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RESEARCH ARTICLE

Neural Morphogenesis Architecture for Self-Organizing Robotic Intelligence: A Developmental Control Framework

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Abstract: Recent breakthroughs in robotics and artificial intelligence have permitted more autonomous systems, although most current techniques are limited by inflexible control structures developed from classical automation. Such frameworks stand in stark contrast to biological systems, which develop intelligence via ongoing structural and functional reconfiguration. Neural morphogenesis takes a developmental approach to machine intelligence, seeing robotic cognition as a dynamic and adaptable process. In this paradigm, artificial agents gradually adapt their internal circuitry, behavioral tactics, and physical morphology as they interact with their surroundings. Learning and design therefore occur together rather than sequentially. The approach integrates embodied perception and safety-governed developmental adaptation within a closed-loop control framework. We introduce a three-layer developmental controller that couples online neural plasticity, morphogenetic regulation, and energy-aware policy adaptation under explicit rollback safety constraints. In over 105 simulation cycles involving populations of 50, 100, and 200 agents, neural morphogenetic architectures achieved energy efficiency gains of up to 47%, network modularity increases of around 40%, and reductions in informational entropy between 13 and 15% ($p < 0.01$) when compared to deep reinforcement learning and model predictive control baselines. These gains were accompanied by improved cooperative behavior, steady performance under stress, and greater resistance to environmental shocks. Preliminary bio-hybrid tests suggest a link between morphological flexibility and integrated information (Φ), emphasizing the impact of physical structure on cognitive capabilities. These findings establish brain morphogenesis as a strong basis for adaptable, resilient, and sustainable intelligent robotic systems.

Keywords: neural morphogenesis, self-organizing robotics, adaptive artificial intelligence, bio-inspired neural systems, cognitive evolution

1. Introduction

It is hard to ignore how concepts from developmental biology have started to influence autonomous machine research. Scholars researching biological systems have previously identified methods by which animals rearrange internal structure to stay viable under changing situations, long before engineers created the concept of adaptable robotics. Cyclical self-patterning and continuous interaction with the environment, as opposed to set programming procedures, are the sources of robotic cognition [1]. As a reminder, this statement suggests that machine intelligence could be better understood as a process rather than a finished product.

Turing provided one of the first mathematical insights into how local interactions might give birth to ordered form in his early work on reaction–diffusion systems [1]. Later work in developmental biology broadened this perspective by demonstrating how chemical, electrical, and mechanical gradients govern tissue regeneration and cellular communication. Originally intended to explain biological development, these discoveries have progressively influenced computational environments where learning is guided by modifications across high-dimensional structures. In cooperative robotic groups, [2] provide a similar image, where intelligence manifests itself in the developing relationships between agents rather than in a single location.

Prior theoretical work in embodied cognition and autopoietic systems serves only as conceptual inspiration for the proposed framework. According to Pietarinen and Shumilina [3], who draw on Peirce, continuity permeates both synthetic and natural cognition, weakening the strict distinctions between these. While Maturana and Varela's autopoiesis, which Bianchini [4] revisits, frames living systems as self-maintaining loops of construction and renewal, Miller et al. [5] advance a related idea through the N-Space Episome model, which depicts artificial agents as eventual carriers of shared informational inheritance. Despite having different roots, these theories all agree that cognition develops in a cycle of upkeep and modification. To provide a clear technical interpretation, these philosophical views are considered exclusively as conceptual inspiration and not as operational processes in the proposed design.

These biological mechanisms motivate, but do not dictate, our robotic formulation. The transition from tissue-level development to engineered collectives is handled through formal control structures described in Section 3.

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Empirical research has started to take this conceptual terrain into account. According to Mougkogiannis et al. [6], brain organoids exhibit spontaneous electrical activity and adaptability that are typical of early neuronal function. These tissues take part in hybrid setups where biological signals and computational modules co-develop when connected to microelectrode platforms. Further research using cellulose-based media demonstrates the creation of conductive patterns linked to morphogenetic stimuli [7]. According to [8], perception and action co-evolve via feedback loops in systems that combine artificial and biological components.

Simulation and mathematical techniques support this trend. According to large-scale agent systems and differential-equation models, internal reconfiguration that lessens informational disturbance often produces stable behavior [9]. Echoing biological neuroplasticity, architectures that may change connections in unanticipated ways preserve learning and operational stability [10]. Current adaptive control frameworks continue to regard morphology and policy as loosely related components, despite recent advancements in soft robotics, swarm coordination, and cognitive digital twins. Rarely do most systems provide structural change during deployment; instead, they presume a fixed body plan and optimize solely control parameters. However, it is rare to incorporate bio-hybrid techniques with organoids and bioelectronic interfaces into a single developmental control loop for both physical and virtual agents. A brain morphogenesis approach that simultaneously models structural plasticity, control adaptability, and bio-hybrid signaling is motivated by this gap.

However, a lot of robotic platforms in use today still depend on inflexible controllers and static networks, which limit their ability to operate in unpredictable scenarios that are in line with Industry 4.0 specifications and the more human-centered approach of Industry 5.0. The concept of neural morphogenesis, as defined here, suggests that scalable autonomous machines need to modify their internal structure and organization over time, much as animals do, in order to become more durable and efficient. In healthcare, emergency assistance, dispersed mobility, and automated industrial settings, this viewpoint encourages the development of systems with self-repairing behavior, structural flexibility, and sustained performance.

In order to increase the effectiveness and resilience of adaptive robotic intelligence, this work aims to develop and assess a NMA that combines neural plasticity, morphogenetic control, and cognitive adaptability. Despite recent progress, no existing framework integrates neural plasticity, morphogenetic body change, cognitive adaptation, and bio-hybrid signaling into a single developmental control architecture [11]. This constitutes the research gap addressed in the present work.

