

PERSPECTIVE **OPEN ACCESS**

Toward Mechanical Intelligence in Robotics

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ABSTRACT

Conventional robotic systems concentrate sensing, control, and actuation in electronic hardware, creating constraints in harsh environments, energy efficiency, and miniaturization. The physical body of a robot is more than a passive executor of control commands; it is an active substrate that transforms inputs into functional operations through its intrinsic mechanical dynamics. This perspective describes this capability as mechanical intelligence and identifies three core operations: filtering, routing, and switching. These operations address three fundamental questions in physically mediated transformation: what inputs are selectively admitted, where signals propagate, and when the system transitions between states. Together, they enable selective responsiveness, spatial coordination, and state-dependent behavior without dedicated electronic hardware. Design variables and quantitative metrics are proposed for each operation, and the framework is illustrated in locomotion and manipulation, providing guidance for designing mechanically intelligent robots. Responsive materials extend this framework by transducing environmental stimuli into mechanical signals while also harvesting ambient energy for actuation. Rather than replacing digital computation, mechanical intelligence complements it by embedding part of sensing, processing, and actuation into the physical body, pointing toward hybrid systems in which mechanical and digital intelligence work together.

1 | Introduction

Robotic systems have long been organized around a classic architecture: sensors acquire information, controllers compute responses, and actuators execute commands. This sense-compute-act paradigm has enabled remarkable advances across a wide range of applications, from autonomous vehicles [1] and surgical manipulators [2] to industrial assembly [3] and planetary exploration [4]. By concentrating sensing, control, and actuation in electronic hardware, conventional robots can be rapidly reconfigured, precisely controlled, and deployed across diverse tasks (Figure 1 Top).

Yet as robotic systems are pushed toward new frontiers, this reliance on electronic hardware gives rise to fundamental constraints in harsh environments, energy efficiency, and miniaturization. Electronics are inherently vulnerable to harsh conditions: in

deep-sea exploration, extreme pressure and corrosive saltwater degrade sensors and circuitry [5, 6]; in nuclear inspection or space deployment, ionizing radiation disrupts digital processors [7, 8]; and in high-temperature industrial environments, thermal stress accelerates component failure [9]. Mitigating these vulnerabilities often requires protective shielding, redundant hardware, and higher power budgets. Meanwhile, continuous sensing, computation, and communication demand substantial energy [10], limiting operational duration and constraining deployment in untethered or resource-limited settings. As robotic systems become more distributed, miniaturized, and modular, these burdens further intensify. In particular, distributed and modular architectures require sensing, communication, and control to be replicated and coordinated across many interacting units, increasing integration complexity, synchronization demands, and overall energy consumption. At small scales, wiring, interconnects, and onboard

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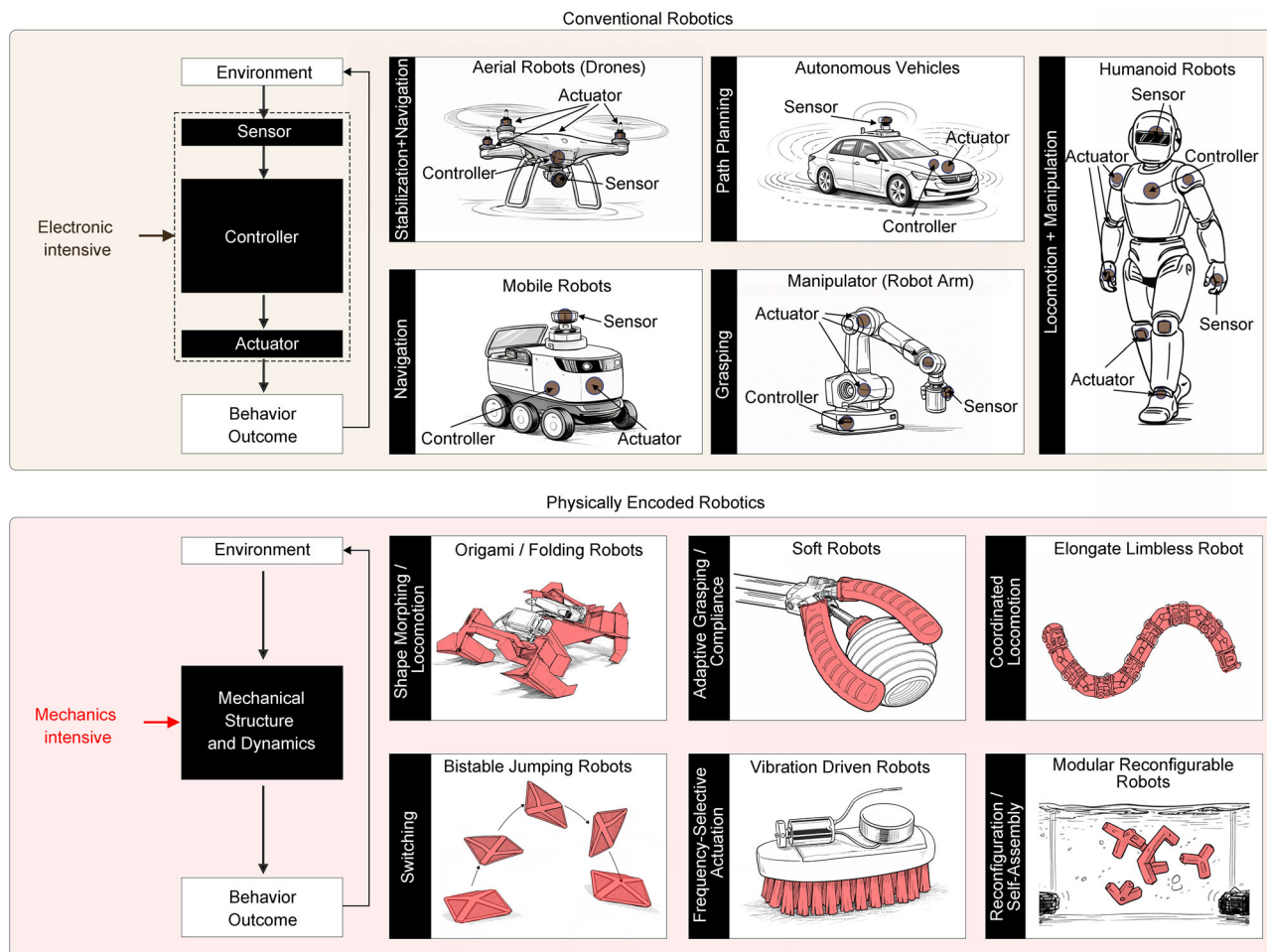


FIGURE 1 | From controller-based to structure-embedded robotic function. Conventional robots (top) rely on a centralized sense-compute-act pipeline, where functional transformation resides in a controller (blue) that processes sensory input to generate actions. The physical body primarily serves as a passive executor of controller commands. In contrast, mechanically driven robots (bottom) embed functional transformation directly in structure and dynamics (red), allowing behavior to emerge from physical interaction with the environment without centralized computation. Representative systems illustrate how morphology and intrinsic mechanics can implement functions such as locomotion, grasping, switching, frequency-selective actuation, and reconfiguration. These panels are conceptual schematics inspired by representative systems in soft grasping, vibration-driven locomotion, bistable jumping, origami-inspired reconfiguration, and modular robotic structures, rather than direct reproductions of individual platforms.

processors often dominate system volume and mass, imposing practical limits on miniaturization [11].

