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# Evolution of Physical Intelligence Across Scales

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## ABSTRACT

Nature shows that intelligence did not begin with brains or algorithms—it began with matter itself. This review spotlights “physical intelligence,” the problem-solving capability of materials, structures, and interactions that sense, adapt, and compute directly through physics. Long before brain emerged, cells, plants, and insect swarms were exploiting physical laws to navigate, coordinate, and thrive. Today, these same principles inspire breakthroughs in robotics and engineering: soft robots that move without explicit programming, origami architectures that reconfigure on demand, and swarms of simple agents that collaborate like living colonies. By tracing physical intelligence across scales, from molecules to collectives, we highlight its role as the foundation of embodied intelligence and a blueprint for rethinking machine design. Embedding intelligence into matter itself, rather than treating hardware as passive vessels for software, offers a pathway to systems that are resilient, efficient, and adaptive. The future of artificial intelligence may depend as much on intelligent physical bodies as on smart code.

## 1 | Introduction

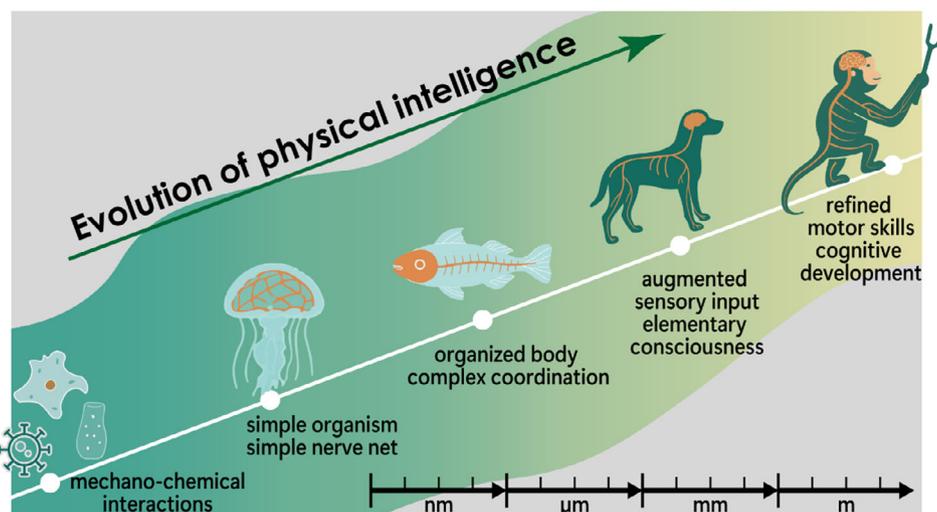
The quest to understand intelligence often begins with biological cognition or artificial neural networks [1–3]. In recent years, scientists increasingly recognize embodied intelligence as a paradigm-shifting approach where intelligent behavior emerges through physical interactions between agents and their environments [4, 5]. Although most studies still focus on the computational side, it should not be overlooked that a profound form of problem-solving capability exists far earlier in the evolutionary chain: physical intelligence intrinsically embedded within materials, structures, and their interactions with the environment [6–10]. The innate capacity of materials, structures, and dynamical systems to process information, adapt, and solve problems through physical laws, which lays the physical foundation of embodied intelligence [11, 12]. This phenomenon transcends biological boundaries, manifesting from molecular machinery to collective swarms [13, 14], and represents an evolutionary bedrock upon which neural and computational intelligences scaffold [15–17]. Here, ‘across scales’ does not solely denote geometric length scales, but rather hierarchical levels of physical organization and information processing, spanning material responses,

structural mechanisms, embodied interactions, and collective dynamics.

Natural selection has refined physical intelligence across scales for billions of years [18, 19], as illustrated in Figure 1. Primitive organisms lacking neural systems relied solely on morphology-triggered behaviors, such as the Physarum’s nutrient-seeking via chemical feedback [20, 21], and plants’ seed dispersal mechanisms exploiting fluid mechanics [22, 23]. This material-based decision-making emerged through evolutionary tinkering, optimizing responses to environmental pressures like gravity, fluid dynamics, or surface chemistry [13, 24, 25]. Crucially, this physical layer preceded and shaped neural intelligence: the evolution of multicellularity demanded distributed sensing and response networks, driving the development of neural systems that could interpret and augment pre-existing physical computations [26, 27]. For instance, musculoskeletal biomechanics coevolved with neural control, offloading motion coordination tasks to resonant dynamics, effectively embedding smart physical shortcuts that reduce computational burden [28, 29]. This synergy persists in modern organisms, where neural systems leverage physics to achieve efficiency unattainable through computation alone, as

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**FIGURE 1** | Evolution of physical intelligence across scales in various dimensions (e.g., length, time, quantity, and complexity) of physical organization in biological systems. From single cells interacting with their environment to refined motor skills and cognitive development in primates, each stage illustrates how increasing complexity in physical body scaffolded the emergence of higher intelligence.

exemplified by arthropod exoskeleton enabling rapid locomotion with minimal neural input [30, 31].

In recent years, the same principles that govern biological physical intelligence are inspiring breakthroughs in artificial systems [32, 33]. Engineers increasingly exploit material properties and mechanical interactions to create robots that require minimal programming, such as origami metamaterials with encoded fold sequences [34, 35], and jamming grippers conforming passively to objects [36]. Swarm robots of simple agents self-organize using physical cues like vibration or airflow, mirroring insect colonies [37–39]. Yet designing such systems demands a paradigm shift beyond conventional computational intelligence [32, 40]. Rather than treating hardware as a passive executor of digital algorithms, we must codesign matter and computation by embedding intelligence in mechanics, topology, and material responses from inception [41–43].

