and accumulation operations [213], thus enabling the execution of low-level tactile sensory processing tasks such as noise reduction and edge detection directly at the hardware level. The benefits are substantial; a reported system achieved a more than 22-fold reduction in power consumption for a single sensing–computing operation compared with conventional mixed electronic systems. Taking integration even further, location-and-pressure intelligent tactile sensors exemplify the ultimate integration of sensing, computing, and logic at the sensor level (Figs. 11c and 11d) [214]. Such sensors perform feature transmission, fusion, and differentiation directly on their core integrated layered structures, which eliminates the need for data transfer among functional units. This approach fundamentally breaks from the traditional von Neumann architecture, drastically simplifying data dimensionality while maintaining outstanding location and pressure resolutions.

Event-driven sensing is moving away from traditional, continuous, high-data-redundancy amplitude encoding to a sparse representation based on events or time. Li et al. [215] constructed an event-driven sensing system using flexible VO_2-based memristors, directly perceiving and encoding multimodal stimuli (e.g., pressure and temperature) into biological spike signals. This in-sensor encoding bypasses the

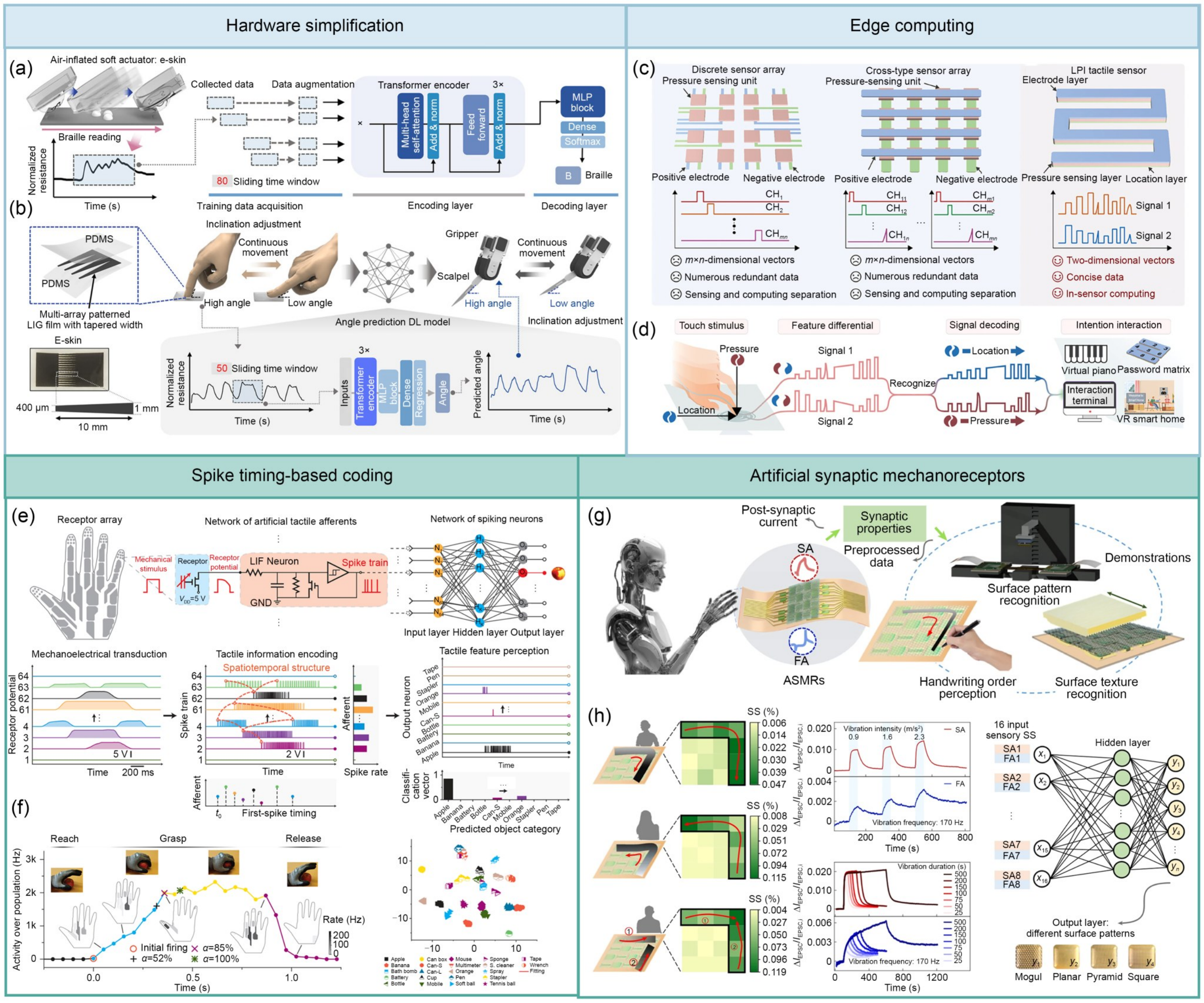

Fig. 11 In-sensor computing for robotic e-skins. Braille (a) and human motion (b) recognition using simple e-skin driven by DL. Reproduced from [210], licensed under CC BY 4.0. (c) Schematic of in-sensor tactile fusion and logic. (d) Schematic of intention recognition based on the in-sensor computing in (c). Reproduced from [214], with permission from Wiley-VCH GmbH. (e) Schematic of spike timing-based coding. (f) Dynamic object classification based on the spike timing-based coding in (e). Reproduced from [160], with permission from AAAS. (g) Concept of bioinspired intelligent perception of tactile information using artificial synaptic mechanoreceptor arrays. (h) Performance test results and an artificial neural network of the intelligent perception system in (g). Reproduced from [217], with permission from Springer Nature Limited

