


## REVIEW

# Omni-Scale Biomimetic Robotics

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**Correspondence:** Ke Liu ([liuke@pku.edu.cn](mailto:liuke@pku.edu.cn))**Received:** 22 January 2026 | **Revised:** 23 April 2026 | **Accepted:** 7 May 2026**Keywords:** embodied intelligence | intelligent structures | robotics | smart materials | swarm intelligence

## ABSTRACT

Nature achieves extraordinary functional complexity through hierarchical organization across multiple physical and behavioral scales. For instance, biological organisms seamlessly integrate material properties, structural architectures, individual-level autonomy, and collective intelligence into coherent systems capable of robustness, adaptation, and multifunctionality. On the contrary, although modern biomimetic robotics has made significant progress in multiple areas, most existing systems still lack seamless integration across these different scales. In this review, we present a unifying roadmap for omni-scale biomimetic robotics, a paradigm aimed at bridging the current gaps between material, structural, individual, and collective levels of biomimetic designs. We first survey progress in materials-level biomimicry, which provides foundational capabilities in actuation and sensing. We then review structural-level advances that leverage mechanical intelligence for embedded logic and computing. Next, we examine individual-level agents, and finally, collective-level swarm behaviors. We argue that achieving omni-scale biomimetic robotics requires unifying these four scales into integrated, hierarchical systems.

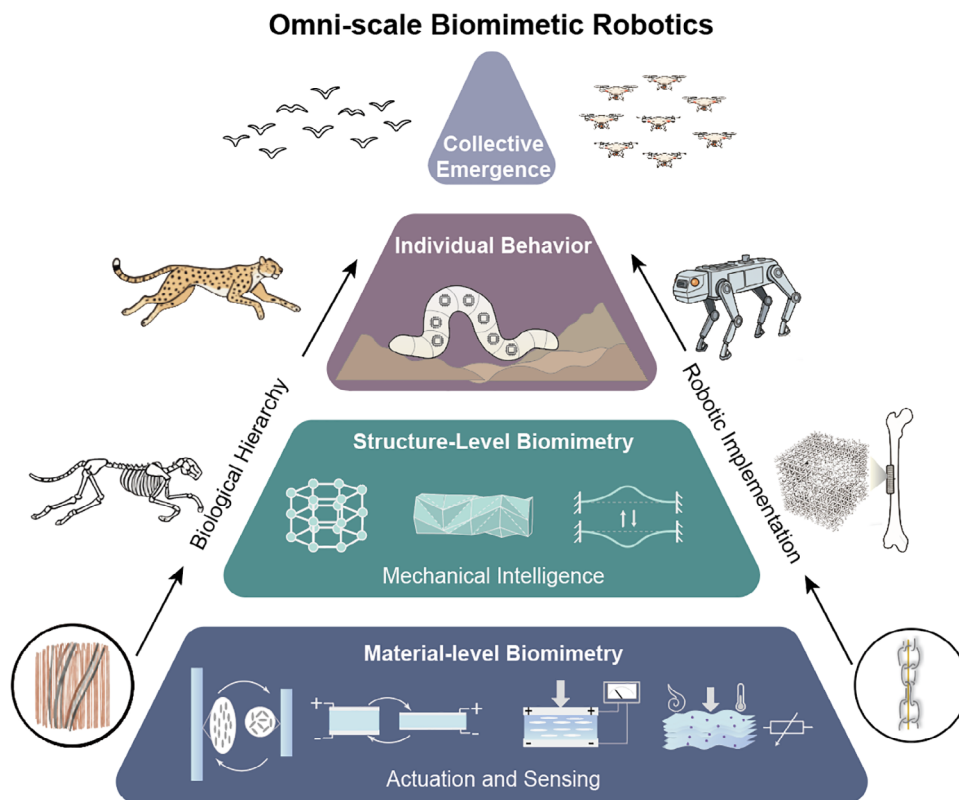
## 1 | Introduction

The quest to replicate the extraordinary capabilities of biological organisms, such as agility, robustness, adaptability, and multifunctionality, has long been a driving force in robotics and engineering [1, 2]. Despite monumental advances, a significant performance gap persists between natural systems and their artificial counterparts [3]. This disparity is increasingly attributed not to a shortfall in any single technology, but to a fundamental difference in design philosophy [4]: biological functions are not isolated to a single scale but are the emergent result of tightly coupled interactions across a hierarchical architecture [5].

These interactions span from the molecular to the collective level. At the material scale, proteins, tissues, and fibers provide active, sensing, and responsive properties that form the foundational layer of biological intelligence [6, 7]. These materials are organized at the structural scale into architectures that geometrically

amplify forces, enable dramatic shape changes, and regulate stiffness on demand [8–10]. Integration at the individual scale leverages these physical substrates through embodied intelligence, sensory feedback loops, and adaptive control, enabling organisms to navigate complex and unpredictable environments [11, 12]. Finally, at the collective scale, numerous species exhibit sophisticated cooperative and emergent behaviors, such as flocking, swarming, and distributed construction, which transcend the capabilities of any single individual [13, 14].

This fragmentation motivates the need for a new, more holistic paradigm. In this review, we introduce and define the concept of omni-scale biomimetic robotics, which we articulate as: A unified design approach that intentionally integrates bioinspired principles across material, structural, individual, and collective scales to create robotic systems whose overarching performance and capabilities emerge from their coordinated multi-scale interactions (Figure 1).



**FIGURE 1** | Schematic diagram of the hierarchical architecture for omni-scale biomimetic robotics. The framework sequentially supports the functional realization of individual behavior and collective emergence from the bottom layers of material-level biomimicry and structure-level biomimicry.

Here, we clarify the distinction between omni-scale biomimetic robotics and related paradigms. Unlike multiscale designs, which focus on the co-existence of multiple spatial scales, the omni-scale approach emphasizes spatiotemporal coupling across material, structural, individual, and collective levels. In this framework, different levels are not only present but functionally integrated, enabling lower-level properties to directly influence higher-level behaviors.

Within this framework, the four levels are not independent, but hierarchically coupled. Material-level functionalities provide the foundation for actuation and sensing, which are organized and amplified by structural design. Building on this hierarchy, individual behavior emerges from the coupling of material reactions and structural responses, while collective intelligence arises from interactions among individuals. This progression, from material to structure to behavior to collective, defines the core principle of omni-scale biomimetic robotics.

Despite this theoretical synergy, research has historically remained isolated. However, recent rapid advances in smart materials, bioinspired structures, individual behavior, and multi-robot systems provide the necessary building blocks to integrate these components together. This review aims to synthesize progress across these traditionally disparate fields, highlighting the latent potential of their integration. We will first survey the key advances and core principles at each individual scale, as material, structural, behavioral, and collective. Subsequently, we will analyze the nascent efforts that have begun to bridge these