In this review, we chart the development of physical intelligence in artificial systems, across hierarchical scales. Similar to biological evolution, we start from the foundational layer of intelligence embedded in programmable matter and adaptive structures (Section 2). This intrinsic capability is then expressed and extended through physical interactions with the environment, where force, flow, and field exchanges perform computation and enable real-time adaptation (Section 3). These agent-level interactions, in turn, provide the substrate for collective intelligence to emerge at the system scale through decentralized physical couplings (Section 4). Weaving through these scales, we finally synthesize the cross-scale constraints and design principles that govern how intelligence is integrated across different physical regimes. This trajectory underscores physical intelligence as the bedrock upon which embodied intelligence (Section 5) is built, framing it as a universal principle for adaptive systems (Section 6).

## 2 | Intelligence Embedded in Materials and Structures

The foundational layer of physical intelligence arises not from centralized processing or explicit programming, but from the

innate properties, architectural design, and delocalized, distributed information processing of physical matter. Importantly, not all stimulus–response material behaviors qualify as material intelligence. In this review, material-level physical intelligence refers to deliberately encoded material responses that are task-relevant, reusable, and functionally coupled to higher-level structural or system behaviors, rather than generic thermodynamic reactions. For instance, the material itself becomes an active participant [44–48], encoding mechanisms for sensing [49–52], response [6, 53–55], adaptation [54, 56, 57], and even rudimentary ‘decision-making.’ [58, 59] This section explores the inherent intelligence of materials and structures in sensing and adapting to their environment, showcasing how ingenious physical designs enable autonomy. This foundational intelligence provides the essential substrate for more complex, emergent forms of physical intelligence, including the structural intelligence often termed mechanical intelligence [60, 61]. This embedded intelligence is mechanism-agnostic, emerging equally from the chemistry of polymers [62–65], the mechanics of metamaterials [66–68], or the geometry of a folded origami structure [69, 70], blurring the line between passive substance and active cognitive entity, and forming the bedrock for truly embodied cognitive systems.

### 2.1 | Material-Level Intelligence through Self-Sensing, Self-Actuation, and Self-Healing

Materials are able to perform self-sensing [71, 72], self-actuation [73–75] as well as self-healing [76, 77] by leveraging their inherent chemical or physical properties [50]. Instead of relying on centralized control, the intelligent behavior of materials often arises from the local responses of distributed functional units within the material, enabling complex and adaptive behaviors. With these capabilities, material-level intelligence is attracting increasing attention in fields such as aerospace and biomedical engineering, offering promising avenues for building adaptive, responsive, and autonomous systems [78–80].

Self-sensing materials detect changes in temperature, stress, or light and convert them into measurable signals [81–84]. For

example, piezoelectric materials generate electrical signals under mechanical stress [85, 86], while photochromic and thermochromic materials change color with light or temperature variations [87, 88]. Recent advances have further enabled multimodal self-sensing materials, in which multiple physical signals are simultaneously encoded within a single material system. Notably, MXene-based conductive coatings and composites have emerged as highly sensitive self-sensing platforms due to their high electrical conductivity, large surface area, and strong interfacial coupling with polymer matrices, enabling real-time sensing of strain, pressure, temperature, and even chemical stimuli [89, 90]. In addition, hard magnetic graphene nanocomposites have been demonstrated to simultaneously sense electrophysiological, mechanical, and electrochemical signals within a unified material architecture [91].

Self-actuation materials transform stimuli into mechanical motion or shape changes [92–96]. Thermally responsive materials like shape memory alloys/polymers and liquid crystal elastomers deform above threshold temperatures [73, 97]. Magnetic and electric fields trigger actuation in magneto-responsive composites [98, 99] and electroactive polymers [55, 100], respectively. There are also other materials that respond to light, pH, or humidity [101, 102].

Self-healing materials autonomously repair structural damage to restore functionality, enhancing durability [76, 77]. Commonly, polymer networks with dynamic covalent or reversible hydrogen bonds reform broken linkages after damage [103, 104], such as many hydrogels.

Together, self-sensing, self-actuation, and self-healing functions can be combined pairwise or fully integrated within a single material, enabling multifunctional intelligent systems tailored to diverse applications [49, 50, 63].

## 2.2 | Structure-Level Intelligence through Adaptive and Responsive Deformations

Beyond material-level functions, intelligent behaviors can also emerge from structural design itself. Structures can exhibit adaptive and responsive deformations under external stimuli by leveraging (i) bioinspired geometries at the architectural level [105, 106], (ii) mechanically programmable metamaterials with tailored microstructures [69, 107], or (iii) controlled mechanical instabilities as functional mechanisms [108–110]. Rather than requiring centralized control or electronics, the intelligent behavior of structures often arises from spatially distributed mechanical interactions encoded into their form, enabling dynamic and environment-responsive functions. These capabilities propel the rise of structure-level intelligence in fields like soft robotics and adaptive architectures [111].

Bioinspired structures mimic the forms and mechanics of natural systems to achieve adaptive and efficient deformations [112, 113]. Examples include honeycomb and nacre-inspired architectures known for strength and toughness [114, 115], as well as spiral structures like climbing plant tendrils and drill-shaped seeds that autonomously coil or unwind in response to environmental cues [116, 117].