need for analog-to-digital conversion and cumbersome data transmission between different modules found in conventional chips. By directly converting sensory inputs into spikes, the system facilitates real-time haptic feedback for human–machine interactions and can form the basis of crossmodal in-sensor spiking reservoir computing systems, achieving high accuracy in dynamic object identification. More efficient temporal coding mechanisms, such as first-spike timing coding, can be employed to represent dynamic tactile information with millisecond-scale temporal resolution. This sophisticated form of in-sensor processing allows the system to capture highly dynamic information, enabling rapid feature extraction and object classification (Figs. 11e and 11f) [160].

5.5.2 Neuromorphic robotic e-skin

Whereas in-sensor processing focuses on efficiency, neuromorphic e-skin delves deeper into mimicking the biological functions of natural skin and the nervous system, aiming to achieve advanced cognitive abilities such as learning, memory, and adaptive responses. The corresponding research seeks to build artificial skins that not only sense but also preprocess, learn, and react in a manner analogous to biological sensory systems. A key enabler for neuromorphic e-skin is the realization of synaptic transistors. These devices are designed to emulate the crucial behavior of biological synapses, which are fundamental to learning and memory. For instance, an e-skin incorporating ZnO nanowires printed on flexible substrates demonstrated excellent biolike synaptic behavior [216]. The corresponding synaptic transistor exhibited excitatory (inhibitory) postsynaptic currents, spiking rate-dependent plasticity, and a transition from short-term to long-term memory when subjected to pulse stimuli. A computational e-skin was created by combining synaptic transistors with event-driven sensors and spiking neurons. This e-skin exhibited real skin-like perception, meaning that it could sense touch and even learn complex behaviors such as a pain reflex through associative learning. This localized learning, similar to that observed for the peripheral nervous system, makes robots more autonomous and intelligent by reducing data delays and processing demands.

The development of a monolithic soft prosthetic e-skin showcases efforts to simultaneously mimic the mechanical properties and sensory feedback of natural skin [170]. Through sophisticated material design and system architectures, e-skin achieves multimodal perception, generates neuromorphic pulse-train signals, and enables closed-loop actuation. Crucially, e-skin incorporates solid-state synaptic transistors that mimic the biological sensorimotor loop, with increasing stimulus pressure eliciting stronger actuation. This integrated approach toward biomimicry extends beyond mere sensing, aiming at the complete emulation of the biological feedback loop, which is crucial for next-generation robotic and medical devices.