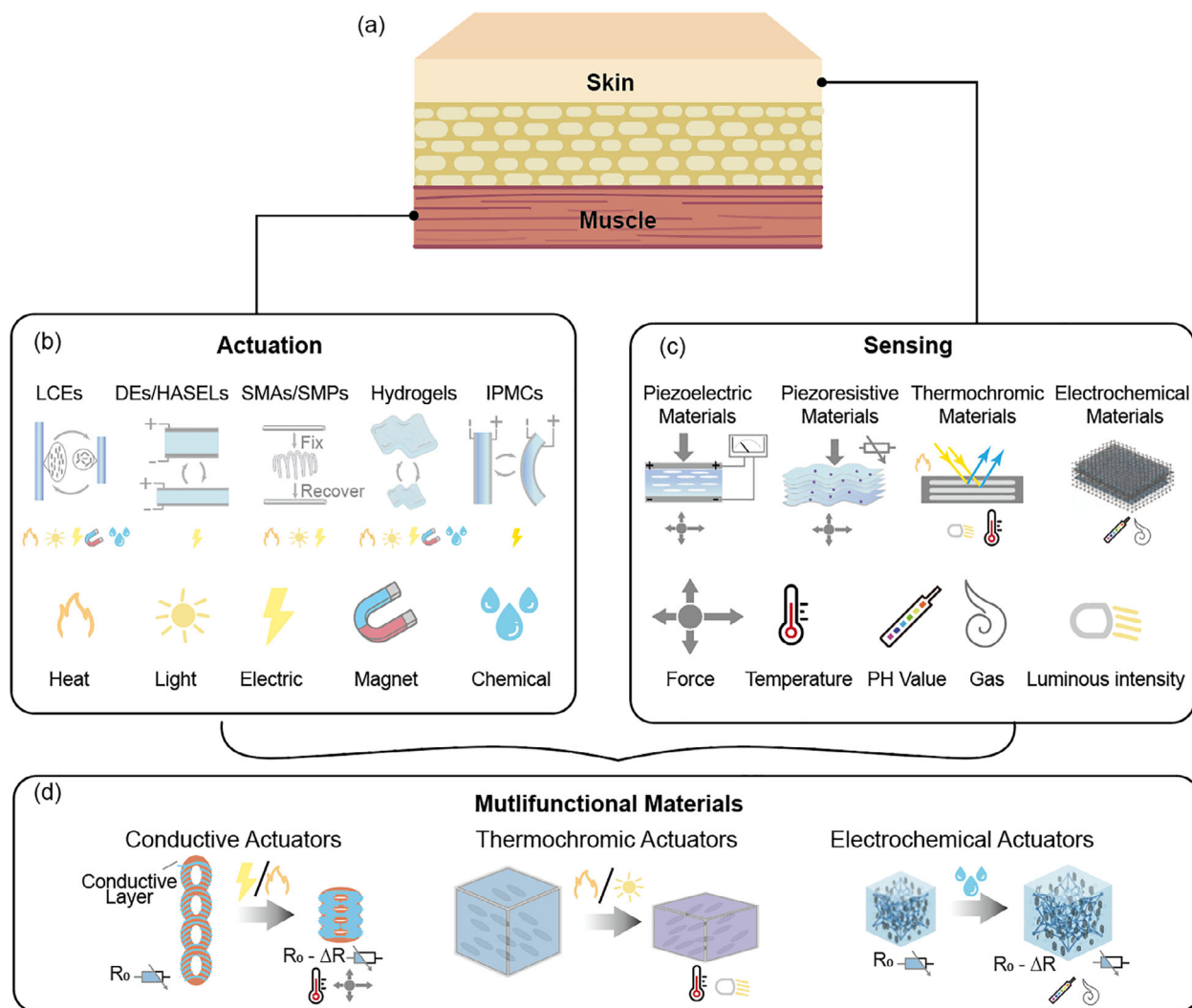
scales, such as the development of materials with structural functionality and the creation of robots whose bodies compute and control action. Finally, we will outline the grand challenges and future research directions essential for realizing the full vision of omni-scale biomimetic robotics, arguing that the path toward closing the performance gap with nature lies not in deeper specialization at any single level, but in the purposeful, synergistic integration across all of them.

## 2 | Material-Level Biomimicry

Biological tissues are intrinsically multifunctional systems that seamlessly integrate actuation, sensing, and adaptation within a single, cohesive material matrix [15, 16]. This stands in stark contrast to most engineered systems, which typically rely on the discrete assembly of separate components for each function. Emulating this functional synergy at the material level is the foundational step toward creating robots with embodied intelligence [17, 18]. This section surveys the progress in developing bioinspired materials that replicate the core functionalities of biological muscles, skins, and sensory organs, focusing on advances in soft actuation and somatic sensing.

### 2.1 | Bioinspired Actuation Mechanisms

The quest to create artificial muscles has driven the development of soft actuators that mimic the key attributes of their



**FIGURE 2** | Schematic illustration of the material-level biomimicry. (a) Biological Model: Stratified structure of skin and muscle serving as design inspiration. (b) Bioinspired actuation mechanisms: Examples include LCEs, DEAs/HASELs, SMAs/SMPs, hydrogels, and IPMCs, which transform external stimuli (heat, light, electric fields, magnetic fields, or chemical signals) into mechanical work. (c) Bioinspired sensing materials: Representative material systems such as piezoelectric, piezoresistive, thermochemical, and electrochemical materials enable the detection of mechanical, thermal, chemical, and optical stimuli. (d) Toward multifunctional materials: Integrated designs that combine actuation and sensing capabilities within a single material substrate, such as conductive actuators, thermochemical actuators, and electrochemical actuators, illustrate the trend toward material-level functional convergence.

biological counterparts: high strain, high power density, and rapid, reversible response [19–21]. These systems translate various physical and chemical stimuli into mechanical work, offering new paradigms for motion generation in robotics (Figure 2a).

Currently, a variety of bioinspired actuation mechanisms based on different physicochemical principles have been extensively explored [22, 23]. The development of liquid crystal elastomer actuators is inspired by the microscopic alignment of muscle fibers. Their molecular-level ordered structures undergo reversible phase transitions under external thermal fields or specific wavelengths of light, resulting in significant macroscopic deformation [24, 25]. Such materials can achieve linear strains exceeding 50%, and their deformation modes can be pre-programmed through molecular alignment, offering the potential for complex motion patterns [26, 27]. However, their energy conversion efficiency, response speed, and durability

under long-term cyclic loading still require further optimization [28, 29].

Electrostatic-based soft actuators constitute a major category, with Dielectric Elastomer Actuators (DEAs) [30, 31] and Hydraulically Amplified Self-healing Electrostatic Actuators (HASELs) [32, 33] being two prominent examples. DEAs utilize the electrostatic attraction (Maxwell stress) between compliant electrodes to compress a dielectric film, generating mechanical output [34, 35]. This mechanism enables millisecond-fast responses and high power densities, showing unique advantages in applications requiring explosive force, such as jumping and fast grasping [36, 31]. However, the requirement for operating voltages in the kilovolt range not only raises safety concerns but also imposes significant constraints on electrode design and material dielectric strength. In contrast, HASELs operate on a similar electrostatic principle but employ a distinct architecture:

a liquid dielectric (often an oil) is encapsulated within a flexible polymer shell. The applied electric field induces charges on the compliant electrodes, which then exert pressure on the liquid dielectric, causing a hydraulic deformation of the shell [37, 38]. This liquid-mediated, hydraulically amplified mechanism offers several key advantages: it enables linear contraction modes that more closely mimic skeletal muscle; the liquid dielectric can potentially self-heal after dielectric breakdown, enhancing robustness [39, 40]; and the operating voltages can, in some designs, be lower than those for comparable DEAs [38]. The development of HASELs represents a significant architectural innovation within the electrostatic actuation paradigm, bridging the high performance of DEAs with improved modes of actuation and failure tolerance [41, 42].

For applications that require operation in aqueous environments or direct interaction with biological organisms, actuation methods based on ionic mechanisms demonstrate irreplaceable value [43]. Hydrogel actuators achieve motion through the swelling and contraction of internal hydrophilic network structures, with the driving force originating from changes in osmotic pressure [44, 45], temperature response [46, 47], or pH variation [48, 49]. This mechanism closely resembles the motion principles of many biological tissues [50]. Ionic polymer-metal composites (IPMCs) generate bending or twisting motions by the directional migration and redistribution of ions under an applied electric field, creating internal stress gradients [51, 52]. These ionic actuators typically operate at low voltages, possess natural compliance and good biocompatibility, but their output force is relatively small, response speed is slower, and environmental stability remains a key bottleneck restricting their practical application [53, 54].

Beyond these mainstream continuous actuation methods, non-continuous actuation mechanisms based on phase-change principles also show unique value. Shape memory alloys/polymers (SMAs/SMPs) can recover from a temporarily deformed state to a pre-set permanent shape under specific stimuli [55–57]. This capability offers new possibilities for building reconfigurable, lockable robotic structures [58, 59]. Such materials have clear advantages in applications requiring intermittent large deformations or structural reconfiguration, but their cyclic response time and energy efficiency still need improvement.

An in-depth comparison of various bioinspired actuation mechanisms reveals an important truth: no single actuation method can be optimal across all performance metrics [50]. In practical applications, the selection of an actuation mechanism requires a comprehensive trade-off across multiple dimensions, including strain, stress, response speed, energy efficiency, driving voltage, and environmental adaptability [19]. This trade-off relationship determines the suitable application domains for different mechanisms and drives researchers to explore innovative solutions such as hybrid or multi-modal actuation [60, 61].

## 2.2 | Bio-Inspired Sensing Materials and Multifunctional Materials

In biological systems, actuation is inseparable from sensation. Muscles, skin, and connective tissues inherently encode proprioceptive and tactile feedback, enabling continuous monitoring of

force, strain, and environmental interaction [62, 63]. Replicating this tight coupling between actuation and sensing at the material level is a critical step toward embodied intelligence in robotic systems [64, 65].