These challenges point to a common opportunity rooted in the physical body itself. In conventional architectures, the body is treated as a passive executor of control commands rather than an active participant in computation. However the mechanical properties of a structure, including its geometry, compliance, and energy landscape, are not merely incidental. They directly determine how forces propagate, how inputs are amplified or suppressed, and how energy is stored or released without going through a central electronic controller. When designed deliberately, these properties allow the body to serve as an active substrate that directly transforms inputs into functional operations through its intrinsic mechanical dynamics in a local yet robust manner, performing roles that would otherwise require routing every action through dedicated electronic sensing-computation-control loops.

A growing body of work illustrates this potential. Soft robotic grippers, for instance, exploit passive structural compliance, where

elastic bodies deform predictably under contact load to conform to and secure irregular objects, achieving adaptive grasping without dedicated contact sensors or feedback controllers [12, 13]. The grasping function is not computed; it is embodied in the mechanical response of the structure itself. This does not replace the electronic systems that coordinate the broader task, but it reduces the sensing and computational burden placed on them and makes the grasping function inherently robust to the electrical noise, temperature variation, and power fluctuation that would compromise a sensor-driven alternative. More broadly, across vibration-driven locomotion systems [14–16], bistable jumping robots [17, 18], and origami-inspired reconfigurable structures [19, 20], mechanical design is increasingly recognized as a means of extending robotic capability beyond what electronics alone can efficiently or reliably provide (Figure 1 Bottom).

In this perspective, we use the term mechanical intelligence to describe the capacity of the physical body to directly transform inputs into functional operations through its intrinsic mechanical dynamics. The term itself is not new and has appeared in earlier

discussions of mechanically mediated robotic functions (e.g., [21]). Our goal here is not simply to restate that the body can contribute to intelligent behavior. Rather, we make this idea more explicit by identifying filtering, routing, and switching as three core recurring mechanical operations through which the physical body realizes functional behavior. Filtering governs which inputs are selectively admitted, attenuated, or amplified; routing governs where stresses, deformations, or mechanical signals propagate within the structure; and switching governs when the system transitions between discrete mechanical states. Together, these operations provide a mechanism-level design vocabulary for understanding, comparing, and designing mechanically intelligent robots. This framework is not limited to soft robotic systems. Although compliance and large deformation make mechanical intelligence especially visible in soft robots, the relevant distinction is not soft versus stiff material but whether the robot body plays an active functional role in transforming inputs into behavior. This distinguishes the systems considered here from conventional rigid-link robots, where links are typically idealized as rigid bodies, and function is primarily assigned to joints, actuators, sensors, and controllers. Mechanical intelligence can also arise in robots assembled from nominally stiff materials when compliant mechanisms, flexures, metamaterials, latching structures, resonant elements, underactuated transmissions, origami-inspired structures, or deformable end-effectors encode filtering, routing, or switching through mechanical dynamics rather than solely through electronic sensing and control. Even in the absence of specialized materials, mechanical structures can directly sense and process mechanical inputs such as impact, force, vibration, or contact through their intrinsic dynamics. Responsive materials further extend this framework by transducing nonmechanical environmental stimuli, including light [22], heat [23], magnetic fields [24, 25], or chemical signals [26, 27], into mechanical state changes that are subsequently processed by the same structural mechanisms while also harvesting ambient energy for actuation. In this way, material responsiveness expands the range of accessible inputs, while filtering, routing, and switching remain the core operations through which structure senses, transforms, and coordinates information. By mapping these physically mediated operations onto robotic behaviors and system-level architectures, this perspective suggests a redistribution of function across the physical body and the electronic controller, pointing toward a new paradigm in which robots are conceived as unified physical–computational systems. The central contribution of this perspective is therefore not merely the recognition that the body matters but the specification of how it contributes: through mechanical operations that can be mapped onto robotic functions in locomotion, manipulation, responsive materials, and hybrid mechanical–digital architectures. This framework bridges broad conceptual paradigms such as embodied intelligence and physical intelligence with the concrete engineering of mechanically intelligent robots.

2 | Core Mechanisms of Mechanical Intelligence

The functional behavior of mechanically intelligent systems can be understood in terms of how physical structures receive and process environmental inputs through their intrinsic dynamics and how they can modify the environment to take advantage of useful environmental features. As illustrated in Figure 2, environmental

inputs, whether mechanical in origin, such as impact, vibration, gravity, contact, or fluid interaction, or transduced from nonmechanical stimuli, such as light or temperature (discussed in later sections), generate internal deformation governed by the system's geometry, compliance, contact conditions, and topology. These structural parameters, e.g., beam thickness, joint and flexure stiffness, contact geometry, and lattice connectivity, determine how inputs are transformed into observable responses such as directed motion, configuration change, or stored elastic energy [28, 29]. Once expressed mechanically, inputs are not simply transmitted but shaped by the physical architecture. Through this shaping, structures can perform three core operations without relying on explicit computation: filtering, routing, and switching.

Filtering refers to the selective reshaping of input components based on their frequency, direction, or magnitude. Rather than uniformly transmitting all inputs, mechanical structures reshape them by preferentially enhancing certain modes of deformation while suppressing others. This selectivity arises from resonance, geometry, and compliance, effectively encoding response characteristics in physical properties rather than in dedicated electronic hardware. As shown in Figure 2 (top panel), this behavior is realized in structures such as beams with varying thickness that concentrate strain through geometric gain [28, 29] and directional hinges that produce anisotropic responses sensitive to input direction [28], collectively acting analogously to a mechanical bandpass or high-pass filter.

Routing describes how mechanical energy, stress, or deformation is directed through a structure along geometry-defined pathways. The arrangement of components, joint connectivity, and local compliance determine how inputs propagate spatially, enabling signals to be guided toward specific regions or degrees of freedom without centralized coordination [30]. As shown in Figure 2 (middle panel), this path-dependent propagation arises through load paths at contact interfaces, hinge network topology, and lattice connectivity, where some pathways transmit signals preferentially, while others block them, producing a spatially organized response from a globally applied input.

Switching captures the ability of a physical system to undergo discrete transitions between distinct states in response to a changing input. This typically arises through instabilities, thresholds, or bistable energy landscapes, where a small change in input crosses a critical point and triggers a large, qualitative change in configuration or behavior, enabling threshold-triggered responses in which the system transitions to one of multiple mechanically stable states. Such transitions do not imply cognitive evaluation but instead arise from the mechanics of crossing an energy barrier in a multistable landscape [31, 32]. As shown in Figure 2 (bottom panel), such transitions arise across a range of structural forms, including beams, trusses, compliant mechanisms, and thin shell structures, all sharing a common multistable energy landscape that produces sudden binary state changes. In robotic systems, such switching can be used to alter how a structure responds to its environment, enabling threshold-triggered activation, mode changes, and the retention of mechanically encoded state.