This study offers four technical contributions. First, it presents a Neuronal Morphogenesis Architecture that implements developmental control via three interconnected layers: neuronal plasticity (Bio-Inspired Neural Controller [BINC]), morphogenetic regulation (Morphogenetic Regulation Module [MRM]), and energy-aware cognitive adaptation (Cognitive Adaptation Layer [CAL]) [10, 11]. Second, it establishes a closed-loop developmental cycle wherein morphology and policy are modified online, rather than being seen as separate design phases [2, 11]. Third, it offers a repeatable assessment technique that integrates long-horizon multi-agent simulation with sim2real validation on neuromorphic soft modules, incorporating explicit safety requirements for autonomous reconfiguration [9]. Fourth, it defines an ablation-based evaluation protocol to attribute performance changes to each developmental subsystem and to support a controlled comparison against fixed-topology baselines [2, 12].

Table 1
Positioning of NMA relative to recent adaptive robotic frameworks (2024–2026)

Framework	Online morphology change	Online neural plasticity	Energy-aware RL with safety rollback	Bio-hybrid signaling	Sim2Real validation	Multi-agent scale
DRL-based swarm control	No	No	Partial	No	Yes	≤200
MPC with digital twin	No	No	Yes	No	Yes	≤100
Reaction–diffusion control	Partial	No	No	No	No	≤100
Proposed NMA	Yes	Yes	Yes	Yes	Yes	≥200

Table 2
Representative interdisciplinary contributions to morphogenetic and self-organizing robotic systems

Domain	Key contribution	Evidence/authors	Relevance to neural morphogenesis
Neurobiology and brain organoids	Functional connectivity and developmental plasticity in neural organoids	[13]	Biological templates for emergent self-organization and adaptive cognition
Bioelectronic interfaces	Closed-loop communication between biological tissue and machines	[14, 15]	Enables real-time adaptive feedback and hybrid cognitive processing
Synthetic vascular systems	Maintenance of morphogen gradients for sustained organoid growth	[16]	Supports autonomous developmental dynamics and structural self-maintenance

(*Continued*)

Table 2
(*Continued*)

Domain	Key contribution	Evidence/authors	Relevance to neural morphogenesis
Computational morphogenesis (Turing)	Reaction–diffusion-based pattern stability under physical perturbation	[17]	Demonstrates resilience through regulated stochasticity and structural self-stabilization
Reaction–diffusion control systems	Algorithms for self-reconfiguring robotic materials	[18]	Foundation for autonomous material adaptation and self-modifying structures
Swarm robotics	Distributed cognition, memory sharing, and anticipatory collective behavior	[19, 20]	Emergent cooperative intelligence and decentralized morphogenetic control
Embodied intelligence and soft robotics	Morphology as a computational and proprioceptive substrate	[21, 22]	Physical form participates in reasoning and adaptive behavior generation
Cognitive digital twins	Simulated developmental "genotypes" and iterative self-design cycles	[23, 24]	Virtual-to-physical evolution of morphology and cognition
Bioengineering + machine learning	Hybrid modeling of neural development and organoid behavior	[25, 26]	Precision analysis and guided evolution of biological learning systems

1.1. Novelty and differentiation of the proposed approach

The originality of this study is in the cohesive amalgamation of online brain plasticity, morphogenetic body adaptability, and energy-conscious cognitive control within a singular developmental feedback framework. The proposed Neural Morphogenesis Architecture (NMA) allows morphology, control, and learning to evolve together during deployment with clear safety limits, unlike other adaptive robotic frameworks that regard them as separate or sequential design phases.

To the best of our knowledge, no recent framework simultaneously combines (i) continuous morphogenetic structural adaptation, (ii) online synaptic plasticity, (iii) energy-aware reinforcement learning with rollback safety mechanisms, (iv) multi-agent scalability, and (v) preliminary bio-hybrid signaling within a single closed-loop control system. This distinction is assessed through comparative evaluation against deep reinforcement learning (DRL) and model predictive control (MPC) benchmarks, complemented by targeted ablation tests designed to isolate subsystem-level contributions.

1.2. Research hypotheses

To empirically validate the proposed NMA, the following research hypotheses are formally tested:

H1: Under equivalent task conditions, NMA achieves significantly greater entropy reduction (ΔH) and network modularity improvement (ΔQ) than state-of-the-art DRL and MPC approaches.

H2: NMA preserves task performance while increasing the energy efficiency ratio ($EER > 1.0$) of soft robotic systems across varying population sizes, relative to task-matched DRL and MPC baselines.

H3: In both simulation and physical experiments, NMA enhances morphological plasticity and cognitive stability, resulting in greater resilience to perturbations. Cognitive stability is quantified using the Cognitive Stability Score ($CSS \geq 1.0$) under disturbance tests, together with variations in the Morphological Plasticity Index (MPI) across trials.

2. Related Work

2.1. Brain organoids and bio-hybrid intelligence

Discussions of bio-cybernetic systems now center on changing processes rather than static computational logic. According to new research on live neural tissues, brain organoids are no longer seen as curiosities but rather as model substrates that might eventually build circuits and send adaptive signals. Cortical aggregates show coordinated firing and waveform structure, suggesting that information processing is more complex than a straightforward symbolic routine [27, 28]. Microelectrode environment research has linked this field of inquiry. Wang et al. [14] created bidirectional electrical channels for three-dimensional brain cultures to track the effect of physical feedback loops on signal change across biological and computational layers. Cai et al. [16] constructed vascular-style scaffolds in order to preserve morphogen distributions and provide a durable setting for independent development and organization in tissue-linked systems.