Programmable mechanical metamaterials achieve adaptable stiffness and strength through geometry-driven designs rather

than material changes [118, 119]. For example, origami-inspired patterns can tune flexibility and enable complex folding behaviors [108], tensegrity structures provide lightweight frameworks with uniform energy absorption under impact [120], and hybrid mechanical-acoustic metamaterials combine structural support with enhanced shock absorption and vibration damping [68].

Controlled mechanical instabilities like buckling and bistability enable structures to achieve large or rapid shape changes by harnessing nonlinear mechanical responses [121, 122]. Without active materials or external control, these mechanisms allow energy storage and release, shape reconfiguration, and multiple stable states.

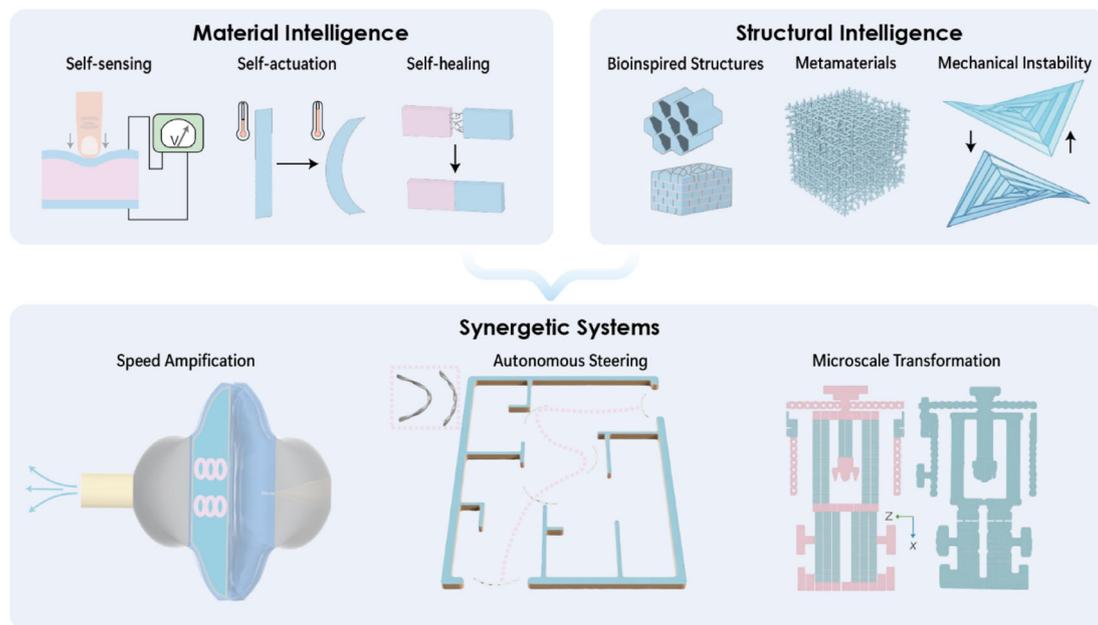
## 2.3 | Synergy of Material and Structural Intelligence

The synergy of material and structural intelligence transforms passive components into active, adaptive systems [122–126]. Material intelligence endows materials with the ability to self-sensing, self-actuation, or even self-healing by leveraging their intrinsic physical or chemical properties. Structural intelligence, on the other hand, complements and extends these capabilities by guiding, amplifying, or reprogramming material responses through geometry, topology, and mechanical coupling. For example, instability-based structures can convert small material deformations into rapid motions such as jumping or swimming [122, 127]; bioinspired helical structures combined with liquid crystal elastomers enable autonomous steering of actuator under uniform thermal stimulation [58]; and metamaterial architectures integrated with photoresist materials achieve microscale transformation in response to pH changes [123]. This synergy between material and structural intelligence enables soft systems that are not only responsive and adaptive, but also programmable and multifunctional, as shown in Figure 2.

The intelligence embedded in materials and structures provides the fundamental physical substrate for adaptive behavior. However, this embedded potential is only activated when the material or structure engages dynamically with its surroundings. The next level of physical intelligence thus emerges not from matter alone, but from the real-time interplay of forces, fields, and flows between an agent and its environment. This shifts our focus from intrinsic properties to interaction-dominant dynamics, where the physics of the engagement itself becomes the medium of computation and control.

## 3 | Intelligence Driven by Physical Interactions

Beyond embedded intelligence, real agents always operate within fields, contacts, and flows. Through force, they exchange energy, momentum, and information with their surroundings [8, 128–131]. In this context, mechanical interactions not only shape motion but also perform computation and control [132–134]. Building on these ideas, this section develops the framework of ‘interaction as computation,’ starting from the fundamentals of force and its organization- and regime-dependent dominance. We explain how agents adapt through physical couplings, how weak interactions generate emergent order, and finally outline cross-scale limits and design principles for robotics.