Recent advances in sensing materials have expanded their functional scope, particularly in multimodal sensing, environmental robustness, and sensing–actuation integration. A wide range of self-sensing materials has been developed to transduce mechanical deformation, pressure, temperature, or chemical stimuli into electrical, optical, or magnetic signals [66]. Piezoelectric polymers and their composites generate electrical signals under mechanical loading, maintaining mechanical compliance while offering high sensitivity for dynamic force and vibration sensing [67, 68]. Similarly, piezoresistive materials, often incorporating conductive fillers such as carbon nanotubes, graphene, or liquid metals, allow direct mapping between strain and resistance, enabling soft structures to function simultaneously as actuators and deformation sensors [69–71].

Beyond purely mechanical feedback, multimodal sensing capabilities have been systematically embedded within soft materials through strategies such as functional coatings, heterogeneous micro-nano structural integration, and multi-material system composites [72, 73]. For instance, MXene- and graphene-based conductive coatings, as well as emerging liquid-metal-based composites and stretchable electronic systems, not only exhibit high stretchability and environmental robustness, but their electrical conductivity can also simultaneously respond to strain and temperature variations, enabling dual-mode mechanical-thermal sensing [74–77]. Thermochromic materials [78, 79] (e.g., spiropyran/spirooxazine-based polymers) and photochromic materials [80, 81] (e.g., azobenzene/diarylethene-based polymers) not only undergo reversible color changes but also often exhibit accompanying alterations in electrical resistance or dielectric properties during phase transitions, thereby coupling optical perception with electrical response within a single material [82, 83]. Electrochemical sensing materials, such as graphene-based composites, capable of detecting chemical stimuli such as pH variations or specific ions, further extend the sensing modalities to include real-time chemical feedback [84, 85]. Similarly, magnetically responsive composites (e.g., ferrite-/NdFeB particle-dispersed polymers, magnetorheological elastomers) not only enable non-contact actuation through magnetically induced deformation but also exhibit changes in magnetic permeability that can simultaneously reflect mechanical stress or temperature states [86, 87]. These design strategies progressively blur the functional boundaries between sensing, actuation, and environmental interaction, driving materials toward integrated, coupled, and context-aware intelligent systems (Figure 2b).

Building upon these advances, sensing-actuation integrated materials further merge sensing and actuation functions at the material level, forming self-feedback, self-regulating intelligent material systems. For example, conductive actuators not only deform under an electric field but also provide real-time strain feedback through changes in the resistance of their embedded conductive networks, achieving “actuation as sensing” [45]. Thermochromic actuators exhibit shape-memory recovery under thermal stimuli while simultaneously offering optical and

electrical dual-mode feedback through color and resistivity changes, establishing a sensing-actuation-display integrated response [88]. Electrochemical actuators achieve motion control via ion migration and simultaneously monitor chemical surroundings through variations in electrode potential or impedance, thereby closing the actuation-sensing-environment interaction loop [89] (Figure 2c).

The design of such materials often relies on multi-physical coupling mechanisms and cross-scale structural control [85]. For instance, graphene-polymer composites can function both as piezoresistive sensors and as electric-field-driven deformable structures [90]. Magnetic-particle-enhanced elastomers enable non-contact actuation through magnetostriction while their magnetic permeability variations concurrently reflect stress and temperature states [87, 91]. Through heterogeneous integration strategies such as multilayer stacking, micro-nano patterning, and gradient architectures, materials can combine mechanical, electrical, chemical, and optical multimodal responses within a single substrate, progressively approaching the multifunctional coupling and adaptive characteristics of biological tissues [92, 93].

These design strategies significantly advance materials from “passive response” toward “active adaptation”, gradually blurring the functional boundaries between sensing, actuation, and environmental interaction [94]. They lay a material foundation for constructing integrated, coupled, and context-aware intelligent systems. Although sensing-actuation integrated materials show great potential in simplifying system architecture and improving response efficiency, their practical application still faces challenges such as signal decoupling, dynamic calibration, durability, and scalable fabrication [61]. Future efforts must shift beyond responsive material components toward a functional system to realize embodied intelligence. Strategic structural organization serves as the essential platform to unlock the functional potential of materials, geometrically organizing and amplifying their intrinsic properties to translate local material responses into functional performance.

### 3 | Structure-Level Biomimicry

While multifunctional materials provide the foundational capabilities for actuation and sensing, biological performance rarely emerges from material properties alone. In living organisms, active tissues are embedded within hierarchical structural architectures that geometrically amplify forces, constrain deformation pathways, and regulate energy flow [95]. Bones, tendons, shells, and connective tissues transform local muscle contraction into efficient, robust, and task-specific motion [11, 96]. This organizational layer gives rise to what is increasingly recognized as mechanical intelligence, the ability of physical structures to shape behavior through geometry, compliance, and instabilities, independent of centralized control [97].

In contrast to conventional engineering approaches that treat structure as a passive load-bearing element, bioinspired structural design leverages mechanics as a form of physical computation. By encoding functional rules directly into shape, stiffness distribution, and material anisotropy, structures can filter sensory signals, stabilize motion, and reduce the burden on sensing and

control systems [98]. Structural-level biomimicry thus represents a critical intermediary scale, translating material-level actuation and sensing into system-level functionality [7].

#### 3.1 | Geometric Amplification

In bio-inspired structural design, the strategic geometric configuration for multidimensional mechanical amplification serves as a critical approach to enhance overall system performance [99, 100]. This design philosophy is directly inspired by the deep observation of biological motion mechanisms: organisms do not rely on breakthroughs in single material properties, but rather efficiently transform microscopic deformations into macroscopic functional outputs through multi-scale structural integration [101].

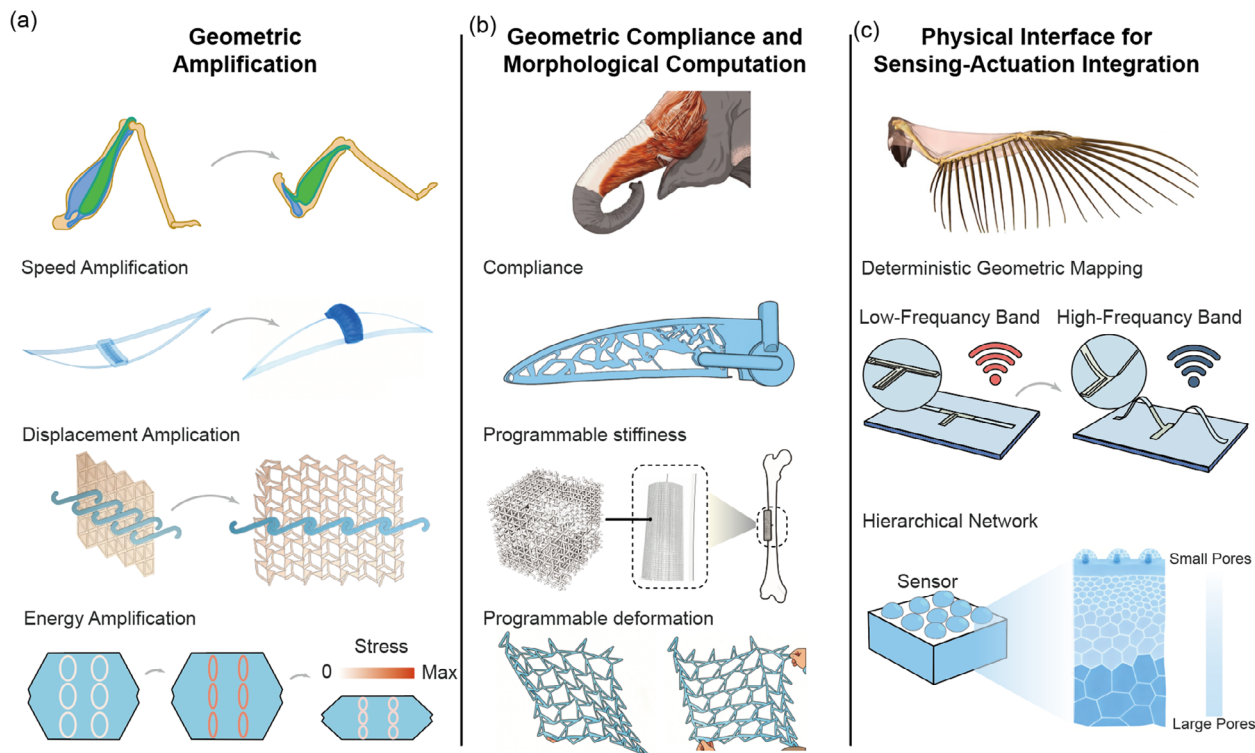
Currently, mainstream bioinspired amplification mechanisms encompass three interrelated yet distinct technical pathways (Figure 3a):

Speed amplification achieves a 2–3 order-of-magnitude expansion in response time scales through asymmetric transmission ratios, elastic lever systems, and transient instability structures [98, 102, 103]. Typical implementations include buckling-beam-based elastic amplifiers, stick-slip transmission systems utilizing frictional change, and bistable release devices inspired by insect jumping [104, 105]. Such designs are particularly suitable for applications requiring rapid responses, such as agile grasping and emergency obstacle avoidance [106, 107].