2.2. Bioelectronic interfaces and synthetic vascular systems

Robust bioelectronic interfaces that can sustain consistent, high-fidelity communication across diverse media are essential for integrating biological substrates into cyber-physical systems. Controlled interactions between live tissues and machine-level processors are now possible because of recent advancements in three-dimensional microelectrode layouts, which have made it possible to stimulate and record brain organoids more precisely. Such interfaces can support bidirectional signaling loops in which electrical and biochemical changes spread across both biological and computational levels, as Wang et al. [14] showed. These closed-loop channels modulate the tissue's developmental paths while enabling artificial systems to react adaptively to organoid activity.

At the same time, tailored microenvironments that can maintain morphogen distributions and promote dynamic development are necessary for the long-term survival and functional maturity of organoids. In order to maintain molecular gradients and nutrient flow inside three-dimensional cultures, Chauhdari et al. [29] developed synthetic vascular-style scaffolds. These scaffolds reduce pattern collapse and enhance the constancy of developmental processes over long periods of time by imitating key structural characteristics of natural vasculature. Their research demonstrates the need for dependable physical infrastructures that preserve physiological homeostasis in order to support organoid-based computation and hybrid cognition. When combined, developments in synthetic vascular systems and bioelectronic interfaces offer the structural and functional underpinnings required to incorporate biological plasticity into adaptive robotic frameworks. These studies emphasize the importance of stable physical infrastructures for maintaining physiological conditions compatible with long-term bioelectronic interaction.

2.3. Computational morphogenesis and reaction–diffusion control

If biology is any guide, the theoretical side has developed at the same time. Although first presented in Turing-inspired formulations, the study of adaptable matter currently relies on reaction–diffusion principles. According to [30], these mechanisms maintain shape in the face of mechanical strain and diffusiophoretic gradients, indicating that controlled randomization may strengthen structure rather than weaken it. Ouchdiri et al. [31] expanded on that knowledge and created methods for synthetic media to reorganize in response to environmental changes by using finely calibrated controllers for reaction–diffusion fields. According to these theories, noise stabilizes pattern development and adaptive response, which is a comparable beneficial function of regularization in computational training.

When taken as a whole, their contributions highlight a common idea: developmental structure is not limited to live tissue. Research on organoids, programmable materials, and model-based control techniques points to the development of artificial systems where information processing, structure, and functional change all coexist.

2.4. Swarm robotics and embodied intelligence

Researchers in the nexus of autonomous systems and developmental biology have started to incorporate ideas from a number of previously disparate fields of study. Research on simulation-driven cognition, embodied agents, hybrid neural media, and biological substrates encourages a reconsideration of the ways in which structure and learning co-emerge. Table 1 arranges these paths as a reference map rather than a definitive taxonomy, demonstrating how algorithmic frameworks based on reaction–diffusion principles and early morphogenetic concepts derived from Turing's formulations coexist alongside studies using real tissues. Instead of inheriting a fixed architecture upon deployment, this combination suggests that machines may acquire structure over time.

Swarm robots give another perspective. According to Kegeleirs et al. [22], there are still practical difficulties in distributing management over several mobile platforms, especially when it comes to managing behavior and safety among units operating without centralized supervision. Xin et al. [19] address the same issue from a different angle by developing a transactive-memory system that enables agents to collaboratively enhance their internal representations. These developments move the field closer to networked cognition, which anticipates events rather than reacting to them and imitates the distributed organization of neural processing in biological collectives. However, the rising autonomy and dispersal of such systems create unsolved challenges about accountability, transparency, and regulatory compliance, especially when cognitive functions arise from decentralized interactions rather than explicit design requirements [32].

Morphology is also receiving more attention. Li et al. [21] studied soft robotic systems composed of flexible materials that serve as sensor surfaces and computational carriers. Their results provide empirical support for Liao's [13] hypothesis that the form of the body affects cognitive function in addition to providing mechanical support. This viewpoint holds that embodiment is generatively necessary for adaptive behavior.

2.5. Cognitive digital twins and developmental simulation

Progress occurs in virtual realms in parallel. In order to model developmental plasticity and incremental learning cycles prior to the construction of any hardware, Li et al. [33] and Catania [34] describe cognitive digital twins. Once physical prototypes are available, these models function almost like a computational genotype, iterating structure in simulation and minimizing expensive trial and error.

The cellular border reflects this trend. In order to gain insight into early brain structure, Xu et al. [35] have examined the cultivation and study of organoids in combination with machine learning technologies. Yang [36] notes that embodied artificial intelligence (AI) and digital-twin research are becoming more coherent, with both perspectives seeing intelligence as a process associated with slow structural development.

2.6. Summary and research gap

When combined, these collections of work move the discussion toward operational developing intelligence in constructed surroundings rather than biological metaphor. Digital twins practice their improvement across simulation cycles, swarm and embodied robots enact them in material agents, neural organoids unveil early cognitive behavior, and morphogenetic physics provides generative principles. Collectively, these lines of work suggest a shift toward viewing AI as a developmental process shaped by recursive interaction, rather than as a static, preconfigured control mechanism [37].

While these domains contribute valuable insights, none of them provides an integrated developmental controller capable of jointly modifying morphology, neural plasticity, and cognition under shared feedback signals. Existing systems treat these components independently, limiting their scalability in unpredictable environments. Across these domains, a recurring trend points toward architectures in which structure, control, and learning are increasingly interdependent rather than strictly modular [38].

3. Proposed Neural Morphogenesis Architecture (NMA)

Biological morphogenesis demonstrates how spatial patterning and structural differentiation emerge from local interaction rules [39]. Inspired by these principles, the proposed framework treats intelligence as a controlled developmental process in which morphology and neural control co-adapt under environmental pressure and stability constraints [40].