Together, these three operations, filtering, routing, and switching, constitute core recurring mechanisms through which

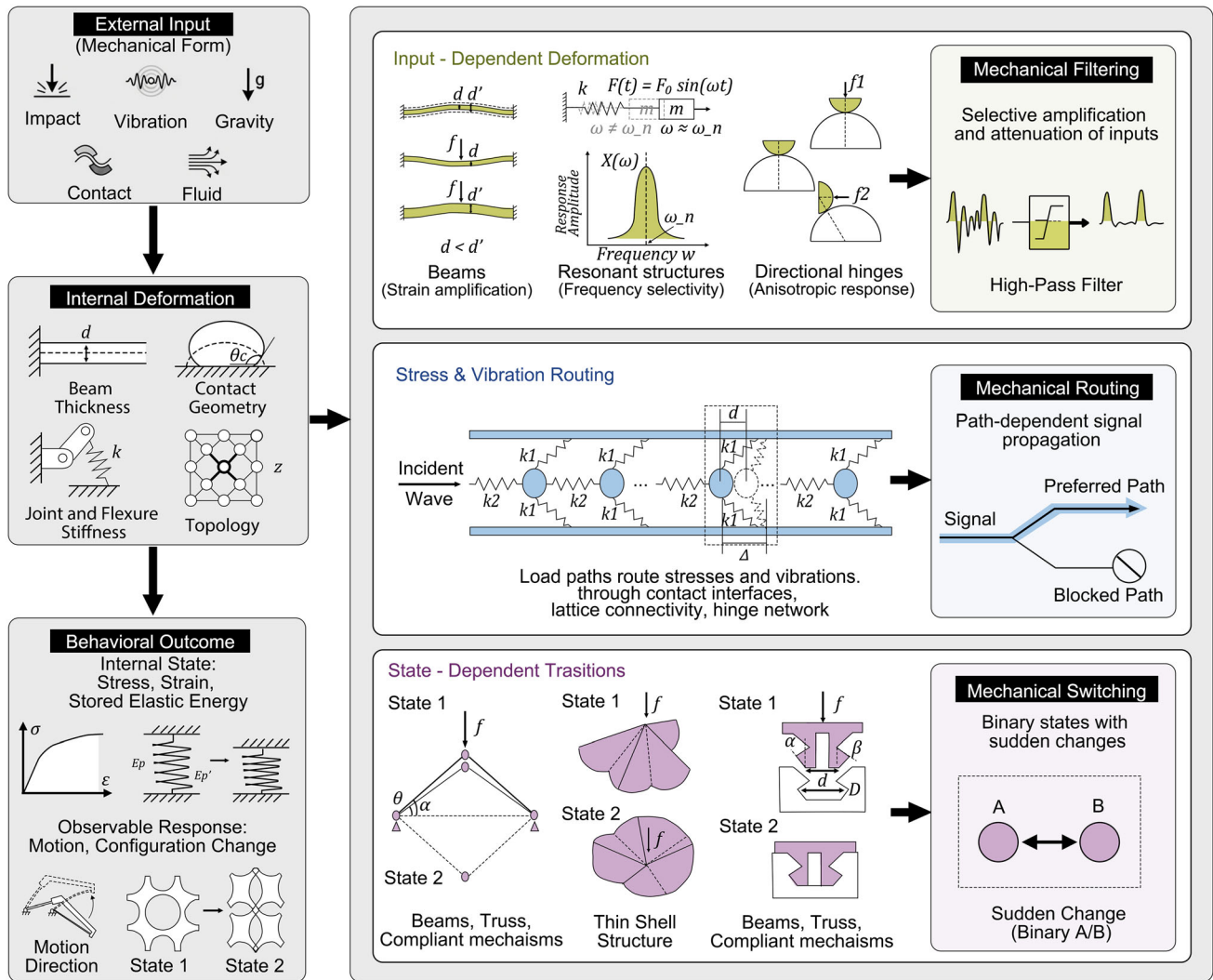


FIGURE 2 | Core mechanical operations underlying mechanical intelligence. Environmental inputs, from direct mechanical interactions or non-mechanical stimuli transduced into mechanical form, generate internal deformation governed by geometry, compliance, contact, and topology. These structural responses give rise to three recurring operations: filtering, where input-dependent dynamics selectively admit, attenuate, or amplify inputs; routing, where stresses, vibrations, or deformation propagate along geometry-defined pathways; and switching, where thresholds or multistable energy landscapes enable discrete state transitions. The panels provide conceptual abstractions of representative mechanisms, including compliant strain amplification and directional hinges for filtering, geometry-defined propagation pathways for routing, and multistable structures for switching, rather than direct reproductions of specific systems.

mechanical intelligence is realized in physical structures. They are identified as core operations because they address three fundamental questions that any physically mediated functional transformation must resolve: what inputs are admitted and how they are reshaped (filtering), where signals propagate within the structure (routing), and when the system undergoes a discrete change in state (switching). In this sense, filtering governs input selectivity, routing governs spatial coordination, and switching governs state-dependent behavior, collectively spanning the pathway from environmental input to functional output. Table 1 summarizes representative design variables and evaluation metrics for these operations, along with system-level metrics for hybrid mechanical-digital allocation.

Other mechanically relevant operations, such as amplification, synchronization, oscillation, and memory, play important roles in specific robotic systems but can be understood as compositions or

special cases of these three core mechanisms rather than independent primitives. Amplification arises as a limiting case of filtering, in which specific input components are selectively enhanced through geometric gain or resonance. Synchronization emerges from routing when physical coupling between components enforces phase-locked or temporally coordinated responses. Oscillation can result from the cyclic interplay between filtering and switching, where a system repeatedly approaches or crosses instability thresholds. Memory corresponds to state retention after a switching event, enabled by multistable energy landscapes that maintain a configuration in the absence of continued input. More broadly, filtering, routing, and switching are not mutually exclusive categories but coupled operations that coexist and interact within a single physical structure. A resonant structure that selectively amplifies a specific frequency (filtering) may simultaneously direct the amplified response along a geometry-defined pathway (routing) and, if the amplified signal exceeds a critical threshold, trigger a snap-through

TABLE 1 | Operation-level design guidance for mechanical intelligence. Representative design variables and evaluation metrics are listed for filtering, routing, and switching, together with system-level metrics for hybrid mechanical–digital allocation. These metrics provide measurable entry points for evaluating how mechanical structures selectively admit inputs, direct signal propagation, trigger state transitions, and offload sensing, computation, or actuation from electronic control.

Operation	Design variables	Metrics	Role in robotic systems
Filtering	Stiffness, damping, mass distribution, geometry, resonance frequency	Selectivity ratio, bandwidth, gain, cutoff frequency	Selectively admits, attenuates, or amplifies inputs, reducing sensing burden by making the body preferentially responsive to task-relevant signals.
Routing	Topology, joint connectivity, contact path, anisotropy, structural coupling	Transmission ratio, routing contrast, spatial localization, propagation delay	Directs stress, deformation, vibration, or energy through geometry-defined pathways, reducing the need for distributed actuation and control.
Switching	Energy landscape, barrier height, friction, prestress, multistable geometry	Threshold force or energy, response time, hysteresis width, reset energy	Triggers discrete state transitions through instabilities or thresholds, enabling event-driven behavior and mechanically stored state.
Hybrid allocation	Body-controller function allocation, sensor placement, controller update rate, tunable mechanical parameters	Sensor reduction, computation reduction, power reduction, robustness under perturbation	Measures how much function is shifted from electronics into the physical body, improving efficiency, robustness, scalability, and adaptability.

transition (switching). These operations are therefore distinguished as analytically separable functions, each capturing a distinct aspect of how structure processes input, while real systems typically engage them simultaneously. In this sense, filtering, routing, and switching are not proposed as a provably complete or minimal basis in a formal mathematical sense but as an essential functional vocabulary through which mechanical structures transform inputs into robotic behavior and through which more complex mechanically intelligent behaviors can emerge by combination and coupling.

3 | Robotic Functions Enabled by Mechanical Intelligence

The three operations described above, filtering, routing, and switching, map onto a range of robotic functions. Rather than treating sensing, control, and actuation as separate electronic modules, these functions emerge directly from the interaction between physical structure and environmental inputs. In this view, the environment is not merely an external disturbance or boundary condition but an active part of the intelligence-generating process, since contact, terrain, flow, and object geometry shape the mechanical inputs through which locomotion and manipulation are organized. We illustrate this through two canonical robotic domains, locomotion (Figure 3) and manipulation (Figure 4), which are conventionally addressed through distinct electronic architectures yet share the same underlying mechanical operations when viewed through the lens of mechanical intelligence.