**FIGURE 2** | The schematic of material- and structure-level physical intelligence. Material intelligence imparts innate smart capabilities such as self-sensing, self-actuation, and self-healing. Structural intelligence utilizes bioinspired architectures, metamaterials, and programmable instabilities to achieve adaptive shape-morphing. Together, they form synergetic systems, where the integration of material and structural intelligence gives rise to advanced behaviors: structural mechanisms such as chamber buckling amplify the deformation of self-actuated materials to achieve high-speed actuation [122]; the coupling of bioinspired helical structures with responsive materials enables autonomous steering under uniform stimuli [58]; and the combination of metamaterial architectures with self-actuated materials allows for microscale transformation in response to environmental cues [123]. This framework illustrates a pathway toward next-generation soft robotics and intelligent structures [60]. These panels are adapted from refs [108, 109, 113].

### 3.1 | Fundamental Interaction of Forces

Force is the basic medium of exchange between agents and environments [132]. The four fundamental interactions—strong, weak, electromagnetic, and gravitational—channel energy and information transfer across scales [133, 134]. They may be conservative, shaping landscapes of motion, or dissipative, converting energy into heat and stabilizing dynamics. From a different perspective, reciprocal couplings conserve momentum, while nonreciprocal ones, common in active matter, enable directional motion [135].

Physical interactions exhibit distinct dominant forces across different scales. At the macroscale, phenomena such as locomotion and material transport are governed by gravity, inertia, and friction [135–137]. In contrast, microscale interactions are dominated by van der Waals forces, hydrogen bonding, and electrostatic effects, which primarily control adhesion and molecular assembly [138–140]. At the interfaces between media, capillary forces sculpt morphological features like droplets and thin films [141, 142]. These multiscale regimes can be unified through key dimensionless groups: the Reynolds number distinguishing inertial and viscous flows, the Capillary number comparing viscous to interfacial forces, and the Bond number contrasting gravity with surface tension [143]. Additionally, the Deborah and Péclet numbers respectively characterize material relaxation timescales and transport efficiency [144].

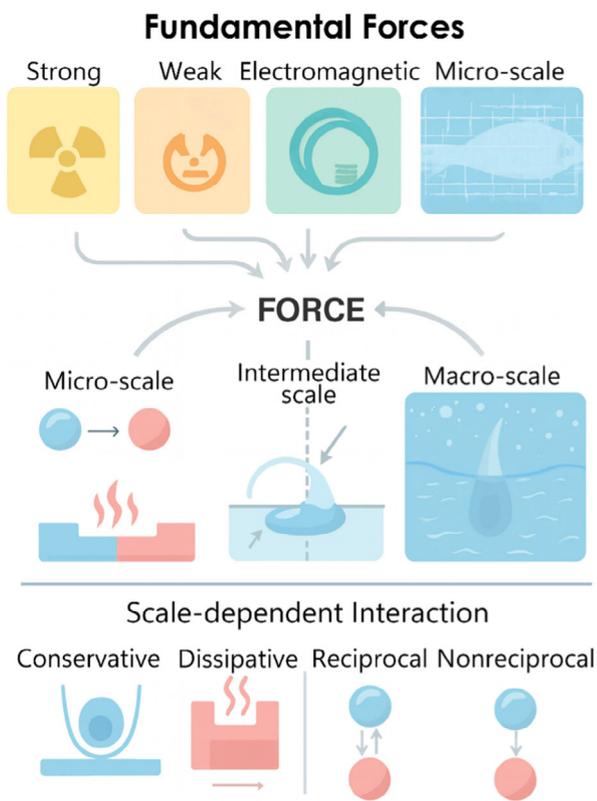
These physical interactions transmit information as well as energy. Impedance governs power transfer, while hysteresis, multistability, and phase transitions act as memory and logic [5, 145]. Stick-slip, snap-through, and jamming embody

mechanical computation. Port-Hamiltonian models describe agents and environments as energy-exchanging systems where stability arises from shaping stored and dissipated energy [5]. Figure 3 shows how the fundamental forces shape behavior at micro-, meso-, and macro-scales, and how scale-dependent interactions govern energy transfer, stability, and control in physically intelligent systems.

### 3.2 | Physical Interactions as Single-Agent Adaptation

Adaptation emerges from physical feedback loops—‘policy in physics’—where body, environment, and actuation realize control without heavy computation [5]. Magnetically actuated microrobots steer under rotating fields while viscous drag regulates speed [145]. Acoustic fields trap and propel via radiation forces and streaming, with resonance doubling as sensing. Gradients of light, chemistry, or temperature drive phoresis, producing chemotaxis-like motion. In all cases, actuation and sensing share the same coupling through interaction with the environment, unifying perception and action.

Contact mechanics is one of the design resources for intelligent behavior. Friction and compliance, often treated as noise, provide adaptive control: crawlers switch gaits by altering contacts [146], granular substrates stabilize through rate-dependent friction, and jamming or fibril adhesives conform to shapes for reversible grasping. Fluid–structure interaction further illustrates embodied intelligence. At low Reynolds numbers, nonreciprocal strokes like helical rotation or traveling waves are required for



**FIGURE 3** | Physical intelligence emerges from scale-dependent interactions. Microscale surface forces, mesoscale capillarity and elasticity, and macroscale inertia and gravity. Conservative or dissipative and reciprocal or nonreciprocal couplings, together with field–matter and contact-mediated mechanisms, embed control logic in physics, enabling adaptation and computation with minimal onboard processing.

swimming [132]; geometric mechanics maps shape cycles to displacement. At higher Reynolds numbers, compliant fins and foils exploit vortices and resonance for thrust and stability [135–137].