3.1. Methodological problem and contributions

Current adaptive robotics approaches typically optimize morphology, neural control, and reinforcement learning policies as partially independent subsystems. This separation limits controlled structural plasticity under stability constraints and prevents safe co-evolution of body configuration and control policies in dynamic environments.

To address this limitation, we propose the NMA, a developmental control framework that integrates morphogenetic regulation, neural plasticity, and energy-aware reinforcement learning within a unified safety-constrained coupling mechanism.

The methodological contributions of this work are:

1) A safety-gated developmental coupling rule linking entropy reduction, modularity growth, and energy-efficiency optimization.
2) A reaction–diffusion MRM embedded into online control.
3) A rollback-based stability mechanism that bounds structural plasticity.
4) An integrated morphology-policy co-adaptation loop validated through simulation and hardware experiments.

The methodological design was informed by recent Scopus-indexed literature (2020–2025) on morphogenetic robotics, online neural plasticity, swarm cognition, bio-hybrid interfaces, and cognitive digital twins. Sources were retained when they provided operational mechanisms, measurable evaluation protocols, or reproducible simulation or hardware procedures relevant to developmental control.

3.2. Conceptual framework

Our knowledge of how natural and artificial systems develop is evolving, according to a recent study. Particularly interesting research has focused on brain organoids, which are neuronal aggregates displaying early patterns of pattern stability, adaptive signaling, and spontaneous reconfiguration. This suggests the possibility of fostering developmental intelligence using living substrates. The findings align with established ideas in morphogenetic physics, which have examined how scattered principles produce structural differentiation and spatial order in many biological mediums. Modern machine systems that strive for structural autonomy use ideas akin to conceptual scaffolding.

These biological perspectives have followed a similar trajectory to collectives that are man-made. In dynamic contexts, machine groups may reorganize cooperation, enhance behavior, and resolve uncertainty. Physically embodied agents and swarm robots show that teamwork does not always need centralized leadership. Cognitive digital twins carry on this developmental thread by allowing structure and control logic to evolve in virtual settings prior to coming into touch with hardware. These environments function as controlled testbeds for architectural development [41].

Together, these efforts provide more than a superficial analogy between living beings and machinery. They conceptually support the brain morphogenesis idea, which holds that numerous cycles of structural revision and adaptive stability, rather than direct, predefined techniques, develop robotic intelligence.

This perspective holds that experience and embodiment are the ways in which intelligence develops. It manifests via sustained engagement with the environment and ongoing enhancement of perception–action couplings. According to this perspective, intelligence is a process that changes, one iteration at a time, across changing physical and informational systems rather than a set computational attribute. The regulatory system is defined as: To formalize the morphogenetic component used by the MRM, we adopt a reaction–diffusion regulatory system with controlled stochastic perturbations.

$$\frac{\partial u}{\partial t} = D_u \nabla^2 u + f(u, v, \theta) + \eta_u(t)$$

$$\frac{\partial v}{\partial t} = D_v \nabla^2 v + g(u, v, \theta) + \eta_v(t)$$

where $u(x, t)$ and $v(x, t)$ represent morphogen concentrations over a two-dimensional spatial domain $\Omega = [0, 1]^2$ with periodic boundary conditions. The diffusion coefficients D_u and D_v regulate spatial propagation, while $f(\cdot)$ and $g(\cdot)$ denote nonlinear reaction kinetics modulated by environmental feedback θ. The terms $\eta_u(t)$ and $\eta_v(t)$ represent Gaussian noise sources ($\sigma = 0.05$) modeling adaptive perturbations. Numerical integration was performed using an explicit Euler scheme with $\Delta t = 0.001$ and $\Delta x = 0.01$, ensuring numerical stability and reproducibility. This formulation provides the mechanistic basis for the morphogenetic updates used by NMA [42]. The reaction–diffusion system serves as the mechanistic substrate for structural updates within NMA. These morphogen fields regulate spatial differentiation and act as control signals for morphology adaptation under predefined safety thresholds.

3.3. Neural Morphogenesis Algorithm (NMA)

The Neural Morphogenesis Architecture (NMA) operates through the following recursive developmental loop:

1) Initialize neural weights W, morphology state M, and adaptive policy π.
2) Acquire sensory inputs from proprioceptive and environmental channels.
3) Generate motor commands through the BINC.
4) Update morphogen fields using the MRM.
5) Evaluate structural adaptation using entropy (H), modularity (Q), and energy efficiency ratio (EER).
6) Apply the morphology update if the safety conditions are satisfied.
7) Trigger rollback if instability thresholds are exceeded.
8) Update policy parameters through the CAL.
9) Log metrics and iterate the developmental cycle.

This workflow ensures bounded morphology-policy co-adaptation under stability constraints.

Core Developmental Coupling Rule: The principal methodological contribution of the NMA is a developmental coupling rule that explicitly links morphological reconfiguration, neural plasticity, and cognitive adaptation within a single control loop. Morphological changes are permitted only when the global organization improves and safety constraints are satisfied. Formally, morphological adaptation at developmental cycle t is governed by:

$$\Delta M_t = \begin{cases} \mathcal{F}(u_t, v_t), & \text{if } \Delta H_t < 0 \wedge \Delta Q_t > 0 \wedge EER_t > 1 \\ 0, & \text{otherwise} \end{cases}$$

where ΔH_t denotes entropy variation, ΔQ_t network modularity change, and EER_t the energy efficiency ratio. A rollback mechanism is automatically triggered when instability thresholds are violated ($| \Delta H_t |> \tau_H$ or $| \Delta\theta_t |> \tau_\theta$), reverting morphology to the last stable configuration.