3.1 | Locomotion

Filtering enables selective responsiveness in locomotion. By amplifying specific frequencies, directions, or magnitudes of input while attenuating others, mechanically intelligent systems can exhibit

input-dependent activation without explicit sensing or computation. This selectivity allows robots to respond only under particular environmental conditions, effectively encoding task-relevant sensitivity directly in their structure. In this context, environmental features such as substrate compliance, obstacle geometry, and contact conditions are not passive but actively shape the input signals that are filtered and transformed by the body to produce locomotion. As shown in Figure 3 (top), a vibration-driven locomotion system with frequency-selective leg structures responds only when the excitation frequency matches the natural frequency of the target leg group. Because distinct leg groups can be tuned to different eigenfrequencies, a single global vibration input can be routed to different subsets of legs simply by shifting the excitation frequency, producing qualitatively different locomotor modes such as forward motion, backward motion, and turning [33]. The frequency response curve illustrates how the structural geometry acts as a mechanical filter, producing selective locomotion from a globally applied input without any sensing or control logic [34].

Routing enables spatial organization and coordination in locomotion. Mechanical energy, stress, or deformation can be directed along predefined pathways, allowing signals to propagate across different parts of the system. Conventional elongate limbless and myriapod robots typically rely on distributed actuation, with independent motors or pressure channels at each segment prescribing a traveling wave through cyclic feedforward signals [35–40]. In these systems, body compliance still performs a routing-like function by absorbing local perturbations, redistributing contact forces, and allowing the realized body shape to adapt passively to terrain or obstacles [41–45]. Further, recent work demonstrates that mechanical routing can extend to systems with a single actuator, shifting coordination from explicitly prescribed segment-level commands to mechanically mediated propagation from a single input. In pulse-driven robots, a single pneumatic actuator initiates nonlinear elastic waves that propagate through coupled mechanical units to produce net forward motion [46] and

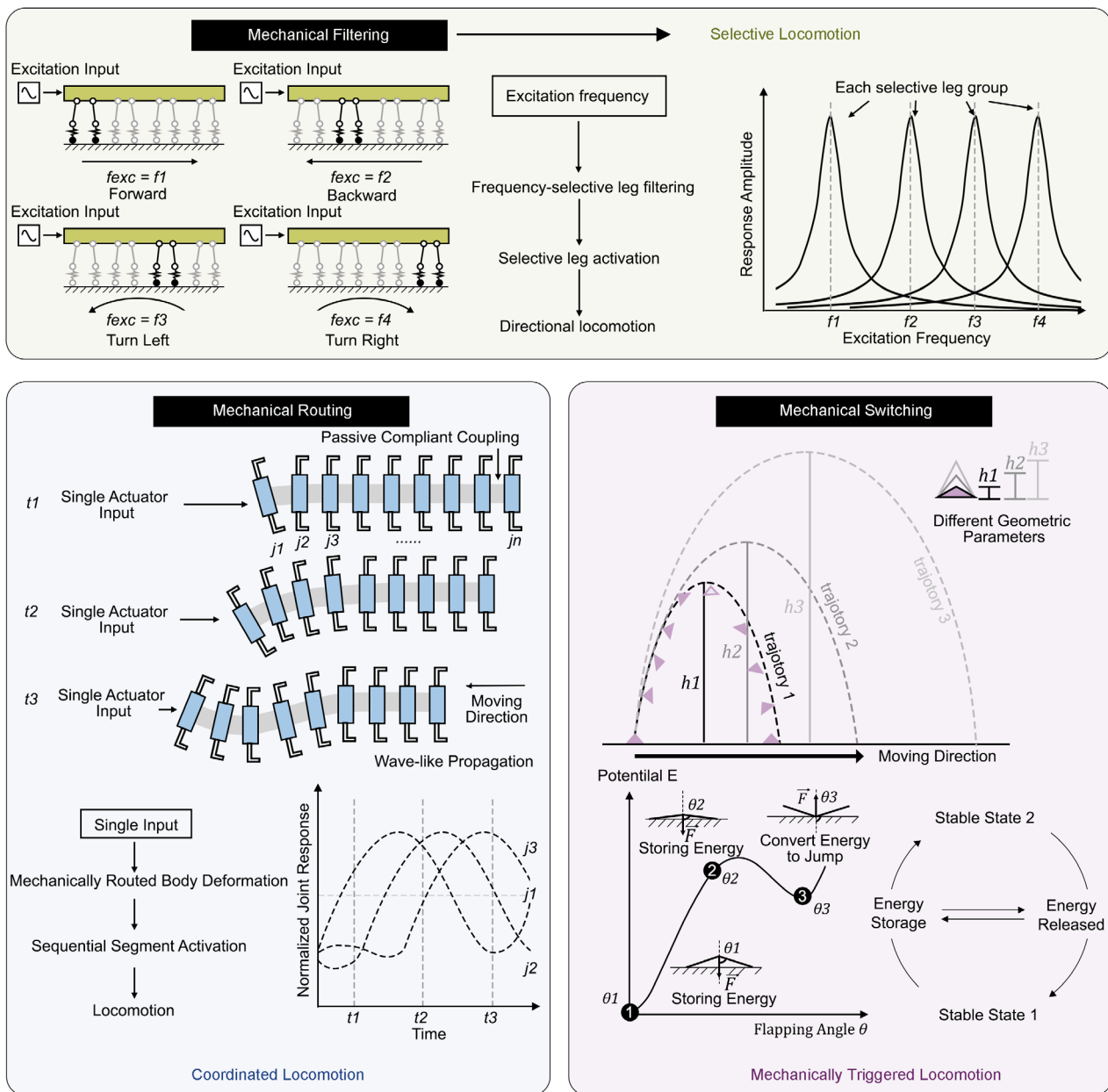


FIGURE 3 | Mechanical filtering (top) maps excitation frequency into selective leg activation by exploiting leg groups tuned to different natural frequencies, enabling directional locomotion such as forward motion, backward motion, and turning. Mechanical routing (bottom left) passively propagates a single actuator input through a compliant multisegment body, producing phase-delayed joint responses, wave-like deformation, and coordinated locomotion. Mechanical switching (bottom right) uses a bistable mechanism to convert trigger loading into snap-through, driving rapid release, and mechanically triggered locomotion. Together, these examples show how locomotion can be achieved through frequency selectivity, passive coupling, and energy landscape design without relying solely on conventional sensing and control. The panels are conceptual schematics distilled from representative systems, including frequency-selective vibration-driven locomotion, pulse- or soliton-mediated crawling, and bistable jumping mechanisms, rather than direct reproductions of any single platform.

in soliton-driven crawling metamaterials, a single actuator excites topological solitons that traverse a multistable lattice and locally modulate friction to generate locomotion [47]. As illustrated schematically in Figure 3 (bottom left), the underlying principle is that a single input, when routed through passive compliant coupling between segments, produces phase-delayed joint responses that give rise to wave-like body deformation and coordinated locomotion. Across these systems, the wave pattern is not prescribed by a controller but emerges from the interaction between a single input and the structure's intrinsic mechanical coupling.

Switching enables discrete behavioral transitions in locomotion. Through instabilities, thresholds, or multistable configurations, mechanically intelligent systems can transition between distinct states in response to changing inputs. These transitions enable threshold-mediated state selection, allowing robots to transition between modes of operation depending on environmental conditions or internal states. As shown in Figure 3 (bottom right), bistable elements accumulate elastic energy under slow loading and release it through snap-through transitions, triggering sudden configuration changes that convert quasistatically stored energy into

impulsive jumping motion [17, 18]. The energy landscape governs both the threshold condition and the resulting trajectory, embedding the transition rule entirely in the physical structure without requiring sensory feedback or control commands.