The intricate preprocessing of signals observed in biological tactile perception—involving synapse-like interactions between mechanoreceptors and afferent neurons—inspires the creation of artificial synaptic mechanoreceptors. A novel device integrating synaptic functions directly into the sensing element was developed, mimicking the adaptation and sensory memory functions of biological systems (Figs. 11g and 11h) [217]. By vertically integrating synaptic transistors (e.g., those with reduced graphene oxide channels) with an elastomeric receptive layer, the artificial mechanoreceptor exhibited slow- and rapid-adaptation characteristics crucial for signal preprocessing. Utilizing ML, arrays of these artificial synaptic mechanoreceptors demonstrated capabilities in handwriting style, surface pattern, and texture discrimination, offering the benefit of high data efficiency and contributing to the vision of intelligent skin.

6 Conclusions and outlook

This review underscores the role of AI in transforming the entire e-skin development process, from data-driven material design to cognitive haptic intelligence. AI plays a pivotal role in three key areas.

(1) Design optimization. AI accelerates material discovery and structural design through active learning, generative models, and explainable algorithms and unravels the complex relationships among materials, structures, and properties, thus markedly shortening development cycles.

(2) Signal processing. Neural networks dramatically improve e-skin signal quality and perception accuracy by enabling multimodal signal decoupling, robust noise suppression, and spatial super-resolution.

(3) Cognitive perception. Advanced AI architectures, such as transformers, meta-learning, and neuromorphic computing, endow e-skin systems with intelligent perception capabilities. AI makes tactile systems inherently more information-efficient, shifting from resource-intensive data processing to intelligent data utilization.

The rapid convergence of AI, advanced materials, and robotics has propelled e-skin technology into a transformative phase. However, to achieve truly autonomous robotic perception and cognition, several critical challenges and opportunities must be addressed (Fig. 12).

(1) Hardware–algorithm co-design for systemic optimization. Future e-skin systems should shift from modular development to tightly integrated hardware–algorithm co-engineering, where sensor characteristics and computational models are jointly optimized. This involves designing neural networks that intrinsically compensate for sensor nonlinearities (e.g., piezoresistive hysteresis) or limited spatial resolution, leveraging material properties for physical preprocessing (e.g., viscoelastic substrates reducing computational load), and employing differentiable sensor simulation to co-optimize hardware parameters (e.g., electrode layout) and task performance. Such a systemic design will enable more efficient and adaptive tactile perception.

(2) Data-efficient learning paradigms for real-world deployment. A major bottleneck in AI-driven e-skin development is the scarcity of diverse, high-quality tactile data. Future research should focus on physics-grounded simulations (e.g., finite-element models incorporating contact mechanics and material fatigue) to generate realistic synthetic datasets, self-supervised learning strategies where robots autonomously explore environments to collect task-relevant data, and crossmodal transfer learning to leverage pretrained vision or auditory models for tactile tasks. These approaches will reduce reliance on costly real-world data collection while improving generalization.

(3) Trustworthy AI for safety-critical applications. As e-skins transition from research laboratories to real-world medical and industrial applications, ensuring reliability and interpretability becomes crucial. Future systems must integrate explainable tactile processing techniques (e.g., attention heatmaps for contact localization) and certifiable robustness guarantees against sensor degradation (e.g., electrode failure). Developing formal verification methods for AI-driven tactile perception is essential for deployment in high-stakes scenarios such as robotic surgery or human–robot collaboration.