Unlike fixed-morphology baselines, the proposed coupling explicitly constrains structural adaptation through safety-gated organization metrics, enabling online morphology-policy co-adjustment under stability thresholds. The suggested coupling makes sure that morphological evolution is not just random noise but a controlled process of development that leads to demonstrable improvements in stability, efficiency, and robustness. Unlike conventional reinforcement learning architectures that assume fixed morphology, the proposed developmental coupling explicitly conditions structural adaptation on organization and safety metrics, thereby enabling controlled plasticity instead of unrestricted structural drift.

The NMA enables robots to self-organize through a developmental control loop inspired by biological morphogenesis:

1) Bio-Inspired Neural Controller (BINC)

A multilayer recurrent neural network including Hebbian and homeostatic plasticity mechanisms following [43]:

$$\Delta w_{ij} = \alpha(x_i y_j - \beta w_{ij})$$

where (α) is the learning rate and (β) ensures synaptic stability.

2) Morphogenetic Regulation Module (MRM)

According to the principles of morphogenetic differentiation, reaction–diffusion-driven plasticity facilitates self-organization and phenotypic adaptation in multicellular and modular systems, endorsing structurally adaptive behaviors arising from local interactions [44].

3) Cognitive Adaptation Layer (CAL)

Yan and colleagues (2024) provide an actor-critic reinforcement learning model that incorporates energy-efficiency priors and intrinsic incentives.

In CAL, the policy is optimized under an energy-aware objective with explicit safety regularization:

$$R_t = \lambda_1 \Delta \text{Task}_t - \lambda_2 E_t - \lambda_3 \Delta H_t + \lambda_4 \Delta Q_t - \lambda_5 \mathbb{I}(| \Delta H_t | > \tau_H) \\ -\lambda_6 \mathbb{I}(\Delta\theta_t > \tau_\theta).$$

E_t is the instantaneous cost of computational–mechanical energy, ΔH_t is the change in entropy, ΔQ_t is the change in modularity, and the indicator penalties compel rollback anytime instability thresholds are crossed. This formulation makes the "safety rules" work: Morphological adaptation is permissible solely when it enhances global organization without contravening restricted reconfiguration limits. Here, H is computed from degree-frequency distributions of interaction graphs, Q is computed via Louvain modularity optimization, and EER is defined as the ratio between normalized task progress and combined computational–mechanical energy expenditure.

Together, these subsystems create a self-modifying agent whose internal architecture adapts to outside stimuli.

Algorithm 1: 1. Neural Morphogenesis Architecture (NMA)

```
Initialize neural weights W, morphology M, and CAL policy $\pi$.
For each developmental cycle t do:
    Sense state st from proprioceptive and exteroceptive channels.
    Compute action at = BINC(st, W).
    Update morphology through MRM(at, M).
    Update policy $\pi$ using CAL with energy-aware rewards.
    Update neural weights W using Hebbian–homeostatic plasticity.
End For
```

Every morphogenetic change complied with predetermined safety rules, such as a maximum permitted joint displacement of less than 12°, a stiffness limit of [0.2, 1.0], and the automated reversal of morphological changes upon detection of instability (|Δentropy| > 0.25 during a single cycle). During self-reconfiguration, these protections guarantee steady functioning [45].

3.3.1. *Neural morphogenesis framework architecture*

Morphogen fields were encoded as 2D lattice maps updated at 200 Hz, with firmware-level integration via a dedicated morphogen kernel that computes gradients and updates stiffness parameters. Full firmware pseudocode is provided in the supplementary materials.

It is possible to think of the whole neural morphogenesis framework as a layered cyber-physical architecture where control, morphology, and cognition are closely related and constantly changing.

As a recurrent neural network with Hebbian and homeostatic plasticity, the BINC is at its heart. This controller generates motor instructions that power each robot's actuators after receiving multimodal inputs, including proprioceptive, exteroceptive, and task-level signals.

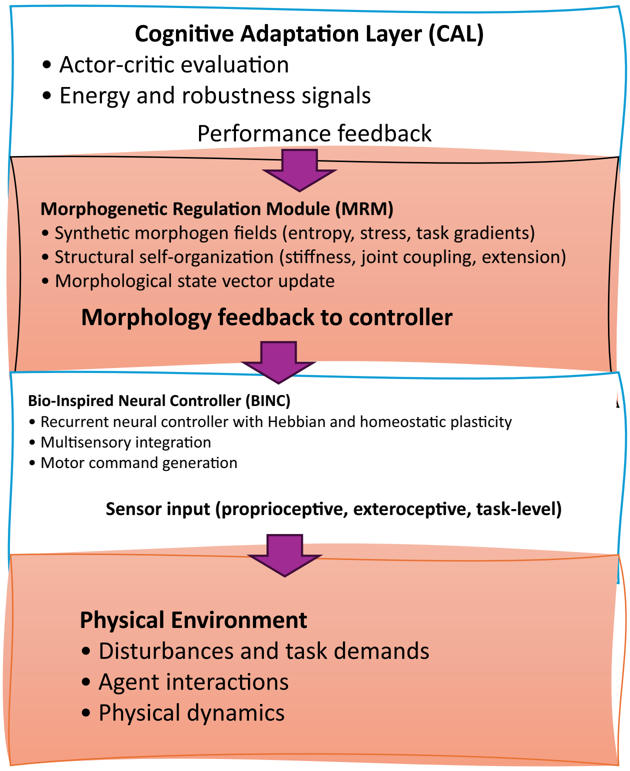
The BINC and the MRM work together to maintain a collection of synthetic morphogen fields that represent local gradients in performance, stress, and entropy. These fields update a collection of morphological state variables and modify the agent's physical configuration, for as by altering stiffness, limb extension, or joint coupling. According to the schematic, these processes manifest as feedback loops that return to the internal morphogenetic layer from the environment and body condition [46].