For locomotion, operation-level metrics can be translated into task-level quantities such as gait speed, cost of transport, turning radius, terrain robustness, frequency-response bandwidth, and the number of independently controlled actuators required to generate coordinated motion. Thus, the contribution of mechanical intelligence can be evaluated not only by whether locomotion occurs but also by how much coordination, sensing, and actuation are shifted from electronic control into body dynamics.

3.2 | Manipulation

Filtering enables selective responsiveness in manipulation. By producing differential responses to different contact geometries, a single compliant end-effector can generate object-specific grasp configurations from a single actuation input without explicit shape sensing or computation. Here, the geometry, stiffness, and surface properties of the object become integral to the computation itself as manipulation emerges from the coupled interaction between the gripper and its environment rather than from internal sensing alone. As shown in Figure 4 (top), a compliant finger structure responds to spheres, cubes, and cylinders with distinct contact-force distributions across its phalanges because

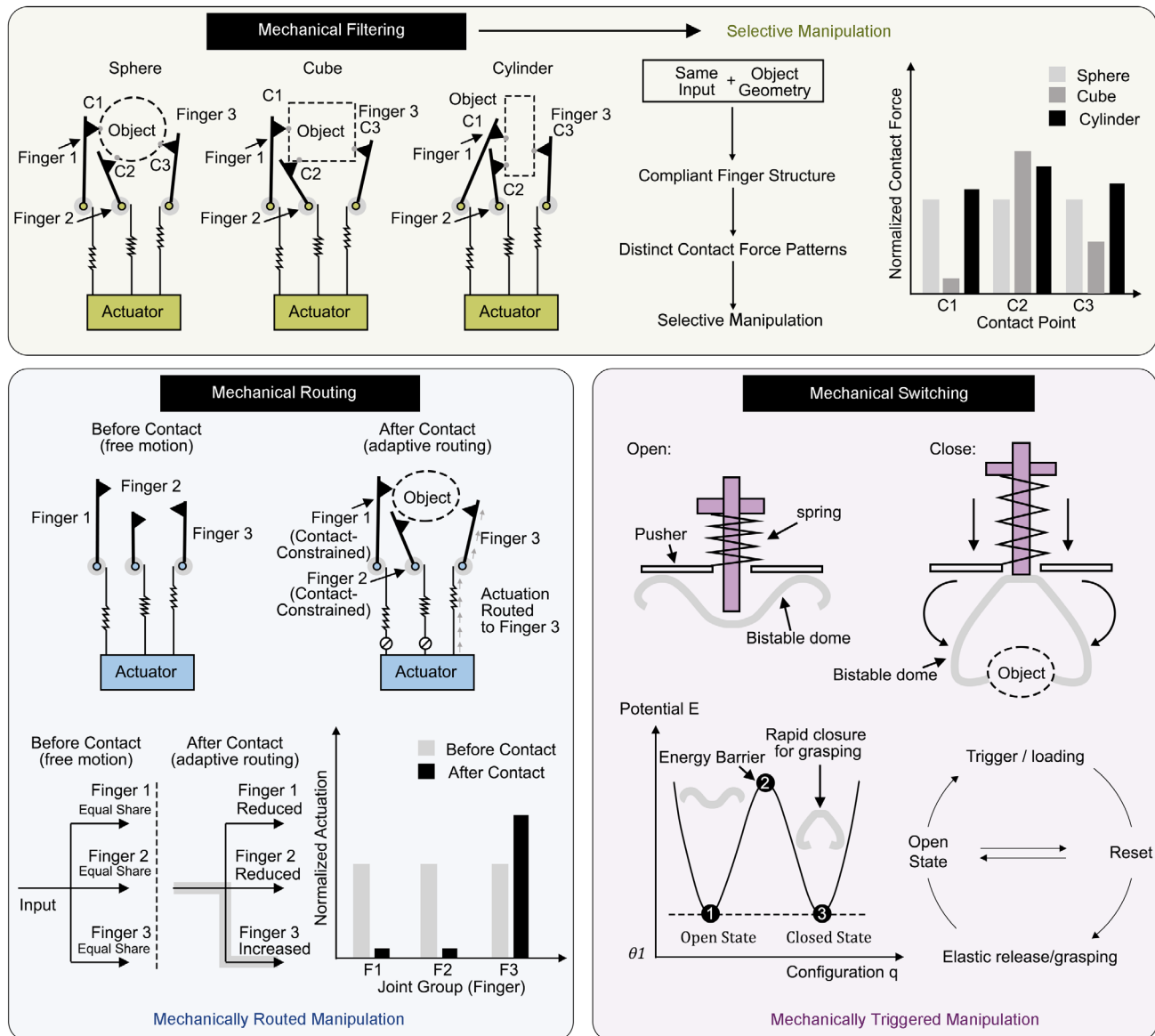


FIGURE 4 | Mechanical filtering (top) maps the same actuator input and different object geometries into distinct contact-force patterns through a compliant finger structure, enabling selective manipulation. Mechanical routing (bottom left) passively redistributes actuation among fingers after contact, such that constrained fingers receive reduced actuation while the unconstrained finger receives increased actuation. Mechanical switching (bottom right) uses a bistable dome to convert trigger loading into snap-through, driving rapid transition from an open state to a closed grasping state. These examples show how manipulation can be achieved through geometry, compliance, and energy landscape design without relying solely on conventional sensing and control. The panels are conceptual schematics distilled from representative robotic systems rather than direct reproductions of any single platform.

the finger's local stiffness profile passively filters the geometric input into a grasp-specific mechanical output [48, 49]. This geometry-dependent filtering underlies the robustness of soft and compliant grippers, which conform to and secure irregular objects across a wide range of shapes without dedicated contact sensors or feedback controllers [12, 13]. Another related example is the universal jamming gripper [50], in which a granular membrane first conforms to an object's geometry and then, under vacuum, selectively solidifies around that geometry through friction, suction, and interlocking, converting object shape directly into grasp stability without finger-level sensing or control.

Routing enables spatial organization and coordination in manipulation. In multifingered hands, actuation can be mechanically redistributed among fingers based on contact state, such that fingers already constrained by object contact receive reduced actuation, while unconstrained fingers receive increased actuation, allowing the hand to passively wrap around objects of unknown geometry. As shown in Figure 4 (bottom left), this adaptive routing arises naturally in underactuated tendon-coupled hands, where a single actuator input is distributed across multiple joints through a compliant coupling network [51]. The routing is not computed but emerges from the coupling geometry and contact-induced constraints, enabling a single-motor hand to achieve stable enveloping grasps across diverse objects that would otherwise require per-joint sensing and control [49, 52].

Switching enables discrete behavioral transitions in manipulation. Bistable structures can accumulate elastic energy under slow loading and release it through snap-through transitions, driving rapid reconfiguration from an open state to a closed grasping state. As shown in Figure 4 (bottom right), a bistable dome gripper stores elastic energy during a preloaded open configuration and rapidly transitions to a closed state when a trigger load is applied, enabling grasp closure times far shorter than the actuation timescale, a strategy exemplified by Venus flytrap-inspired soft grippers that capture prey or objects through snap-through instability [53, 54]. The energy landscape governs both the trigger threshold and the closing dynamics, embedding the grasp-triggering transition entirely in the physical structure.

For manipulation, operation-level metrics can be translated into grasping-specific quantities such as grasp success rate, contact-force distribution, object-shape tolerance, closure time, holding force, reset energy, and the number of sensors or independently actuated joints required for stable grasping. These quantities provide a task-level view of how mechanical filtering, routing, and switching reduce sensing and control requirements during physical interaction with objects.