Displacement amplification focuses on the optimized reconstruction of kinematic pathways [108, 109]. By incorporating folding topologies inspired by origami/kirigami, tendon-like force-transmission networks, and flexible hinges with tunable curvature, the intrinsic material strain (typically <50%) can be amplified by 5–10 times [109, 110]. This amplification not only expands the workspace but, more importantly, enables controllable programming of complex 3D shape changes, providing a foundation for morphological adaptation in soft robotics [111, 112].

Energy amplification targets the step-wise enhancement of power density [113, 114]. Its physical essence lies in constructing tunable energy potential wells: through buckling transitions in pre-compressed beams, state transitions in multi-stable mechanisms, and coordinated release of distributed elastic elements, the system can convert slowly accumulated elastic potential energy into explosive mechanical work output on a millisecond timescale [105, 115]. This “quasi-static storage–dynamic release” paradigm effectively addresses the bottleneck of insufficient power density in soft actuators [116].

It is noteworthy that these three amplification mechanisms are often tightly coupled in practical systems [117, 118]. Future breakthroughs may lie in: developing reconfigurable amplification structures that enable online adjustment of amplification characteristics through stimulus-responsive materials or modular design; establishing cross-scale design theories for integrated optimization from molecular chain arrangement to macroscopic morphological architecture; and exploring nonlinear synergistic mechanisms that actively utilize coupling effects among multiple



**FIGURE 3** | Schematic illustration of the structural biomimicry. (a) Geometric amplification: Bioinspired structures achieve speed, displacement, and energy amplification through intelligent structures, enabling efficient motion with minimal actuation input. These panels are adapted from refs. [104, 110, 116]. Adapted with permission [104]. Copyright 2022, AAAS [110]. Copyright 2024, Wiley [116]. Copyright 2025, Wiley. (b) Programmable compliance and morphological computation: By tailoring stiffness distribution and structural geometry, programmable stiffness and deformation can be realized, allowing the physical body to encode control logic and offload computational burden. These panels are adapted from refs. [139, 143]. Adapted with permission [139]. Copyright 2022, AAAS [143]. Copyright 2022, NAS. (c) Physical interface for sensing-actuation integration: Structures mediate between sensing and actuation through deterministic geometric mapping and hierarchical network designs that perform mechanical pre-processing of distributed sensory information, thereby establishing low-latency, energy-efficient feedback loops at the physical level. These panels are adapted from refs. [155, 159]. Adapted with permission [155]. Copyright 2025, Nature.

instability modes to create new amplification paradigms [119, 120]. Through such in-depth development of “structural intelligence”, the next generation of bioinspired systems is expected to achieve comprehensive improvements in performance, efficiency, and adaptability [121].

### 3.2 | Programmable Compliance and Morphological Computation

A defining capability of biological structures, such as elephant trunks, is their ability to dynamically modulate their own stiffness and guide specific deformation patterns in response to task demands [5, 122, 123]. This wisdom of “pre-encoding function into physical morphology” has inspired the development of programmably compliant structures in robotics [124]. At the heart of this approach is morphological computation, in which mechanical responses are encoded and regulated through the interplay of material properties, geometric constraints, and structural configuration. For example, elastic-wave-based metamaterials enable physical signal processing and behavior coupling [125], while artificial tendon architectures enable intrinsically embedded force sensing [126]. Rather than relying solely on centralized control, the system leverages its intrinsic mechanics to interact with environmental constraints and generate

appropriate responses. This perspective highlights how structural design shapes deformation, stiffness, and force transmission, thereby enabling programmable, responsive, and self-sensing behavior. This strategy focuses on two key dimensions: programmable stiffness and programmable deformation. Through the co-design of materials and structures, robots can “offload” part of the control and computation tasks to their physical body, thereby achieving remarkable adaptability and response speed in resource-constrained or extreme environments [127, 128].

To realize these goals, current research follows two complementary engineering paths (Figure 3b):

Compliant mechanisms achieve programmable deformation through global configuration and stiffness distribution [129, 130]. These designs forego traditional hinges and bearings, relying instead on the elastic deformation of the material itself to transmit motion and force. The core idea is to use topology optimization and carefully tailored stiffness gradients (e.g., tapered beams, curved flexures) to transform a single actuation input into precise, predictable output motion [131, 132]. In essence, the desired motion trajectory and force profile are “encoded” into the geometry and material distribution of the structure, enabling deterministic, passively programmable deformation [133]. For example, an optimally designed compliant gripper can, with only

a single actuator, autonomously produce an enveloping grasp trajectory that adapts to objects of various shapes [132]. Compliant mechanisms not only simplify control but also inherently provide shock absorption, overload protection, and low energy consumption [134].

Mechanical metamaterials and programmable structures, in contrast, operate from the micro-architectural level, focusing on achieving actively tunable stiffness and multifunctional deformation [135–137]. By designing periodic or aperiodic micro-structural units, these materials exhibit extraordinary and dynamically adjustable mechanical properties at the macro scale [138, 139]. Their core capability lies in programmable stiffness: for instance, using phase-change materials (e.g., shape-memory polymers), granular jamming, or field-responsive (magnetic/electrical) elements to enable real-time, reversible stiffness modulation in response to thermal, vacuum, or magnetic stimuli [140, 141]. Moreover, by arranging micro-structures (e.g., fiber orientation) or creating density gradients, one can pre-design anisotropic or graded stiffness fields that guide specific, complex deformation modes such as bending, twisting, or contraction. Furthermore, by incorporating buckling or snap-through instabilities, multi-stable structures can be created that allow rapid switching between discrete configurations and release of stored energy [142, 143].

These two pathways collectively form the physical foundation of morphological computation: one encodes deterministic motion into macroscopic geometry, while the other embeds tunable responses into micro-architecture; one excels at passive, efficient deformation, and the other specializes in active, adaptive stiffness regulation [144, 145]. They are not mutually exclusive but can be functionally integrated within a single system according to task requirements. Designs that fuse programmable stiffness with programmable deformation represent a key direction toward realizing the next generation of highly autonomous, energy-efficient, and highly adaptable bio-inspired robots [146].

### 3.3 | Physical Interface for Sensing-Actuation Integration

Sections 3.1 and 3.2 have addressed how structural design independently enhances actuation performance and embeds computational capacity. However, the deeper mechanism of biological intelligence lies in the endogenous coupling of sensing and actuation achieved through specific structural configurations [147, 148]. This coupling is fundamentally realized by designing structures whose intrinsic deformation dynamics simultaneously serve as both the generator of sensory signals and the regulator of actuation behavior, thereby establishing an efficient, low-latency feedback loop at the physical level (Figure 3c) [149, 150].

Biological prototypes offer direct inspiration for this mechanism. For example, the avian feather follicle system exhibits an intrinsic sensing-actuation unity within the structure: the feather itself acts as an aerodynamic driving surface (generating lift), while its base is embedded within a follicle rich in nerve endings [151, 152]. When airflow changes cause a slight deflection of the feather, it acts as a “mechanical lever” that directly activates the sensors at its root. This structural design enables birds to automatically fine-tune feather angles in response to gusts solely through

physical feedback, without complex central-nervous-system computation [153].

Inspired by this, engineering implementations can establish deterministic mapping relationships through geometric configuration design. Periodic structures such as helices or coils can transform continuous deformation from actuation into measurable electrical or optical signal changes, governed by predefined geometric transformation rules [154, 155]. These structures achieve multi-parameter sensing not through distributed sensor arrays but via morphological changes of a single continuum [156, 157]. Their response characteristics are directly dictated by geometric parameters, offering excellent predictability and reconfigurability [158].