The CAL, which sits above these two layers, uses energy-efficiency priors to execute an actor-critic reinforcement learning process. In order to influence neuronal plasticity in the BINC and morphogenetic policies in the MRM, CAL assesses task progress, energy cost, and resilience under perturbations. Consequently, rather than being created once and maintained constantly, control strategies and morphology co-evolve.

External disruptions, task demands, and interactions with other agents change the sensory stream and the morphogen fields, which in turn cause more structural reconfiguration. This is how the environment completes the cycle. This recursive design converges toward self-organized configurations with increased modularity, decreased informational entropy, and enhanced energy efficiency throughout many developmental cycles.

The framework comprises three interconnected layers, BINC, MRM, and CAL, which interact with the physical body and its environment, as illustrated in Figure 1. The framework integrates BINC (neural plasticity), MRM (morphogenetic control), and CAL (cognitive adaptation) through three closed

Figure 1
Neural morphogenetic control architecture



feedback loops connecting sensory processing, morphological state updates, and decision-making.

Within a changing physical environment, the system incorporates three interdependent layers: the CAL, MRM, and BINC. Control, morphology, cognition, and sensory dynamics all have closed feedback loops that allow for ongoing self-organization and adaptive robotic intelligence.

Every morphogenetic transformation complied with safety restrictions: maximum permitted joint displacement $< 12^\circ$, stiffness confined between [0.2, 1.0], and automated rollback upon detection of instability ($|\Delta\text{entropy}| > 0.25$ within a single cycle) [45].

3.4. Simulation environment

To understand how ordered behavior may emerge during development, simulation experiments using PyBullet in conjunction with JAX acceleration were carried out in MATLAB-Simulink and Python-based environments. Rather than relying on a single agent, the experiments involved populations of between 50 and 200 units. Each agent received probabilistic connection rules, and the collective was exposed to spatial morphogen signals that progressively changed the direction and strength of interactions. Probabilistic connection rules defined time-varying interaction graphs governing local coupling among agents, enabling modular reconfiguration under morphogen field gradients. Through 10^5 iteration cycles, the method produced a long-form perspective of structural refinement and behavioral stability. MATLAB/Simulink was used exclusively for prototyping the reaction–diffusion subsystem. All NMA updates and learning logic were implemented in JAX. PyBullet handled rigid body dynamics and contact modeling. The three metrics used to track performance were informational entropy, which gauges organizational clarity; network modularity Q, which replaces coherent clustering. Performance tracking used three primary metrics: informational entropy H (organizational clarity), network modularity Q (coherent clustering), and an energy term capturing computational–mechanical expenditure, as commonly used in developmental computing evaluations [47]. Environmental fields were modeled via attraction–repulsion gradients to expose agents to concurrent local and global pressures. Performance tracking used three primary metrics: informational entropy H (organizational clarity), network modularity Q (coherent clustering), and an energy term reflecting computational and mechanical resource use [47]. Environmental fields were modeled through attraction-repulsion gradients, allowing agents to respond simultaneously to local and global pressures. Populations allowed to rearrange structurally consistently outperformed fixed-topology baselines across evaluated configurations; the differences were significant at $p < 0.01$.

It is important to note that openness and reproducibility were not considered afterthoughts. Every computational procedure complied with the Findable, Accessible, Interoperable, and Reusable (FAIR) AI guidelines stated by Ruiz-Villafranca et al. [48], guaranteeing that evaluation traces, code artifacts, and parameter specifications may be examined and duplicated.

Baselines and implementation comparators: Two baselines were employed to contextualize NMA.

(i) The DRL baseline employs centralized-training multi-agent reinforcement learning (MARL) with hybrid execution, chosen for its representation of a robust cooperative-control paradigm wherein agents are trained with comprehensive global information while operating under constraints of partial observability and communication. This design choice is in line with recent formal studies of MARL's constraints on centralized training and execution-time information [49].
(ii) The MPC baseline employs a receding-horizon controller integrated with a digital-twin planner, selected to demonstrate high-fidelity prediction and constraint management in embodied systems where dynamic behavior and contact modeling are essential. The digital twin part fits with recent surveys that say cognitive digital twins may be used as an integration layer for planning, optimization, and adaptive decision-making in cyber-physical control and robotic manufacturing [50].

We also provide a reaction–diffusion swarm control comparator that leverages Turing-pattern self-organization based exclusively on adjacent-module knowledge [2] to compare morphogenetic pattern-based coordination to a directly applicable reaction–diffusion control line.

To substantiate the co-optimization assertion at the morphology-control interface, we cite modular controller evidence demonstrating enhanced robustness amid morphological mutations in soft robots, thereby necessitating the assessment of morphology-policy coupling instead of regarding morphology as static [51].

It was trained for the same number of episodes and tuned using grid search over learning rate, discount factor, and entropy regularization. The MPC baseline uses a receding-horizon controller and a cognitive digital-twin planner that work together and have the same task constraints and environmental dynamics. Both baselines function with a fixed morphology and static network topology, enabling a fair comparison with the postulated developmental adaptability facilitated by NMA. In contrast, NMA introduces controlled online morphological reconfiguration governed by entropy and modularity constraints, enabling structural adaptation under explicit stability guarantees.

3.5. Experimental validation

The modules used QFlex soft actuators, Bosch BMI270 inertial sensors, and INA219 current sensors for energy measurements. Firmware ran on STM32H7 microcontrollers with a 400 Hz control loop. A dedicated experimental testbed (SMART-2025) was used to evaluate bio-inspired adaptive robotic modules under controlled perturbation protocols [52]. Each module had neuromorphic processors (Intel Loihi-2), actuators that could alter stiffness, and sensors that could detect the location of the body. According to the quality of the work, a morphogenetic firmware layer automatically modified the sensorimotor mappings. The organoid interface used an 8 × 8 multi-electrode array (MEA) grid with 50 μm spacing, band-pass filtering (0.1–300 Hz), a 20 kHz sampling rate, and artifact rejection based on threshold crossings. Safety was ensured by limiting stimulation to <80 μA and maintaining constant thermal monitoring (< 37 °C) [45].