More broadly, these operations blur the conventional separation between locomotion and manipulation. ReachBot [55], which traverses lava tubes by grasping rocky surfaces with microspine-tipped booms, exemplifies this unity: its grippers combine compliant filtering, which selects viable contact points among surface asperities, with local switching transitions as individual spines latch onto graspable features under load. The same mechanically intelligent interface therefore serves as both feet and hands, suggesting that the boundary between locomotion and manipulation reflects the granularity of electronic control rather than an intrinsic physical distinction. So far, this framework has focused on

mechanical inputs directly applied to the structure; responsive materials extend it further, enabling nonmechanical environmental stimuli to participate in mechanically intelligent behavior.

4 | Responsive Materials as a Transduction Layer

Responsive materials extend the mechanical intelligence framework by enabling nonmechanical environmental stimuli to participate in structure-embedded behavior. These materials act as a transduction layer that converts thermal, optical, magnetic, hygroscopic, or chemical inputs into mechanical changes of the constituent material [56]. Specifically, stimulus-induced molecular reconfiguration within the material, such as phase transitions, anisotropic swelling, or domain rotation, modifies local properties, including viscoelasticity, strain, and internal stress. These material changes either generate mechanical deformation that enters the structure or tune the structure's mechanical parameters, such as stiffness, damping, internal stress, and instability thresholds. Responsive materials therefore do not constitute the fourth mechanical operation. Instead, they expand the range of environmental inputs that can be mechanically expressed and subsequently processed through filtering, routing, and switching. The following subsections organize responsive materials by the stimuli they transduce while tracing how each transduction pathway alters input selectivity, signal propagation, and state transitions (Figure 5).

4.1 | Thermal Transduction

Thermal input drives mechanical state changes by altering material phase or viscoelastic properties. In shape-memory polymers, crossing the glass transition temperature produces a sharp reduction in stiffness that releases stored strain and triggers deformation [23]. More generally, thermally induced changes in stiffness and damping modify characteristic response times and shift structural cutoff frequencies, thereby tuning filtering by altering the selectivity and bandwidth of the mechanical response [57]. Spatial temperature gradients produce nonuniform deformation fields that preferentially direct strain along thermal pathways, enabling routing of mechanical signals through the structure by establishing geometry- and stimulus-defined propagation paths [58]. When heating drives the system across an instability threshold, abrupt configuration changes occur, enabling switching between discrete states as the thermal input crosses the energy barrier separating stable configurations [59].

4.2 | Optical Transduction

Optical stimuli provide remote and spatially programmable activation [22]. Through photothermal conversion, light absorption induces local heating and generates thermally driven mechanical responses [60]. In photomechanical systems, light-driven molecular reconfiguration produces anisotropic internal stress upon illumination [61]. These changes modify deformation amplitude and response dynamics, thereby tuning filtering by shifting which input frequencies or intensities elicit a significant structural response. Patterned illumination directs deformation along prescribed

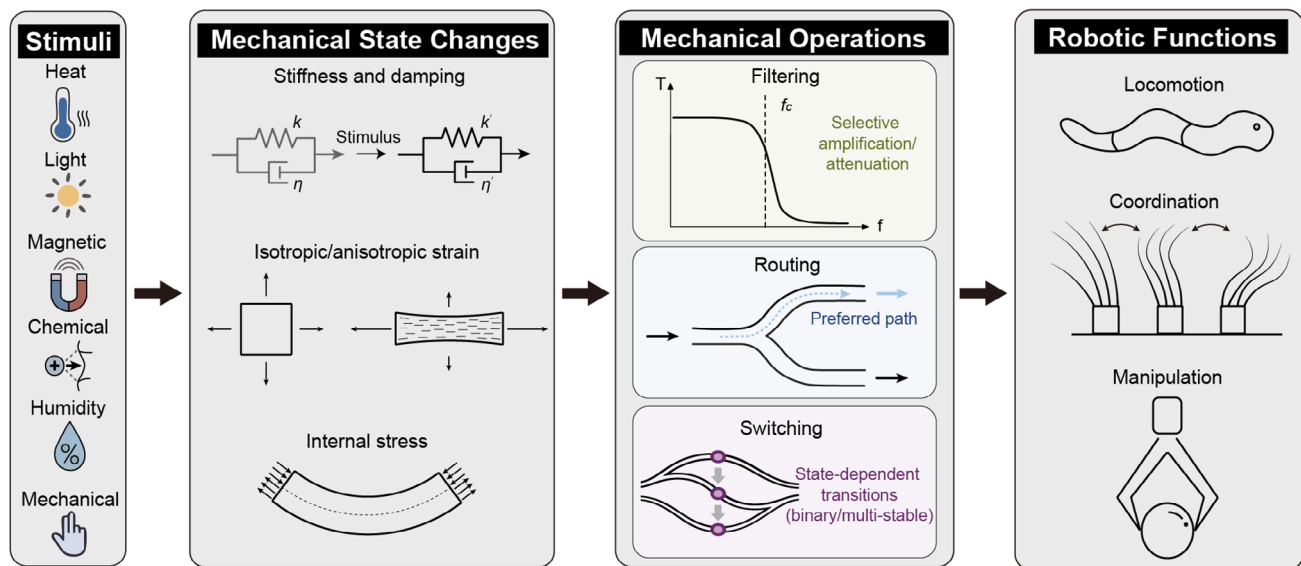


FIGURE 5 | Responsive materials as a transduction layer for mechanical intelligence. Nonmechanical environmental stimuli, such as heat, light, magnetic fields, chemical species, and humidity, are transduced into mechanical state changes within responsive materials, including viscoelasticity modulation, isotropic or anisotropic strain, and internal stress. These state changes are subsequently processed by the three core mechanical operations of filtering, routing, and switching, enabling robotic functions including locomotion, coordination, and selective activation.

pathways, enabling routing of mechanical response through spatially selective activation that defines preferred signal propagation paths within the structure [62]. When light-induced deformation drives the structure across instability thresholds, switching between configurations occurs, with the optical dose serving as the control parameter that triggers discrete-state transitions [63].

4.3 | Magnetic Transduction

Magneto-responsive materials convert magnetic fields into mechanical response through forces and torques acting on embedded magnetic particles or domains [24, 64]. Field strength and direction modulate deformation amplitude and response time, tuning filtering by controlling which input magnitudes and orientations produce significant mechanical output [65]. Spatially encoded magnetization establishes preferred directions for stress generation, enabling routing along geometry-defined pathways where the programmed magnetic domain pattern determines the spatial organization of the mechanical response [66, 67]. When magnetic loading drives the structure across an energetic threshold, abrupt configuration changes occur, enabling switching between discrete mechanical states, with the applied field acting as the trigger that crosses the bistable energy barrier [68, 69].

4.4 | Chemical and Hygroscopic Transduction

Hygro-, solvent-, and chemo-responsive materials couple environmental composition into mechanical deformation through mass sorption and chemical equilibration [56]. Swelling modifies stiffness and generates internal stress, changing response amplitude and timescale, thereby tuning filtering by shifting the characteristic frequencies and magnitudes to which the structure responds selectively [70]. Spatially patterned or anisotropic swelling routes deformation along prescribed paths, where the spatial

distribution of material composition defines preferred propagation directions for the mechanical response [71, 72]. Changes in stiffness or interfacial constraints shift instability thresholds, enabling switching between configurations as the chemical or hygroscopic input crosses the critical condition for snap-through or buckling [73]. In these systems, the stimulus that drives deformation also encodes environmental information, allowing the material to function as both sensor and actuator.