At the signal-processing level, bio-inspired topological designs further enable mechanical pre-processing of signals [160, 161]. Hierarchical network structures mimic the operational principles of biological fractal systems, utilizing their hierarchical conduction properties to perform spatial integration and feature extraction on distributed physical signals [159, 162]. Through carefully designed structural conduction paths, weak continuous field signals are converted into concentrated responses at a few key nodes. This process enhances the signal-to-noise ratio while achieving physical dimensionality reduction of the data, thereby providing pre-processed, high-quality inputs for subsequent control algorithms [160, 163].

These structural mediation mechanisms collectively point toward a core paradigm: offloading part of the information-processing task from the digital to the analog domain through physical structure design [144, 164]. Deterministic geometric mapping provides direct state feedback, and hierarchical network structures accomplish physical pre-processing of signals [165]. This offloading of intelligence to the physical layer not only enhances system response speed and energy efficiency but, more importantly, provides the control system with reliable state information that has been validated by physical laws [166, 167]. This transition marks a pivotal evolution in robotics: from the creation of mechanically intelligent structures toward the realization of truly autonomous embodied agents—systems in which perception, decision, and action are coherently integrated within a unified physical architecture [168]. It should be noted that many of these structurally amplified functions implicitly rely on fabrication processes that preserve geometric fidelity across scales, rendering structure not only a mediator of material intelligence but also a direct consequence of manufacturing constraints. However, these structurally mediated mechanisms remain latent potential until instantiated within a unified physical agent. Through the coupling of material properties and structural design, they give rise to integrated functional units that form the physical substrate of the robotic system.

## 4 | Individual-Level Behavior

At the individual scale, adaptive behavior emerges from this physically instantiated system, rather than existing as a separate layer of control. It reflects the integrated effects of underlying material properties and structural architectures within the embodied agent. In omni-scale biomimetic robotics, the passive

mechanical intelligence inherent in the hardware is seamlessly integrated with active control strategies to produce coherent, goal-directed behavior [5, 17]. In biological organisms, adaptive behavior does not arise from complex centralized computation alone, but from the tight coupling between body morphology, local sensory feedback, and simple control rules [169, 170]. This embodied approach enables remarkably capable behavior to emerge from systems with limited neural resources [171].

In this framework, sensing and actuation are intrinsically provided by the material system, forming a physically coupled functional basis. Structural design actively regulates and amplifies these material responses, shaping how the individual interacts with external forces and environmental stimuli. For example, bistable origami structures can convert continuous thermal actuation into discrete snap-through switching [172], while buckling soft chambers can transform slow muscle actuation into rapid jet propulsion [116]. These examples highlight that adaptive behavior arises from the coordinated coupling between material actuation and structural mechanics. Through this integration, the individual establishes continuous physical interaction and feedback with the environment, which forms the basis of adaptive and autonomous behavior.

Guided by this principle, biomimetic robotics is shifting away from overparameterized control architectures toward behavior generation that exploits physical intelligence [173, 174]. By leveraging material compliance, structural constraints, and embedded sensing, individual robotic agents can achieve robust performance using comparatively simple control strategies [128, 18]. Such simplicity is not a limitation, but a key enabler of adaptability and resilience, particularly in unpredictable or extreme environments.

#### 4.1 | Simple Control and Emergent Behavior

At the individual behavior level, a core manifestation of intelligence lies in the emergence of highly complex and adaptive behaviors through relatively simple control mechanisms [175]. This “achieving more with less” paradigm is ubiquitous in nature: insects, worms, and other organisms with minimal nervous systems accomplish robust locomotion, foraging, and obstacle avoidance [176, 177]. The key insight is that coordinated whole-body movement does not arise from precise central computation and command, but from real-time coupling between local sensory feedback and the body’s physical dynamics [169]. Control signals (e.g., neural pulses) primarily act to trigger or modulate predefined “behavioral attractors” encoded in the body’s morphology, rather than micromanaging individual actuators [178].

In the field of biomimetic robotics, this biological inspiration has driven the development of two dominant control architectures: Central Pattern Generator (CPG) control [179, 180] and distributed control [181, 182], both of which reflect a paradigm shift from computation-intensive to physically-embedded intelligence.

CPG control, inspired by rhythmic neural circuits in animals, generates stable periodic motion patterns through low-dimensional parameters such as oscillation amplitude, phase difference, and frequency [179, 183]. For instance, in a quadrupedal soft robot, a

CPG controller only needs to coordinate the phase relationships between legs; the body’s compliance and ground reaction forces then naturally modulate gait details, allowing stable walking and even obstacle traversal to emerge spontaneously from physical interaction (Figure 4a) [184]. The core advantage of CPG control lies in decoupling rhythm generation from dynamical adaptation: the central controller merely sustains a basic oscillatory signal, while gait adjustments are entrusted to the continuous physical dialogue between the body and the environment [185, 186].

Distributed control further delegates decision-making to local units [187]. Each body segment or joint executes simple rules (e.g., “bend upon obstruction”, “contract upon stretching”) based on local sensory information such as strain, contact, or tension, with coordination propagating through physical coupling across the system [188, 189]. For example, a worm-like robot can achieve global undulatory locomotion solely through local stretch feedback between adjacent segments, while an octopus-arm-inspired soft manipulator relies on local triggering of suction cups for adaptive grasping (Figure 4b) [190]. This architecture requires no central processor, exhibits inherent robustness, low communication overhead, and strong environmental adaptability, making it particularly suitable for dynamic, uncertain, or extreme environments [191, 192].

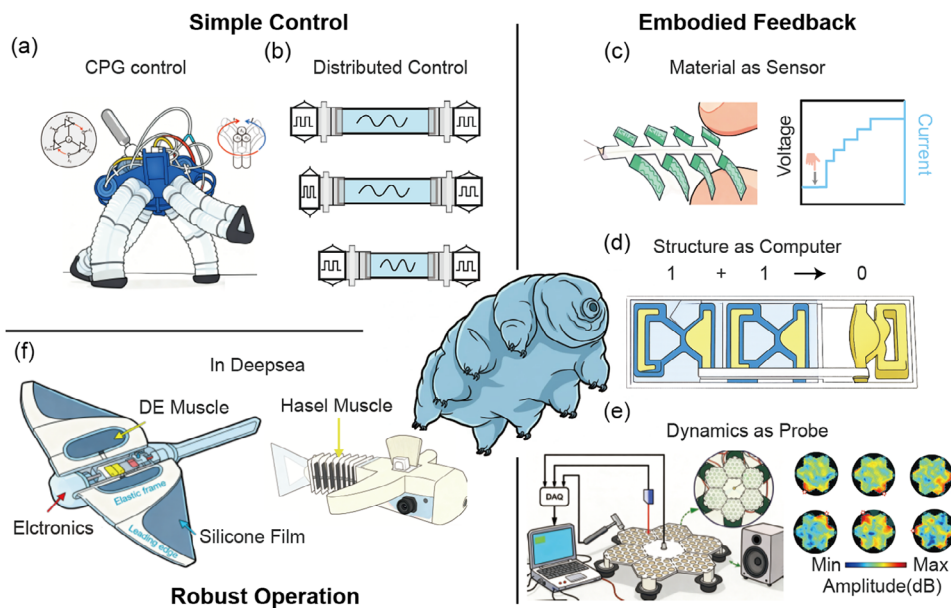
Both pathways embody the principles of morphological computation: by embedding control and computation tasks into the physical structure, the system achieves efficient, adaptive, and energy-efficient behavioral intelligence under resource constraints [17]. Robotic intelligence thus extends beyond algorithms and processors, becoming deeply rooted in the ongoing physical conversation between the body and its environment [18].

#### 4.2 | Adaptation Through Embodied Feedback

While the simple control rules discussed in Section 4.1 provide the initial ‘seed’ for behavior generation, maintaining robustness and efficiency in dynamic, uncertain environments requires the individual agent to close the perception-action loop in real time. This capability, which we term adaptive behavior through embodied feedback, represents the critical leap from passive emergence to active adaptation. It leverages the multifunctional materials (Section 2) and intelligent structures (Section 3) as its physical substrate, but focuses on how these substrates are orchestrated at the system level to enable continuous interaction with the world.

In biological systems, this manifests as insects adjust their locomotion rhythm via strain receptors distributed across their joints, while octopuses modulate grasping force through chemical receptors embedded in their skin, both exemplifying deep spatial and functional coupling between sensing and actuation [193, 194]. Drawing from this principle, the field of biomimetic robotics aims to create closed-loop control systems where perception, decision, and action are tightly coupled within the physical agent itself, often operating independently of external sensor networks or centralized computation [188, 195].