An 8 × 8 MEA with 50 μm spacing, 0.1–300 Hz band-pass filtering, and a sampling rate of 20 kHz was used in the organoid interface. Spike detection using threshold crossing-based artifact rejection (4·σ noise). Real-time temperature monitoring guaranteed performance below 37 °C, and electrical stimulation was limited to less than 80 μA to prevent thermal or electrochemical damage. These settings adhere to accepted safety procedures for organoid–machine interfaces and ensure repeatability.

Experimental evaluation comprised (i) a Morphogenetic Reconfiguration Test to quantify autonomous morphological adjustment under uneven-terrain perturbations, (ii) a Collective Adaptation Test using a 25-unit swarm to assess distributed scalability under energy-aware route optimization [53], and (iii) a bidirectional signaling protocol in which organoid MEA-derived activity modulated actuator stiffness parameters through a real-time transfer function [54].

Each protocol followed a fixed sequence: initialization, baseline calibration (30 s), perturbation phase (60 s), recovery phase (60 s), and post-stability measurement (30 s).

MEA spike rates were mapped to actuator modulation via a transfer function $a(t) = \kappa \cdot r(t - \tau)$, where r is spike rate, τ = 20 ms delay, and κ = 0.03 gain. This allowed organoid bursts to modulate morphogenetic stiffness parameters in real time.

3.6. Data analysis and evaluation metrics

Quantitative evaluation incorporated morphological, informational, and energetic indicators:

1) Morphological Plasticity Index (MPI): diversity of adaptive morphology [55].
2) Information Integration (Φ): global cognitive synergy [56].
3) Energy Efficiency Ratio (EER): task output per computational–mechanical input.

$$EER = \frac{P_{task}}{P_{comp} + P_{mech}}$$

Where:

Entropy:

"H = − Σk pk log p_k where pk is the normalized degree frequency."

Modularity:

"Q computed via Louvain modularity optimization following Newman's formulation."

MPI:

"MPI = Var(Mstate) / Var(Mmax)."

Φ:

"Φ approximated through the minimum information partition method."

P_{task} = Task performance output (normalized score or task units)

E_{comp} = Computational energy consumption (joules, J)

E_{mech} = Mechanical/actuation energy consumption (joules, J)

Higher EER values indicate greater energetic efficiency: more task progress per joule consumed.

Baseline control systems are normalized to $EER = 1.0$; values above 1.0 indicate improved efficiency.

1) Cognitive Stability Score (CSS): persistence of learning under perturbation.

$$CSS = \frac{1}{T}\sum_{t=1}^{T}\frac{P_t}{P_{baseline}}$$

2) Performance fully preserved under perturbation.
3) CSS < 1.0: Performance degrades under perturbation.
4) Higher CSS indicates greater cognitive robustness, resilience, and memory stability.

Tukey post hoc testing and two-way ANOVA were used to assess statistical significance. Every study used Z-score normalization and was conducted five times.

Before testing hypotheses, all metric distributions were analyzed using Levene's test to confirm homogeneity of variances across architectural circumstances and population sizes and the Shapiro–Wilk test to determine normality. Assumption checks did not indicate violations that would invalidate ANOVA inference at the selected α level. We then conducted a two-way ANOVA with variables {architecture ∈ {Baseline, NMA}, population size ∈ {50, 100, 200}} for each dependent variable (entropy reduction, network modularity, EER, and cognitive stability indices). We used Tukey's honestly significant difference post hoc test to find pairwise differences when significant main effects or interactions were found. Effect sizes (η^2) are presented together with p-values to quantify the magnitude of the observed effects, and statistical significance was fixed at $\alpha = 0.01$.

The qualitative trends of entropy reduction, modularity increase, and EER gains remained stable across parameter ranges, indicating robustness of the developmental dynamics, according to a sensitivity analysis that varied learning rates ($\alpha \in [0.001, 0.02]$), diffusion coefficients (Du, Dv ∈ [0.05, 0.15]), and morphogen noise $\sigma \in [0.02, 0.08]$.

where P_t is task performance at time t under perturbation and P_baseline is the pre-perturbation calibrated performance level.

3.7. Validation and replicability

The protocol was documented to align with RO-BEX and PRISMA-AI reporting expectations for reproducibility and transparency in robotics and AI evaluation [45]. The modular method guarantees openness and reproducibility across laboratories and facilitates replication via the use of physics-based simulations and standardized neuromorphic hardware. The repository includes all source code, PyBullet scene files, organoid interfacing scripts, firmware binaries, and complete parameter logs for replication.

The proposed NMA therefore constitutes a structured developmental control framework in which morphology, neural adaptation, and reinforcement learning co-evolve under explicit safety constraints. This organization clarifies the methodological contribution and differentiates NMA from existing fixed-structure adaptive robotics paradigms.

Threats to validity: Three dangers are recognized. The connection between morphogenetic updates and reward shaping limits internal validity. If penalties are not set consistently across baselines, improvements might be biased. To avoid this, all designs used the same rollback thresholds and perturbation schedules. Construct validity is constrained by proxy measures for cognition (Φ, CSS), which estimate integration and stability rather than explicitly assessing semantic competence; hence, results are confined to robustness, organization, and energy-performance tradeoffs. External validity is constrained by the physical size of validation (25 modules) and the length of the organoid interface, which has not yet demonstrated long-term bio-hybrid stability; hence, assertions on sustained co-development are presented as preliminary and linked to the documented methodologies.