Beyond multiphysics signal coupling, responsive materials can also serve as media for harvesting ambient energy to drive filtering, routing, and switching. Environmental energy, such as heat, light, humidity, or magnetic fields, can be absorbed and converted into mechanical work through phase change, swelling, or field-induced stress [27, 56], generating deformation, shifting instability thresholds, or releasing stored elastic energy, thereby enabling actuation without dedicated power electronics [59]. In this way, responsive materials expand both the range of accessible inputs and available energy sources, while structural dynamics determine how mechanically expressed signals propagate and produce robotic behavior. Across these examples, the specific stimulus varies, but the architectural role of responsive materials remains the same: they convert environmental information and ambient energy into mechanical variables that can be selected, directed, or thresholded by the body. Responsive materials therefore strengthen mechanical intelligence not by replacing filtering, routing, and switching but by supplying new input and energy channels through which these operations can be activated, tuned, and combined.

5 | Positioning Mechanical Intelligence in Existing Frameworks

To clarify the scope of mechanical intelligence, we position it relative to several related concepts in robotics and physical computation.

5.1 | Reservoir Computing

Reservoir computing provides a more specific example of how physical systems can contribute to information processing [74, 75]. In reservoir-computing-based mechanointelligence [76, 77], for example, nonlinear mechanical dynamics project inputs into high-dimensional physical state spaces that can be exploited for tasks such as perception and classification. These approaches demonstrate that physical systems can serve as computational resources, but they do not explicitly characterize the particular functional operations implemented by mechanical structures in robotic contexts.

5.2 | Embodied and Situated Intelligence

The ideas above are also consistent with the broader paradigm of embodied and situated intelligence, in which behavior emerges from the tight coupling among body, controller, and environment rather than from centralized, model-based control alone [78–82]. Importantly, embodied intelligence is not tied to a particular implementation substrate. Intelligent behavior may arise from body–environment interaction even when much of the sensing, processing, and decision-making is carried out by cameras, electronic sensors, and digital computation, including recent paradigms such as vision-language-action models [83, 84] and other foundation-model-based controllers [85, 86].

5.3 | Morphological and Physical Intelligence

A growing body of work has emphasized that physical morphology, material properties, and body dynamics can directly contribute to

behavior [87]. This perspective appears in concepts such as morphological computation [88, 89] and physical intelligence [90–95], which both recognize that part of sensing, processing, or control can be offloaded from centralized computation into the physical substrate. Recent perspectives in soft robotics have further organized these ideas by classifying different forms of intelligence in terms of adaptive shape, function, and mechanics [96, 97].

Mechanical intelligence, as used in this work, can be understood as a more specific concept within the umbrella of physical intelligence. While physical intelligence can arise through various physical processes, such as chemical, thermal, magnetic, and mechanical ones, mechanical intelligence specifically refers to intelligence enabled by mechanical processes. In this sense, mechanical intelligence is not positioned in opposition to the aforementioned ideas but provides a more explicitly mechanistic perspective on how distributed functionality can be realized in robotic systems. This framing connects to a long-standing question in robotics of whether intelligence should primarily reside in centralized control, “brains with bodies,” or be distributed within the physical substrate itself, “bodies with brains” [98]. Mechanical intelligence makes this idea more concrete by identifying mechanical operations such as filtering, routing, and switching through which distributed functionality can be realized in robotic systems. This view also aligns with emerging discussions in robotics and mechanics that recognize the potential for mechanical structures to encode responsiveness, adaptation, and functional behavior directly [99–101].

To clarify these distinctions, Table 2 compares mechanical intelligence with related concepts across several dimensions. Mechanical intelligence is not intended to replace broader frameworks such as

TABLE 2 | Mechanical intelligence in relation to neighboring frameworks. Mechanical intelligence builds on broader concepts such as embodied intelligence, morphological computation, physical intelligence, and reservoir computing, while emphasizing the specific mechanical operations through which body dynamics implement robotic functions.

Framework	Primary question	Substrate	Typical role of body	Relation to this Perspective
Embodied intelligence	How does body–environment coupling shape behavior?	Body, controller, environment	Broad coupling principle	Mechanical intelligence provides a mechanism-level account of how body dynamics contribute to robotic function.
Morphological computation	How does morphology reduce control complexity?	Shape, compliance, dynamics	Offloads computation	Mechanical intelligence specifies recurring mechanical operations, including filtering, routing, and switching.
Physical intelligence	How can physical systems perform intelligent functions?	Materials, structures, fluids, fields	Broad physical substrate	Mechanical intelligence can be viewed as the mechanically mediated subset of physical intelligence.
Reservoir computing	How can nonlinear dynamics map inputs to high-dimensional states?	Dynamical systems	Computational resource	Mechanical intelligence overlaps with mechanical reservoir dynamics, but focuses on robotic function rather than primarily classification or prediction tasks.
Mechanical intelligence	How can mechanical dynamics implement robotic functions?	Geometry, compliance, contact, topology, energy landscape	Directly transforms inputs into robotic operations	This Perspective focuses on mechanical intelligence as a design framework for embedding filtering, routing, and switching into robotic bodies.

embodied intelligence, morphological computation, physical intelligence, or reservoir computing. Instead, it specifies how mechanical structures contribute to robotic function through a concrete set of operations, namely, filtering, routing, and switching. Whereas existing frameworks establish that the body can contribute to intelligent behavior, this perspective emphasizes the mechanism-level pathways through which body dynamics implement robotic functions. This level of specificity is intended to provide actionable design guidance while remaining consistent with the broader conceptual traditions within which mechanical intelligence sits.

6 | Advantages of Mechanical Intelligence

Compared with robotic architectures that rely primarily on electronic sensing, computation, and control, mechanical intelligence offers several system-level advantages. By embedding part of sensing, signal processing, actuation, and even energy transduction directly into structural dynamics and material response, mechanically intelligent systems offer several natural advantages over their electronic counterparts:

6.1 | Robustness

Electronic sensing and control systems are sensitive to environmental extremes such as temperature variation, radiation, high- or low-pressure, and chemical exposure. Maintaining reliable operation in these conditions often requires protective packaging, redundant circuitry, or increased power consumption. When some robotic functions are directly encoded in structural dynamics, robotic behavior can persist even under reduced or no digital control. Responsive materials, acting as a transduction layer, further enhance robustness in two ways. First, they allow environmental stimuli such as heat, light, magnetic fields, humidity, or chemical signals to directly generate mechanical responses, reducing reliance on dedicated electronic sensors for specific environmental stimuli. Second, they provide pathways for harvesting ambient energy for actuation, reducing dependence on onboard batteries, or external power. As a result, robotic systems can maintain function even in environments where conventional electronic subsystems are limited and may even operate without onboard batteries.

6.2 | Miniaturization

Mechanical intelligence enables fabrication-integrated function by embedding robotic capability directly into structural geometry and material composition. Mechanisms such as filtering, routing, switching, and stimulus-driven actuation are built into the physical body rather than being added through discrete electronics. As a result, mechanical intelligence offers a natural advantage for miniaturization. By contrast, in fully electronic systems, batteries, interconnects, and processors often limit how small the overall system can become, especially when distributed sensing and communication are required.

6.3 | Scalability

Mechanical intelligence also offers advantages for scalable robotic systems, especially when fabrication cost, system volume, and integration complexity are important considerations. This is particularly relevant for modular, swarm, and other distributed robotic systems, where equipping every unit with electronic sensors, controllers, batteries, and communication modules can be costly and difficult to implement at scale. In mechanically intelligent systems, part of the coordination can instead emerge from direct local physical interaction [16]. Through structural coupling and material response, deformation, stress, and activation can propagate across neighboring units, allowing large assemblies of relatively simple components to respond selectively to shared or local stimuli and organize through interaction without dense wiring, explicit communication, or centralized computation.