Current technological implementations are advancing along three primary directions:



**FIGURE 4** | Schematic illustration of the individual behavior in omni-scale biomimetic robotics. (a,b) Simple control and emergent behavior: (a) CPG-based rhythmic control and distributed reflexive rules enable complex locomotion and adaptive motion to emerge from the interaction between simple control signals and the physical dynamics of the body [184]. Adapted with permission [184]. Copyright 2021, AAAS. (b) Distributed control: Local sensory-motor loops propagate through adjacent segments, producing coordinated global behavior without centralized computation [190]. Adapted with permission [190]. Copyright 2022, AAAS. (c–e) Embodied feedback: (c) multifunctional materials serve as intrinsic sensors, converting mechanical or chemical stimuli into real-time feedback [198]. Adapted with permission [198]. Copyright 2024, Nature. (d) mechanical metamaterials and programmable structures perform physical computation, regulating behavior without electronic controllers [207]. Adapted with permission [207]. Copyright 2019, Nature; and (e) the robot's own dynamics act as probes to infer environmental properties for adaptive response [209]. Adapted with permission [209]. Copyright 2020, Nature. (f) Robust operation in extreme environments: In deep-sea or high-pressure settings, encapsulated electronics and silicone-based films maintain functionality through structural mediation and material-level adaptation, ensuring continued operation where traditional systems would fail [229, 233]. Adapted with permission [229] Copyright 2019, Nature [233] Copyright 2025, AAAS.

Material as a sensor achieves intrinsic fusion of actuation and sensing [196, 197]. For example, the resistance of a piezoresistive elastomer varies continuously with strain during deformation, allowing an actuator to simultaneously output motion and self-sense its state (Figure 4c) [198]. Thermochromic materials undergo coupled changes in color and electrical resistance under thermal stimulation, enabling thermal-mechanical-electrical multimodal feedback within a single material [199, 200]. Such direct transduction at the material level not only eliminates the signal delay and interface losses associated with discrete sensors but also establishes a low-power, high-bandwidth sensing-actuation unity at the material scale [201, 202].

Structure as a computer encodes logic and computational functions through geometric and topological design [203, 204]. Inspired by biological structures (e.g., the mechanosensory coupling in avian feather follicles), engineered systems can construct physical computing units using buckling beams, multistable mechanisms, or microfluidic networks [205, 206]. For instance, the snap-through behavior of a bistable beam can perform mechanical logic operations analogous to “ $1+1 \rightarrow 0$ ”, while microfluidic circuits can autonomously regulate the motion sequence of a soft robot based on fluid pressure distribution (Figure 4d) [207]. This form of structural computation “hard-wires” control algorithms into the morphology of matter, maintaining reliable operation even under strong electromag-

netic interference, extreme temperatures, or radiative conditions [208].

System dynamics as an environmental probe enables robots to perceive spatial and physical properties of the external world through their own vibration responses (Figure 4e) [209, 210]. The core mechanism lies in the sensitive variation of structural vibration modes with interaction parameters like contact location, stiffness, and loading conditions when the robot interacts with the environment or is dynamically excited [211, 212]. By monitoring shifts in these vibrational features (e.g., changes in amplitude within specific frequency bands), the robot can inversely reconstruct environmental information, achieving contact localization, contour detection, and even material identification without dedicated sensors [213, 214].

Material sensing, structural computation, and dynamic probing are not isolated; rather, they form a synergistic intelligence through cross-scale coupling: materials provide intrinsic sensory signals, structures perform physical preprocessing and logical decisions on these signals, and dynamics endow the system with the ability to continuously sense and interpret the external environment [166, 215]. This deep fusion of perception, computation, and action into “materialized intelligence” allows robots to achieve millisecond-scale closed-loop responses under low-communication overhead and low energy consumption, laying a physical foundation for truly autonomous adaptive behavior

in complex, unstructured environments [18, 216]. With ongoing advances in smart materials, flexible electronics, and bio-inspired structures, embodied feedback systems are evolving from discrete “sensing-actuation” modules toward highly integrated material-fused intelligent entities, not only driving individual robots toward higher-level adaptability but also providing a natural physical interface for swarm cooperation and lifelong learning [217, 218].

### 4.3 | Robust Operation in Extreme Environments

In contrast to conventional robotic systems that rely on centralized sensing, computation, and control, many biological organisms achieve robustness in extreme environments through mechanisms embedded directly in their physical structure [219, 220]. The tardigrade provides a representative example: survival under extreme dehydration or pressure does not depend on neural regulation, but rather on environmentally triggered transitions at the molecular and material levels. Changes in hydration or pressure induce glass-like states within cells, stabilizing structural components and preserving integrity without the need for active control [221].

This principle of embedding functional response into physical architecture is also reflected in soft robotic systems [222, 223]. The Octobot, for example, integrates pneumatic and microfluidic networks within its compliant body, using pressure generated by chemical fuel decomposition to drive basic actuation sequences without electronic components or centralized controllers [2]. This design demonstrates that, in environments where electronics are impractical or unreliable, material compliance and fluidic coupling alone can sustain elementary robotic behaviors [184].

Furthermore, the capacity of structural configurations to dissipate stress under extreme pressure ensures the continuity of sensing actuation integration [224, 225]. The bionic deep-sea soft robot exemplified this by embedding electronic components within a non-homogeneous modulus flexible matrix, achieving a dynamic balance between internal stress and external hydrostatic pressure [226]. In this state of physical equilibrium, the constitutive equations of the DEAs naturally incorporate environmental load terms, allowing the actuators themselves to function as high signal-to-noise ratio sensors [227, 228]. This design eliminates the need for complex compensation algorithms by utilizing physical symmetry to cancel out deep-sea background noise (Figure 4f) [229].

Taken together, these examples indicate that robustness in extreme environments does not necessarily require increasingly complex control architectures [230]. Instead, it can arise from the intrinsic physical compatibility between the robot's material-structural composition and its surrounding environment [224]. By exploiting compliance, structural continuity, and passive load-redistribution, soft material systems can maintain functionality under conditions such as extreme pressure, communication blackout, or electronic failure that would incapacitate conventional rigid robots [231]. This compatibility-driven design provides a practical and scalable pathway for deploying robots in the deep sea and other extreme settings, where survival is

governed more by physical consonance with the medium than by computational power or centralized control [232].

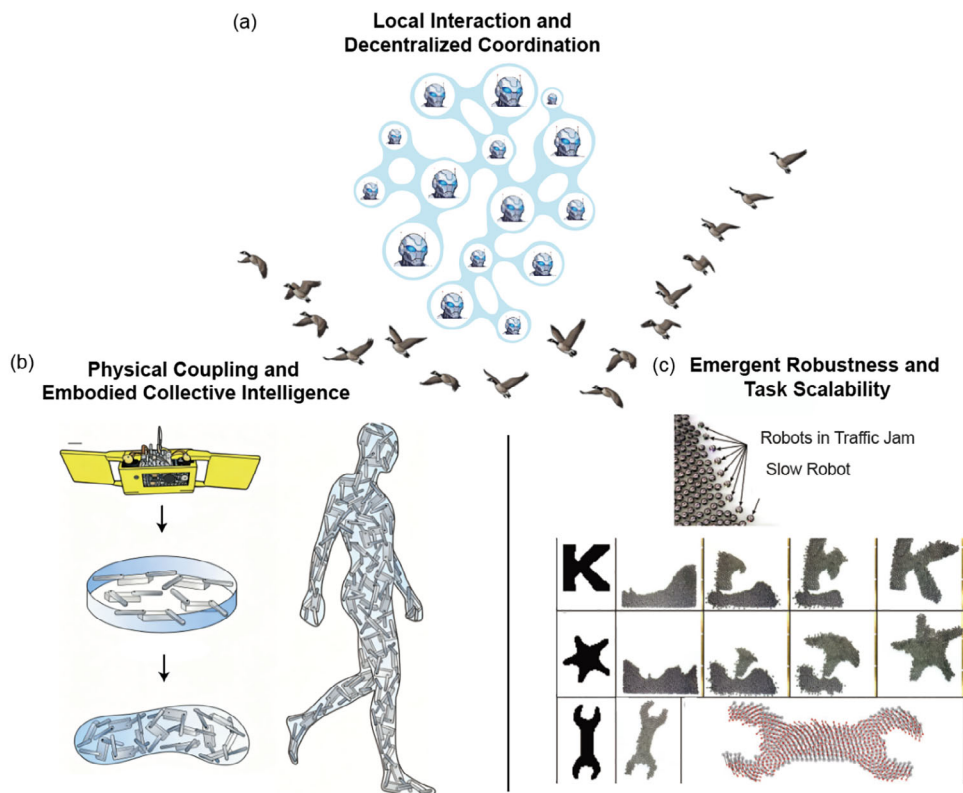
Building on this physical-compatibility principle, we can articulate a broader paradigm for individual robotic intelligence in extreme settings. In summary, by encoding survival logic into material constitution, employing physical computation to replace vulnerable electronics, and utilizing structural mechanics to achieve endogenous balance between sensing and actuation, individual robots can maintain fundamental perception, decision-making, and action capabilities. This “constitutive robustness”, which does not rely on central processors or fragile communication, marks a paradigm shift for robotics from “executing preset programs” toward “possessing physical survival intelligence”. Underlying these embodied strategies is a fundamental energetic constraint: as sensing, computation, and actuation scale with system complexity, relocating intelligence from centralized algorithms to physical morphology becomes not a design preference, but an energetic necessity.