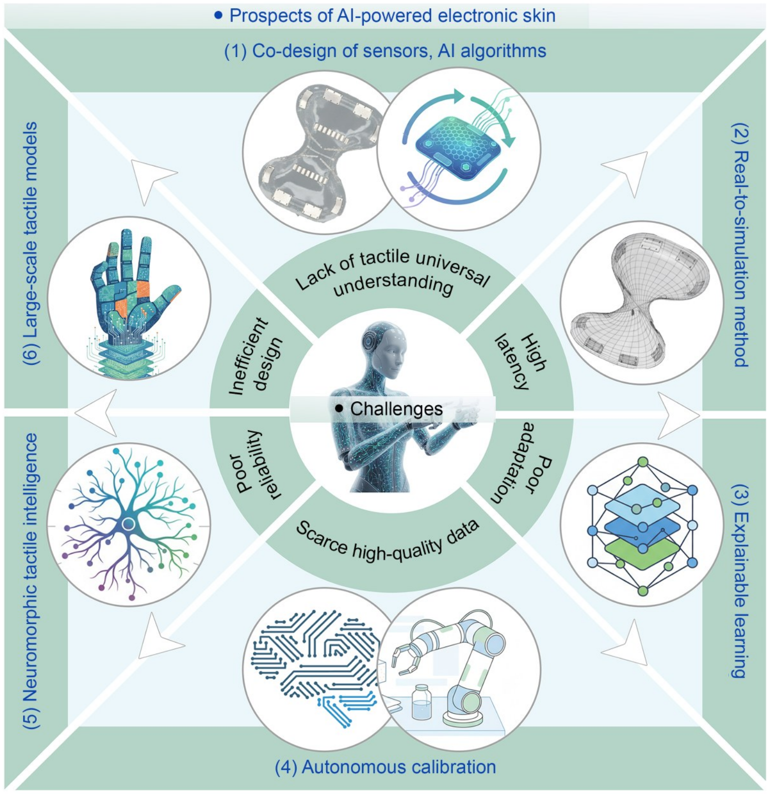

Fig. 12 Challenges and potential solutions of AI-driven robotic e-skins

(4) Self-adaptation and autonomous calibration. Next-generation e-skins should exhibit continual learning capabilities, allowing for adaptation to new environments and tasks without catastrophic forgetting. Online meta-learning techniques could enable rapid adaptation with minimal new data, while autonomous self-recalibration mechanisms (e.g., embedded reference stimuli) could compensate for sensor drift due to material aging or environmental changes. Such adaptability is critical for long-term deployment in dynamic real-world settings.

(5) Neuromorphic tactile intelligence for ultra-efficient sensing. Bioinspired approaches, such as event-based sparse coding with spiking neural networks and dynamic tactile sensor arrays, could drastically reduce power consumption while maintaining high-speed processing. By incorporating memristor-based synaptic circuits, these systems can achieve in-sensor computing that inherently mimics the analog plasticity of the brain, eliminating von Neumann bottlenecks.

(6) Toward foundation models for physical interactions. The development of large-scale tactile foundation models remains an open frontier. Future work should aim to pre-train transformer-based architectures on vast multimodal datasets (spanning textures, 3D geometries, and manipulation contexts) to learn universal tactile representations. Such models could allow robots to generalize tactile understanding across diverse materials and tasks. Additionally, integrating these tactile foundations with proprioceptive and visual modalities may unlock more robust and adaptive physical interaction capabilities in unstructured environments.

Ultimately, the maturation of AI-powered e-skin technologies will not only enhance robotic perception but also redefine the way machines interact with the physical world. By integrating adaptive sensing and efficient computation, future e-skins will allow robots to develop embodied cognition, closing the loop between tactile sensing, real-time decision-making, and dynamic physical interaction in unstructured environments. The path forward lies in interdisciplinary innovation, bridging materials science, robotics, and AI to create truly intelligent, responsive synthetic skins.

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Author contributions BCW and DPK conducted a comprehensive literature review, analyzed the relevant studies, and drafted the manuscript. GY, HYY, and KCX assisted in the writing, review, and editing.

Declarations

Conflict of interest HYY is an editor-in-chief of *Bio-Design and Manufacturing* (*BDM*). KCX is an academic editor of *BDM*. GY is an associate editor of *BDM*, and he is also a guest editor of the Special Column on AI-Powered Biofabrication of *BDM*. They were not involved in the editorial review or the decision to publish this article. The authors declare that they have no conflict of interest.

Ethical approval This article does not contain any studies with human or animal subjects performed by any of the authors.

Use of generative AI tools During the preparation of this work, the authors used Gemini to improve language and readability and check for grammatical errors. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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