Morphological computation is also essential. Cells probe stiffness through focal adhesions [147, 148]; plants amplify stimuli via hydraulics [149]. Inspired designs embed strain meshes, piezoelectric lattices, or magnetoelastic fabrics, turning loads into proprioceptive signals. Resonance reduces control bandwidth, bistability enables fast transitions, and damping smooths shocks. Even noise becomes useful: stochastic resonance and Brownian ratchets rectify fluctuations, while dithering aids navigation. Differentiable physics and physics-constrained learning exploit morphology to improve efficiency and robustness.

### 3.3 | From Weak Interactions to Emergent Intelligence

Large-scale order arises from cumulative weak couplings. Local adhesion acts as logic: gecko setae switch adhesion with shear [149], and capillary bridges act as binary switches. Coupling via elastic substrates or fluids produces avalanches mimicking integrate-and-fire [150]. Hydrodynamic and elastic couplings synchronize collectives. Fish exploit wakes [151], cilia phase-lock [152, 153], and robotic swarms use dipoles or linkages for synchronization, resembling Kuramoto models [154] with Stokes or elastic kernels.

Active matter shows similar principles. Reaction–diffusion process generates Turing patterns [155]; active suspensions undergo motility-induced phase separation, forming dynamic clusters; active nematics drive topological defects that transport cargo and enhance mixing [156]. Topology and directional media add robustness. Mechanical and acoustic metamaterials support protected edge modes that guide energy or signals [157]. Non-Hermitian and ‘odd’ elastic systems introduce directional transport. Interaction range, anisotropy, and timescale separation dictate collective phase and memory [151, 156]. Through these mechanisms, collectives perform distributed sensing and inference directly through physics.

### 3.4 | Cross-Scale Limits and Design Principles

Physical intelligence is constrained by physical laws operating across different levels of organization, among which geometric scaling laws play an important role [157]. At small scales, surface forces and Brownian motion dominate, enabling sensitivity and agility [158–162]; at large scales, inertia and stiffness provide power and stability but reduce sensitivity [159, 163, 164]. Microorganisms adapt through morphology [165, 166], while macroscopic systems exploit inertia for efficiency [163].

Limits arise from thermal noise, fluctuation-dissipation, Landauer’s principle, and finite communication bandwidth [167]. Heterogeneity, though complex, expands computational capacity. Cross-scale coordination requires division of labor: nanoscale for sensing, mesoscale for adaptation, macroscale for energy and load. Interfaces must align stiffness, damping, and delay. Task-oriented metrics—impedance spectra, bandwidth, energetic return—quantify interaction performance [160, 161].

Learning and differentiable physics allow joint optimization of morphology and control under passivity constraints [168, 169]. The environment itself can act as a coprocessor: microfluidic ratchets rectify noise [141], magnetic textures encode spatial logic, and acoustic metamaterials route signals [170]. Across scales, three design principles apply: impedance matching for efficient transfer [5], multistability with dissipation for memory and filtering [145], and symmetry breaking for rectification and robust routing [151, 156, 169]. In summary, material- and structure-level intelligence is realized only when coupled to interactions [8, 128], and such weak local interactions provide the basis for collective intelligent behavior [150, 151].

## 4 | Intelligence Emerging from Collective Behavior

In natural and social systems, even simple agents endowed with limited sensory and cognitive capabilities can, through local interactions and decentralized coordination, collectively exhibit emergent behaviors that transcend individual capabilities, often exemplifying collective intelligence [171–177]. For instance, myxobacteria develop complex multicellular architectures called fruiting bodies to survive nutrient depletion [175], paired fish can jointly detect and evade predators with remarkable efficiency [178], ants are able to discover the shortest path to food sources by pheromone-based trail formation [179], and honeybees effectively share foraging information through the waggle dance

[180]. Dorigo, who first introduced the ant colony optimization algorithm [181], highlights that intelligent systems can spontaneously achieve collective adaptation, optimization, and learning through elementary interaction protocols coupled with feedback mechanisms.

#### 4.1 | Evolutionary Game Theory: A Bridge to Understanding the Emergence of Collective Intelligence

In addition to advanced cognitive abilities in individual agents, collective intelligence emerges through continuous, dynamic interactions among group members, manifesting as a self-sustaining form of system-wide complexity [182]. This phenomenon aligns closely with the foundational principles of evolutionary game theory [183], which posits that individuals need not be fully rational from the outset, but can adapt their strategies through repeated interactions and local feedback such that effective behavioral patterns emerge over time. As such, evolutionary game theory provides a dynamic analytical framework for understanding how local individual adaptations can give rise to system-level intelligent behaviors, thereby elucidating the mechanisms through which the wisdom of crowds can emerge spontaneously from local interactions.

According to the framework of evolutionary game theory, defection is often regarded as the evolutionarily advantageous strategy in self-interested biological systems. Yet, cooperation is a pervasive phenomenon in nature, from unicellular organisms to multicellular life forms, and further to socially organized mammals. Although cooperation may appear to be at odds with individual survival logic, it actually signals an emergent intelligence at the system level. Therefore, uncovering the mechanisms that drive the evolution of cooperation provides a critical entry point for understanding how collective intelligence arises and is maintained.