However, many complex functions that surpass individual capabilities, such as large-scale environmental modification, construction of distributed perception networks, and long-term resource harvesting, cannot be achieved by a single agent [234, 235]. This naturally leads to a higher-level organizational principle: collective intelligence. Just as in nature, where simple individuals like ants and bees exhibit astonishing collective wisdom through cooperation, in robotics, individuals possessing the aforementioned robustness and adaptability lay the physical and behavioral foundation for constructing robot collectives capable of cooperative operation, resilience, and scalability in extreme environments [236, 237]. The following section will explore how these individuals with “constitutive intelligence” can, through local interaction and physical coupling, achieve task emergence and further enhance systemic resilience at the collective level.

## 5 | Collective Emergence

While robustness at the individual level enables survival and sustained operation in uncertain environments, many biological functions emerge only through collective organization [237]. In nature, groups of relatively simple agents cooperate to achieve capabilities that far exceed those of any single individual, including large-scale construction, efficient foraging, environmental modification, and long-term resilience [238, 239]. For example, migrating geese significantly reduce collective flight energy expenditure and extend navigation range through alternating leadership and V-formation flight, demonstrating coordinated intelligence without central command [238]. Collective emergence, therefore, represents the largest organizational scale in omni-scale biomimetic robotics, where interactions among individuals give rise to system-level intelligence without centralized control. Crucially, energy constraints do not vanish with increasing system size; instead, they are redistributed, making collective organization an effective strategy for balancing energetic cost, functional redundancy, and environmental uncertainty.

In biological collectives, such as insect colonies, bacterial communities, and animal swarms, emergent behavior arises from local interactions governed by simple rules, physical coupling,



**FIGURE 5** | Schematic illustration of collective-level emergence in omniscale biomimetic robotics. (a) Local interaction and decentralized coordination: Agents rely on short-range sensing and communication to self-organize into global patterns without central control, exemplifying scalability and robustness in dynamic environments. (b) Physical coupling and embodied collective intelligence: Mechanical connections enable groups to function as integrated material systems, where forces and deformations propagate collectively to achieve adaptive locomotion or shapemorphing. This panel is adapted from refs. [263]. Adapted with permission [264]. Copyright 2019, AAAS. (c) Emergent robustness and task scalability: Even with impaired or heterogeneous agents, the collective maintains global functionality through dynamic role reallocation and decentralized logic, enabling task expansion without proportional increase in failure risk. This panel is adapted from refs. [277]. Adapted with permission [278]. Copyright 2014, AAAS.

and environmental feedback [240]. Importantly, collective intelligence does not require complex individuals; instead, it relies on robustness, adaptability, and consistency at the individual level. This observation directly parallels the design philosophy of embodied robotics, where physically capable agents form the building blocks of higher-order functionality [241].

## 5.1 | Local Interaction and Decentralized Coordination

The emergence of collective intelligence is fundamentally characterized by a decentralized architecture, where complex global behaviors arise not from top-down commands but from local sensing, short-range communication, and real-time responses to neighboring agents [242, 243]. In the context of omni-scale biomimetic robotics, this paradigm shifts the control boundary from a centralized processor to the local interaction layer, fundamentally addressing the scalability bottlenecks inherent in large-scale systems operating in complex environments (Figure 5a) [244, 245].

In biological collectives such as insect colonies or fish schools, coordination is typically governed by simple behavioral heuristics: attraction, repulsion, and alignment [240, 242]. The swarm

provides a landmark empirical validation of this logic in robotics. Comprising thousands of miniature agents that communicate only via low-bandwidth infrared signals with immediate neighbors, the swarm can self-organize into intricate 2D shapes through cumulative local positioning adjustments [246, 247]. This demonstrates that system-level complexity is not a product of individual computational power but of the spatiotemporal superposition of local interaction rules [248].

This reliance on local rules confers intrinsic scalability and communication robustness to the system. In extreme or dynamic environments where global communication is often unavailable, agents must rely on short-range interactions [249, 250]. The s-bot platform from the Swarm-bot project exemplifies how local sensory feedback allows a collective to overcome obstacles and bridge gaps without a global map or centralized pathfinding [251]. By limiting the information processed by each agent to its local vicinity, computational overhead remains constant regardless of group size, enabling coordinated spatial organization in communication-constrained settings [252].

Furthermore, decentralized coordination establishes the foundation for collective resilience by eliminating single points of failure [253, 254]. In a system governed by local interactions, the damage of an individual or a localized loss of communication is contained

within a specific sub-region and does not propagate through a centralized control chain. For instance, the SMAVNET project at EPFL demonstrated that a swarm of micro-UAVs could establish a robust communication network in environments without GPS or central oversight by employing simple local reactive protocols [255, 256].

## 5.2 | Physical Coupling and Embodied Collective Intelligence

Beyond digital information exchange, physical interactions serve as a fundamental medium for collective emergence. In many biological systems, individuals are mechanically coupled to one another or to their environment, allowing forces, constraints, and deformations to propagate across the group as a form of “mechanical signaling” [257, 258]. This is exemplified by army ant bridges (genus *Eciton*), where individuals do not rely on complex computation but instead adjust their grip and posture based on the mechanical tension felt through their limbs [259]. Similarly, tubifex worm aggregations interlace to form a viscoelastic “super-organism” whose collective motion is driven by internal friction and geometric constraints. In these cases, collective mechanics directly shape group behavior, enabling the swarm to function as a unified material entity [260, 261].

Inspired by these biological principles, recent robotic research exploits physical coupling through soft connections, magnetic interactions, or shared deformable substrates to achieve embodied coordination [262]. A prominent empirical example is the “Smarticles” (Smart Active Particles) developed at Georgia Tech [263]. These agents lack individual mobility and digital communication but achieve collective locomotion through stochastic collisions and mechanical entanglement. By modulating the geometry of their “limbs”, the ensemble exploits mechanical frustration and geometric constraints to navigate or escape confined spaces (Figure 5b). This demonstrates that collective intelligence can emerge from physical contact rather than relying solely on explicit data packet exchange [264, 265].

This physical coupling enables groups to spontaneously adapt their morphology and redistribute system loads [266]. For instance, self-assembling soft robotic swarms utilize magnetic or mechanical latching to form a “collective skin”, where the deformation of one agent is physically sensed by its neighbors, triggering a ripple of structural adaptation [266, 267]. This “material-level coordination” allows for the redistribution of stress during heavy lifting or the adaptive softening of the collective body during collision [268].

By offloading coordination tasks to the physical layer, these systems achieve high-level mechanical adaptation, such as fluid-to-solid phase transitions or collective load-bearing, without the latency associated with digital processing [269, 270]. This constitutive coupling ensures that collective intelligence is deeply rooted in the material and structural properties of the individual agents, bridging the gap between discrete entities and integrated multi-scale systems. This approach allows group behavior to exhibit higher immediacy and coordination when facing complex physical constraints [271].