6.4 | Energy Efficiency

Conventional control architectures rely on continuous sensing, state estimation, and feedback computation. Even when environmental conditions are stable, controllers often operate at fixed sampling rates, consuming energy to monitor and process signals. Mechanical intelligence shifts part of this workload into passive physical dynamics. Structural filtering requires no active monitoring, routing occurs through physical coupling, and switching activates only when thresholds are crossed. Because sensing and actuation occur through event-driven physical interaction, systems respond only when environmental conditions demand it. This reduces reliance on continuous computation and external power, improving overall energy efficiency.

7 | Limitations and Design Trade-Offs

While mechanical intelligence expands the architectural design space of robotics, it also introduces distinct constraints that differ from those of purely digital control. Because mechanical functions are embedded in physical structure, their performance depends on geometry, material properties, contact conditions, fabrication quality, and energy landscapes. These dependencies create trade-offs in programmability, durability, reproducibility, modeling, and system integration. Understanding these limitations is essential not only for evaluating mechanically intelligent systems but also for deciding which functions should be embedded in the body and which should remain under digital control.

7.1 | Limited Programmability

Unlike digital controllers, whose behavior can be modified through software updates, mechanically encoded transformations are often defined by geometry, material properties, contact conditions, and energy landscapes. Filtering characteristics, routing pathways, and switching thresholds are therefore commonly determined during design or fabrication. Altering these behaviors may require structural redesign rather than simple parameter adjustment, limiting programmability and task flexibility.

relative to purely digital systems. Responsive materials and tunable architectures can partly relax this constraint by allowing stiffness, damping, internal stress, or instability thresholds to be modified after fabrication, but their range, speed, reversibility, and durability remain important design considerations.

7.2 | Durability and Hysteresis

A second challenge concerns durability under repeated operation. Mechanically intelligent systems often rely on the same physical properties that are susceptible to fatigue, wear, frictional degradation, material aging, or plastic deformation. In filtering systems, repeated cycling can shift resonant frequencies, damping ratios, or bandwidths. In routing systems, wear, contact evolution, or interface degradation can alter load paths, transmission ratios, and spatial localization. In switching systems, hysteresis, threshold drift, or accumulated damage can change the force or energy required to trigger a transition. These effects can be useful when mechanical memory is desired, but they can also reduce repeatability and long-term reliability.

7.3 | Fabrication Sensitivity

Mechanical intelligence is also sensitive to fabrication variability. Because mechanical operations depend on precise structural dynamics, small deviations in geometry, material stiffness, damping, residual stress, surface roughness, or boundary conditions can shift resonant modes, alter deformation pathways, or modify instability thresholds. In systems relying on nonlinear switching or resonance-based activation, such deviations may qualitatively change behavior rather than merely perturb performance. This sensitivity is especially important in miniaturized, modular, or large-scale distributed systems, where unit-level variations can accumulate into system-level variability. Ensuring reproducibility therefore requires tolerance-aware design, calibration, and close integration of modeling, fabrication, and experimental validation.

7.4 | Modeling Complexity

Mechanically intelligent systems often involve coupled nonlinear dynamics, contact interactions, friction, material nonlinearity, and multistable energy landscapes. Predicting behavior across operating regimes can therefore be computationally demanding

and analytically challenging. Unlike digital control architectures, where algorithms can operate on abstract state representations, mechanically encoded intelligence is inseparable from physical embodiment. Accurate design may require multiphysics simulation, reduced-order modeling, experimental identification, and iterative refinement, especially when filtering, routing, and switching are strongly coupled within the same structure.

8 | Summary and Outlook

Taken together, the preceding sections identify filtering, routing, and switching as functional vocabulary for describing how mechanical structures transform inputs into robotic behavior. Specifically, these operations describe how physical structures can selectively admit and amplify inputs, propagate signals across components, and transition between states. In this framework, responsive materials further expand the design space by transducing nonmechanical stimuli into mechanical responses and, in some cases, harvesting ambient energy for actuation. More broadly, this perspective suggests that robotic function need not be implemented solely through electronic subsystems but can instead be partially embedded in the physical body, which directly carries out part of the sensing, processing, and actuation traditionally assigned to electronics. Table 3 summarizes this shift from a controller-centered architecture to one in which intelligence is allocated across body and controller.

8.1 | Hybrid Architecture

The limitations discussed above do not diminish the significance of mechanical intelligence but instead define its complementary role within a broader hybrid architecture. Mechanical intelligence, embedded in the body, is well suited for fast, local, and energy-efficient transformations through structural dynamics and material response. Digital intelligence, implemented in controllers, provides global coordination, programmability, planning, and learning. Rather than competing, the two play complementary roles within a single system. Far from being purely mechanical or purely computational, the next generation of robotic systems will be hybrid, with function distributed across physical and computational layers according to the strengths of each. By working together, such hybrid systems can outperform either purely electronic or purely mechanical systems alone.

TABLE 3 | Redistributing robotic function across body and controller. Conventional robots rely on dedicated electronic hardware for sensing, computation, actuation, and power. In mechanically intelligent systems, these functions are partially redistributed into the physical substrate: structural dynamics and material responsiveness contribute to sensing, processing, and actuation, while responsive materials can harvest ambient energy to reduce reliance on onboard power supplies. This redistribution reframes intelligence and energy as properties allocated across physical and computational layers rather than concentrated solely in electronic control.

Robotic function	Conventional implementation	Mechanical intelligence implementation
Sense	Electronic sensors	Mechanical filtering + material-mediated transduction
Process/coordinate	Digital controller/computation units	Mechanical routing and state transitions
Act	Motors and actuators	Mechanical energy release + material-driven deformation
Power	Onboard battery/external supply	Ambient energy harvesting (thermal gradients, humidity, and light)

8.2 | Future Directions

Viewing robotics as a hybrid system opens up new opportunities while also introducing new challenges for current design frameworks. Several open research directions follow. First and foremost, although this perspective identifies filtering, routing, and switching as core operations of mechanical intelligence, we still lack a systematic framework for combining them into more complex mechanically intelligent systems. Unlike electronic circuits, where functional elements can often be composed modularly, mechanical systems are usually realized as connected structures in which different operations are not implemented independently but are instead strongly coupled. This makes the systematic design of higher-level mechanically intelligent architectures a nontrivial problem. More broadly, this challenge echoes calls for stronger intellectual foundations in robotics, including new dynamical systems theory and physically grounded programming languages [100]. Second, inverse design algorithms are needed to map desired mechanically intelligent functionalities onto structural and material designs, enabling the systematic synthesis of mechanically intelligent systems. Third, hybrid systems must integrate mechanical intelligence with digital control in a coherent way, where mechanical intelligence is designed to reduce the sensing and computational burden on the controller. How to systematically design such mechanical intelligence, or even how to quantitatively measure its contribution, remains an open question. Lastly, advances in responsive and tunable materials may enable reprogrammable and reconfigurable mechanical intelligence but also raise major fabrication challenges for building complex three-dimensional architectures from responsive materials. This direction also clarifies that mechanical intelligence is not limited to passive or fixed behavior: fabrication-encoded structures provide clear examples of filtering, routing, and switching, while responsive materials and hybrid mechanical–digital architectures allow these operations to be tuned, reconfigured, or coordinated after fabrication. In summary, realizing this vision will require codesign frameworks that jointly optimize geometry, material, and control under fabrication constraints, opening a new frontier in robotics where intelligence is engineered across both physical form and computational control.

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Conflicts of Interest

The authors declare no conflicts of interest.

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