#### 4.2 | Evolutionarily Stable Strategy

In pairwise strategic interactions, cooperators incur a personal cost to benefit others, whereas defectors exploit these altruistic acts without bearing any cost themselves. The Prisoner's Dilemma, a canonical paradigm in game theory, captures the choice between cooperation and defection: mutual cooperation yields  $R$ , unilateral defection gives  $T$  to defector and  $S$  to the cooperator, and mutual defection results in  $P$ , subject to  $T > R > P > S$  and  $2R > T + S$ . In classical game theory, defection is strictly dominant, making mutual defection the unique Nash equilibrium, whereas mutual cooperation yields the highest collective payoff. Even in finitely repeated games, backward induction predicts the collapse of cooperation at every stage. This stands in stark contrast to the widespread cooperation observed in nature, indicating that the assumption of perfect rationality is untenable.

Evolutionary game theory resolves this tension by reframing cooperation as a product of bounded rationality, local interactions, and strategy evolution over time. By treating behavior as dynamically shaped rather than statically chosen, it captures how cooperation can take hold and persist in biological populations. Within the framework of evolutionary game theory, the concept of an evolutionarily stable strategy (ESS), formally

introduced by Maynard Smith and Price [183], refers to a strategy that, once adopted by the majority, cannot be invaded by a small fraction of any alternative mutants. The analysis of ESS is typically based on replicator dynamics, a formalism proposed by Taylor and Jonker [184] to describe the temporal evolution of strategy frequencies under natural selection.

Milinski [178] showed that three-spined sticklebacks adopt a Tit-for-Tat-like strategy during predator inspection, approaching predators with cooperative partners but avoiding when paired with defectors, suggesting that reciprocity can prevent persistent exploitation. However, classical ESS analyses in infinite populations generally favor defection; in contrast, real populations are finite, where stochasticity and discrete strategy transmission critically shape evolutionary outcomes. Nowak et al. [185] proposed a model of evolutionary dynamics in finite populations and introduced the notion of ESS in finite populations ( $ESS_N$ ). Crucially, this framework demonstrates that even when a population is initially dominated entirely by defectors, cooperative strategies such as Tit-for-Tat can invade and spread under natural selection.

#### 4.3 | From Local Interactions to System-Level Emergence

Beyond demographic stochasticity, subsequent research has increasingly focused on the role of interaction structure in shaping the evolution of cooperation. Unlike finite-population models that assume well-mixed interactions, real systems are structured by spatial or social constraints, naturally represented as networks. In a seminal study, Nowak and May [186] modeled the Prisoner's Dilemma on a 2D lattice, where individuals interact locally and update strategies by imitating more successful neighbors. Even under these minimal rules, the system can give rise to strikingly complex spatial and temporal dynamics, including patterns, fractals, and spatial chaos.

In a decisive advancement, Ohtsuki et al. [187] proposed the celebrated ' $b/c > k$ ' rule, offering a remarkably concise condition under which cooperation can persist in structured populations: if each individual has  $k$  neighbors, then cooperation is favored by natural selection when the benefit-to-cost ratio  $b/c$  exceeds  $k$ . At its core, the evolution of cooperation arises because cooperators are more likely to be surrounded by other cooperators, which yields a fitness advantage, allowing cooperative strategies to resist invasion and gradually percolate throughout the system.

The theoretical conclusions were later corroborated by experimental evidence from a behavioral game study [188]. However, the general case with variable numbers of neighbors remained unresolved until Allen et al. [189] introduced a general framework of evolutionary dynamics on arbitrary population structures, ranging from regular lattices to random networks. This framework identifies that cooperation is more likely to evolve in networks where stable bilateral relationships between individuals are prevalent, highlighting the foundational role of enduring partnerships in the formation of cooperative societies. More broadly, this framework reveals the pivotal role of population structure in behavioral evolution, demonstrating that the emergence of cooperation at the macroscopic level critically depends on the interplay between local interaction patterns and global network topology.

#### 4.4 | Mechanism Design for the Emergence of Collective Intelligence

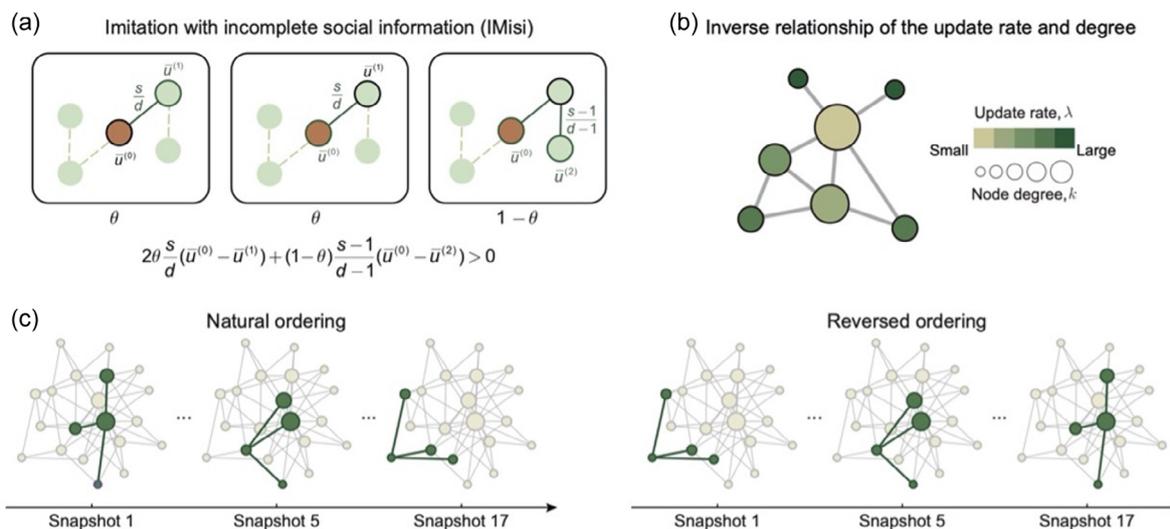
Since the 1970s, the tension between individual-level optimization and collective welfare has garnered sustained interest across various disciplines, including economics, systems science, biology, and computer science. A central focus has been the development of mechanisms that enable the emergence of collectively optimal strategies in decentralized systems. To this end, researchers have drawn upon evolutionary game theory, in conjunction with methods from network science [190, 191], systems science, and artificial intelligence, to investigate the underlying principles governing the emergence of intelligence and the design of incentive structures in complex populations [192]. Figure 4 shows representative mechanistic pathways that have been recently advanced to promote the emergence of the collectively optimal strategy in networked populations.