## 5.3 | Emergent Robustness and Task Scalability

Collective organization inherently enhances robustness by decoupling global mission success from individual reliability. In biological systems, this resilience is demonstrated through the capacity to maintain systemic functionality despite the loss or intermittent failure of individual components [272, 273]. A prime exemplar is the fire ant (*Solenopsis invicta*), which forms self-healing bio-rafts in response to floods [274]. This collective resilience is not derived from a centralized blueprint but emerges from the dynamic interlacing of individual limbs, allowing the raft to redistribute mechanical loads and autonomously bridge gaps caused by damaged members [273, 275].

In biomimetic robotics, this emergent robustness is the primary enabler for task scalability, the ability to expand the scope of operations (such as distributed sensing or long-term exploration) without a proportional increase in system failure rates [249, 276]. Empirical research on massively redundant swarms, such as Kilobots, has shown that these systems can complete complex shape-formation tasks even when a significant percentage of agents suffer hardware failure or localized communication loss (Figure 5c) [277]. The robustness here is a direct result of decentralized logic: because each agent operates on local consensus, the collective can “absorb” individual failures as localized noise, preventing the catastrophic propagation of errors often seen in centralized architectures [278, 279].

Furthermore, scalability is enhanced through functional heterogeneity and dynamic role allocation, as demonstrated by the Swarmanoid project. In this system, specialized agents (Eye-bots, Hand-bots, and Foot-bots) coordinate to execute high-stakes tasks like search-and-rescue [280, 281]. Robustness emerges from the system’s ability to redistribute tasks based on the real-time availability and physical state of its members. When certain agents become incapacitated, the collective reconfigures its hierarchy and interaction patterns to maintain mission persistence. This capability is especially critical in hazardous or communication-denied environments, where the group’s survival depends on its ability to dynamically reallocate redundant resources to compensate for the attrition of individual units [282, 283].

Based on the analysis of the three core dimensions, namely, decentralized coordination, physical coupling intelligence, and emergent robustness, we can develop an integrated understanding of collective-level biomimetic robotics:

The essence of collective intelligence lies in transforming relatively simple individual units into a functional whole with system-level resilience, adaptability, and scalability through distributed architecture, physical interaction, and dynamic redundancy. Decentralized coordination, such as shape formation based on local rules, ensures scalable operation without global control. Physical coupling, such as mechanical entanglement or fluid-to-solid phase transitions, enables the collective to respond to mechanical constraints in a material-like manner. Emergent robustness, including fault tolerance and functional reconfiguration, guarantees the continuous execution of tasks despite individual unreliability or environmental uncertainty. These three aspects are not isolated but mutually reinforcing:

decentralized logic provides the organizational foundation for physical coupling; physical coupling serves as the medium for realizing robustness; and robustness in turn maintains the persistent stability of the decentralized structure [249].

This tripartite framework of distribution, physicality, and resilience collectively forms the design foundation for collective-level omni-scale biomimetic robotics. It demonstrates that complex functions surpassing individual capabilities, such as large-scale environmental modification, long-term distributed monitoring, or dynamic resource cooperation, do not necessarily rely on highly complex individuals or centralized planning. Instead, they can emerge through collective intelligence embedded in physical interactions and local rules. This provides a biologically plausible and engineering-feasible theoretical pathway and practical inspiration for constructing next-generation robot clusters capable of autonomous, cooperative operation in extreme, unknown, or dynamic environments [277].

## 6 | Outlook: Toward Omni-Scale Biomimetic Robotics

The preceding synthesis illustrates that biological intelligence is not a localized phenomenon but a multiscale emergent property arising from the seamless integration of materials, structures, behaviors, and collective organization [174, 284]. While significant progress has been made independently at each scale, the future of the field demands a fundamental paradigm shift: from pursuing performance limits at isolated scales toward constructing a synergistic, cross-scale functional architecture [285, 286]. Omni-scale biomimetic robotics envisions systems whose robustness and adaptability are inherent to their physical and behavioral coupling, not added as an algorithmic afterthought. To realize this vision, several key future research directions can be identified across different scales.

The first priority lies in achieving AI-powered co-design of intelligent materials and structural systems, where structural configurations are computationally optimized to actively amplify and regulate material responses [287–292]. Future designs must develop intelligent geometries, such as origami, mechanical metamaterials, or topological insulators, capable of structural signal conditioning (e.g., filtering, amplification, and stabilization of mechanical responses). These architectures would guide and stabilize the nonlinear responses of multifunctional materials, transforming material structure interfaces from performance bottlenecks into sites for physical computation and information preprocessing.

Moving to the individual level, we emphasize the need to deeply integrate mechanical intelligence with adaptive control and learning algorithms through embodied co-design of morphology and control policies [5, 17, 293, 294]. This calls for moving beyond viewing body compliance as a disturbance to be compensated, and instead leveraging morphological computation to treat the body as a computational resource [295]. Concurrently, learning algorithms, particularly reinforcement learning, must evolve into physics-informed frameworks that incorporate priors derived from the robot's own material dynamics and viscoelasticity [296, 297]. Such an approach would yield control policies intrinsi-

cally aligned with the body's energetics and dynamics, enabling low-latency, energy-efficient autonomy with inherent graceful degradation capabilities.

Beyond individual agents, we envision a shift from purely algorithm-driven coordination toward physically grounded and programmable collective intelligence, where coordination emerges from local interactions and physical coupling among agents and with the environment [298, 299]. By embedding responsiveness into both material properties and structural design, collective behavior can be achieved through local physical interactions rather than explicit communication. At the material level, stimuli-responsive properties enable individual agents to sense and react to local mechanical or environmental cues. At the structural level, contact mechanics, compliance, and mechanical coupling regulate how these interactions are transmitted between neighboring agents. For example, mechanically induced alignment can enable coordination without sensing or communication [300, 301], while viscoelastic stress relaxation can regulate collective morphological evolution [302, 303]. Through this integration, local interactions can propagate across the collective, providing a physically grounded pathway for coordinated and emergent behavior [304, 305].

Another important direction is enabling robust autonomy in extreme environments through AI-guided design and multi-physics optimization [306–308]. In these regimes, systems must prioritize survivability and passive resilience over nominal efficiency. Inspired by biological strategies such as tardigrade vitrification or seed dormancy [309], future robots may incorporate material-level state-switching mechanisms (e.g., phase transitions or stiffness modulation) that can be systematically designed and optimized to withstand transient environmental extremes. Coupled with inherently fault-tolerant and redundant architectures, such designs could achieve mission-level persistence, wherein the collective succeeds even as individual units are expended [246].

These directions collectively point toward a unified omni-scale design paradigm. In summary, the advancement of omni-scale biomimetic robotics hinges on breaking down the traditional barriers between materials, structures, individuals, and collectives. Through cross-scale co-design, intelligence can be truly cast into the physical body of the machine. This path not only promises to yield a new generation of robots capable of autonomous, cooperative, and resilient operation in complex, unknown worlds, but may also deepen our understanding of intelligence itself, particularly its inseparable bond with the physical body and the natural environment.

## 7 | Conclusion

This review reveals that the future of biomimetic robotics lies not in isolated scale-specific optimization, but in omni-scale integration, from responsive materials and structural design, to individual behaviors and collective interactions, forming a system-level intelligence that emerges across scales. The superiority of natural systems stems precisely from this cross-scale coupling: the multifunctionality of materials is harnessed through structural geometry, individual agents exploit the inherent advantages of

material-structure synergy, and collective intelligence emerges from the physical interactions among agents and with their environment, yielding robustness, efficiency, and adaptability. In contrast, current artificial systems are limited by the absence of such systemic integration, and technological advances at any single scale rapidly encounter performance ceilings.

Accordingly, the next generation of research must transcend isolated optimization and adopt a cross-scale co-design paradigm, developing computational tools that unify models across materials, structures, behaviors, and collectives; creating embodied intelligence in individual robots that leverages rather than resists the physical dynamics of their bodies; and designing collective systems that rely on physical interactions rather than purely data-driven communication, enabling emergent coordination from local interactions. This paradigm shift promises robots that not only mimic life, but surpass natural limitations in adaptability, resilience, and energy efficiency, achieving forms of supernatural intelligence.

From a scientific perspective, omni-scale biomimetic robotics provides a new lens on intelligence. It is no longer merely a computational abstraction, but a property deeply rooted in the physical coupling of materials, structures, behaviors, and collectives. Such system-level intelligence offers not only novel solutions to grand challenges, including extreme environment exploration and sustainable technologies, but also a pathway toward understanding the very nature of intelligence itself, from physical emergence to cognitive sophistication.

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### Conflicts of Interest

The authors declare no conflicts of interest.

### Data Availability Statement

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

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