In human societies and multiagent systems, imitation is a key mechanism for learning and adaptation, and cooperation is highly sensitive to the specific imitation rule employed. To unify these effects, a recent study [193] proposed the imitation with incomplete social information (IMisi) model, distinguishing between personal information (one's own strategy and payoff) and external information (neighbors' strategies and payoffs). The analysis revealed that in the canonical framework of pairwise interactions [189], disregarding personal information in strategy updating maximally promotes the emergence of a collectively optimal strategy. When personal information is taken into account, greater access to external information enhances the evolutionary success of a strategy. Interestingly, in networks with low clustering coefficients, the opposite holds: relying more on personal information and less on external cues proves more conducive to fostering the globally optimal strategy.

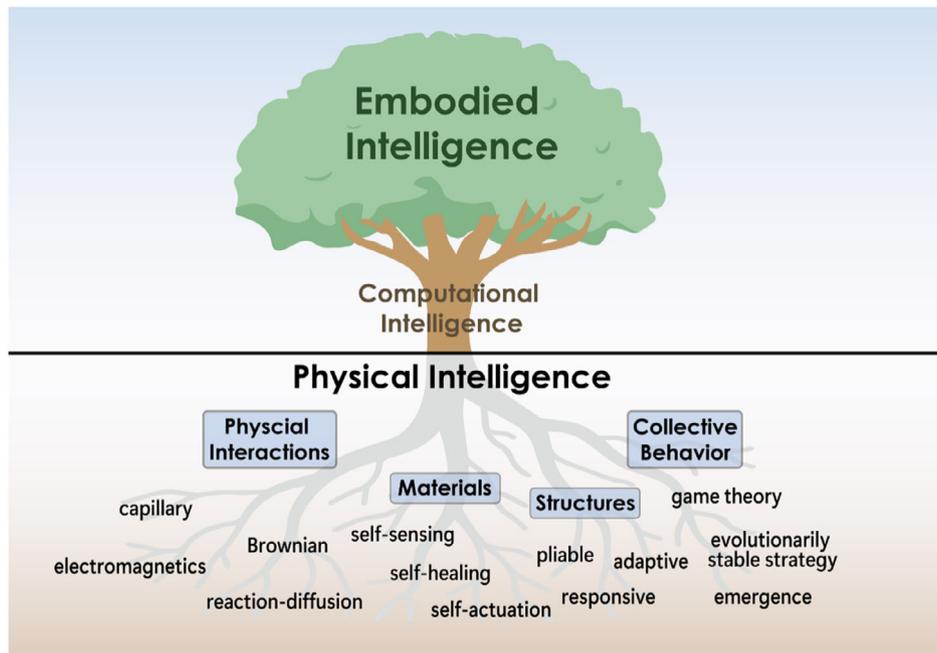
In studies of collective intelligence on complex networks, the update rate of individual strategies is regarded as a key factor shaping evolutionary outcomes. It determines how quickly individuals respond to local information, thereby influencing the diffusion and integration of behavioral patterns within the population. Meng et al. [194] proposed an effective mechanism for personalized strategy updating in heterogeneous populations and demonstrated that, when high-degree nodes update their strategies at a slower rate, the system exhibits a lower analytical threshold for the emergence of the collectively optimal strategy compared to that observed in homogeneous networks.

The emergence of collective intelligence also depends critically on the temporal unfolding of interactions. Unlike static networks, temporal networks capture the dynamic variability of real systems, though their impact on group-level outcomes remains incompletely understood. Recent work [195] highlights that the ordering and timing of interactions shape emergent coordination patterns, with hubs playing a particularly strategic role. Notably, delaying the involvement of highly connected agents can enhance global performance, suggesting a design principle for temporal contact structures that bridges topology with dynamics to foster adaptive collective intelligence.

The mechanisms explored in this section, from evolutionary game dynamics to the pivotal role of temporal networks, demonstrate that collective intelligence constitutes the macroscopic expression of physical intelligence, arising from the orchestration of local interactions. Having charted its progression from the embedded intelligence of materials and structures, through the interaction-driven computation of individual agents, to the emergent order of collectives, we have mapped how physical intelligence operates across interconnected yet distinct scales.



**FIGURE 4** | Mechanistic pathways for the emergence of collective intelligence in networked populations [193–195]. (a) The IMisi model formalizes imitation under incomplete social information, where agents update strategies based on both their personal and external information, neither of which is necessarily complete or fully accessible. (b) For personalized update rates, individuals with higher rates will update their strategies more often, while those with lower rates, typically hubs, act as stable anchors that guide local dynamics. This asymmetry serves as a structural lever to promote the emergence of collective intelligence. (c) The temporal interaction model imposes an explicit time ordering on agent activations in dynamic networks. Delaying the involvement of hubs restructures coordination pathways and improves collective outcomes, revealing the temporal ordering of interactions as a strategic handle for modulating group dynamics. These panels are adapted from refs. [174, 175].



**FIGURE 5** | Schematic of the hierarchical relationship between physical, computational, and embodied intelligence. Physical intelligence, rooted in materials, structures, physical interactions, and collective behavior, provides the foundation from which computational and embodied intelligence emerge. This framework highlights how adaptive capabilities in nature and engineering build upon the intrinsic problem-solving embedded in physics.

## 5 | Physical Intelligence as the Foundation for Embodied Intelligence

The aforementioned factors of physical intelligence serve as the foundation for embodied intelligence by enabling the seamless integration of sensory perception, motor action, and environmental interaction [8, 128] (Figure 5). This relationship manifests through fundamental mechanisms that transform abstract cognition into adaptive real-world agency. Physical intelligence allows embodied agents to acquire direct knowledge through sensorimotor contingencies—the intrinsic relationships between actions and sensory feedback [5, 33]. Consider a robot grasping an object: it learns weight and texture not through data labels but through force feedback in its joints, mirroring how infants develop spatial awareness by physically manipulating their surroundings. This grounding in physics prevents the ‘reality gap’ faced by disembodied AI systems, such as large language models (LLMs) generating implausible scenarios due to the lack of physical intuition [196, 197]. In contrast, physically intelligent systems shall refine behaviors through iterative environmental interactions, embedding material constraints directly into their operational logic [60, 198].

Moreover, physical interactions generate the embodied experiences necessary to construct causally consistent world models. While LLMs infer knowledge statistically from text corpora, their understanding might remain brittle [199, 200]. Physical systems build robust world models through multisensory exploration: drones mapping forests develop spatial awareness by colliding with branches [201, 202], while surgical robots internalize tissue mechanics through real-time haptic feedback [203–205]. These models encode physics—gravity, friction, material fragility—that disembodied algorithms cannot reliably acquire. Physical intelligence further amplifies efficiency through morphological computation, offloading cognitive burden to body dynamics [27, 206].

Arthropods leverage exoskeletal elasticity for energy-efficient locomotion, reducing neural control needs, while soft robots exploit material properties like jamming grippers to simplify manipulation—echoing how human athletes leverage biomechanics for fluid motion with minimal conscious calculation [4, 31, 36, 41].

When scaled up, physical intelligence enables emergent collective behaviors [176, 177, 190]. Swarms of simple agents—whether ants or drones—achieve complex goals through decentralized physical interactions [37, 187, 207]. Bee colonies regulate hive temperature via coordinated wing-beating convection, while drone flocks navigate wind currents through aerodynamic coupling, both demonstrating adaptation arising from embodiment rather than centralized algorithms [179]. Ultimately, physical intelligence crystallizes into embodied intelligence when perception, action, and cognition unify in a continuous loop. Industrial robots fuse vision, touch, and force feedback to maintain precision amid real-world disruptions; autonomous vehicles bridge physics-based simulations with street navigation; humanoids combine task planning with physical intuition to handle delicate objects [13, 42, 208]. This integration resolves the Moravec Paradox—where AI historically struggled with sensorimotor tasks trivial to toddlers—by leveraging physics as a scaffolding for competence [209–211]. As natural evolution has shown, intelligence emerges from dynamic embodiment in a material world rather than data processing alone, necessitating a paradigm shift from computational AI to physical AI [19, 128].

## 6 | Conclusion

Physical intelligence, intrinsically embedded in materials, structures, and interactions, represents the earliest substrate of problem-solving in nature. Long before the emergence of nervous

systems, living systems harnessed morphological design, mechanical resonance, and energy flows as means of sensing, computation, and adaptation. These principles not only shaped the evolutionary trajectory of neural intelligence but also continue to underpin the efficiency and resilience of biological organisms today.

By recognizing physical intelligence as the foundation of embodied intelligence, we gain a unifying perspective: cognition is not solely a computational abstraction but is grounded in the laws of physics. From single-cell organisms navigating chemical gradients, to swarms of insects coordinating via fluid and mechanical cues, nature demonstrates that higher forms of intelligence emerge from the iterative layering of physical problem-solving capabilities. Neural architectures, and eventually human cognition, did not replace physical intelligence but scaffolded upon it, extending the adaptive strategies already present in matter and morphology.

For artificial intelligence, this review aims to provide an alternative approach on how we design machines. Instead of treating hardware as passive vessels for algorithms, we can embed intelligence directly in the body—through responsive materials, adaptive architectures, and physically coupled interactions. Such systems harness morphological computation and distributed adaptation to reduce reliance on centralized processing, closing the gap between digital abstraction and real-world performance. As we learn from nature, physical intelligence offers the robustness, efficiency, and adaptability that computational intelligence alone struggles to achieve. By aligning future AI design with these principles, we may approach machines that think, feel, and adapt with the same seamless integration of body, environment, and mind that characterizes human-level embodied intelligence.

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## Conflicts of Interest

The authors declare no conflicts of interest.

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