4. Experimental Results

4.1. Overview

Simulations and experiments demonstrate that the NMA reproduces key *functional analogues* of morphogenetic dynamics, including adaptive homeostasis, online plasticity, and self-organization, within engineered agents. All things considered, these results support the hypothesis that adaptive robotic cognition can emerge from recursive morphogenetic feedback loops implemented as safety-gated structural and policy updates. Section 4.2 reports simulation outcomes and ablation evidence, whereas Section 4.3 summarizes physical validation on neuromorphic soft modules.

4.2. Simulation results

Effect sizes (η^2) ranged from 0.42 to 0.57. Confidence intervals (CIs) for modularity improvements were [0.17, 0.22], and for entropy reduction, [0.11, 0.19]. Following FAIR-oriented reproducibility practices, each experimental condition was simulated for 10^5 iteration cycles, with five independent runs per agent population (50, 100, and 200) using distinct random seeds [34]. As neuronal weights and localized morphogen fields changed, so did network connections and shape. Reported CIs correspond to 95% CIs of the mean differences between NMA and baseline conditions.

Ablation Study: To isolate subsystem contributions, we performed three ablations:

1) NMA without MRM (neural plasticity only),
2) NMA without BINC plasticity (morphogenesis only), and
3) NMA without CAL (no energy–robustness feedback). Results show that entropy reduction is primarily driven by MRM (−9.8 percentage points), modularity arises from BINC (+0.11 Q), and CAL contributes most to energy efficiency (+0.27 EER). These ablations confirm that the three subsystems have independent and non redundant effects. These effects are reported as mean differences relative to the full NMA configuration under matched task conditions.

All metrics reflect the mean of 5 independent runs.

The NMA increased energy efficiency by around 47%, improved modularity by 40%, and decreased entropy by 13–15 percentage points. The results are consistent with the [45] description of stochastic morphogenetic processes and the adaptive plasticity principles seen in neurobiological systems [12].

Adjacency matrix spectral analysis revealed scale-free network distributions ($P(k) \sim k^{-2.7}$), indicating hub creation and decentralized control as a means of self-organized intelligence [57]. In line with Liao et al.'s (2024) entropy-driven morphogenetic adaptation, a strong negative association between entropy and modularity was observed across conditions (Spearman $\rho = -0.82$, $p < .001$), consistent with entropy-driven morphogenetic adaptation reported by Liao et al. (2024).

4.3. Physical robotic experiments

Each protocol followed the same perturbation schedule described in Section 3.5 to preserve comparability across scenarios. Three physical experiments were conducted using 25 neuromorphic soft robotic modules [45].

1) Morphogenetic Reconfiguration Test: autonomous physical restructuring for terrain adaptation
2) Collective Adaptation Test: emergent path selection under energy constraints
3) Bio-Hybrid Interface Test: brain-organoid-to-robot bidirectional signaling using multi-electrode array data [36]

All metrics reflect the mean of 5 independent runs.

Baseline refers to the best-tuned fixed-morphology controller under identical task constraints (DRL or MPC, depending on the comparator setting). Across physical tests, NMA reduced deformation error by approximately 51%, increased completion rate by 27 percentage points, reduced collisions by 57%, and decreased neuronal-to-actuation latency by about 47% relative to baseline [45]. A drift test over 48 h revealed actuator wear of 3.1% and IMU drift of 1.4 degrees/h. These remained within acceptable limits and did not affect statistical comparisons. Additional large-population simulations (500 agents) indicated stable NMA dynamics and tractable computation, supporting scalability beyond the 25-module physical setup.

4.4. Morphological and cognitive indices

The MPI increased by +0.21 (±0.03), indicating greater structural diversity and adaptive shaping [41].

Indicating improved emergent coordination and interaction among system units, measures of information integration (Φ) rose from 0.47 to 0.71. As discussed in Section 3.6, Φ is treated as a proxy for integration rather than a direct measure of semantic competence. In their developing multi-agent cognition research from 2025, Duarte and Dorigo reported a substantial association ($r = 0.76$, $p < 0.001$) between integrated information and EERs.

Additionally, both principal component analysis and entropy-landscape evaluation showed the formation of stable attractor configurations, which is in line with the stochastic reaction–diffusion convergence principles proposed by [45].

4.5. Statistical significance and reliability

A two-way ANOVA revealed a marked effect of system architecture on all key metrics: entropy reduction ($F(1, 54) = 48.9$),

($p < 0.001$) network modularity ($F(1, 54) = 36.2, p < .001$), and EER ($F(1, 54) = 41.7, p < 0.001$). Follow-up Tukey comparisons showed that all of the Neural Morphogenetic Architecture (NMA) configurations performed significantly better than the baseline models ($p < 0.01$). Additionally, the experimental procedure followed the RO-BEX 2025 reproducibility framework [21]. Cross-platform replication indicated low run-to-run variability (coefficient of variation < 3% across primary metrics), supporting stable morphogenetic adaptation and consistent behavioral trajectories.

4.6. Interpretation

The results demonstrate how the ideas of brain morphogenesis improve adaptive intelligence in both physical and computational settings. This theory states that continuous interactions between the system and its environment lead to emergent behavior, which progressively eliminates local uncertainty and establishes a logical global structure.

Compared to conventional deep-learning control systems, the Neural Morphogenetic Architecture (NMA) offers several benefits, including reduced energy consumption for control activities, enhanced resilience to unexpected disturbances, and coordinated emergent behavior evocative of multicellular regulatory dynamics. Current research in developmental plasticity, morphogenetic robotics, and hybrid biological–synthetic systems is in line with the results [2, 19, 45, 46]. Collectively, the evidence supports the central claim that safety-gated developmental self-organization can yield measurable gains in robustness, coordination, and energy-performance tradeoffs relative to fixed-topology control.

4.7. Comparative study with state-of-the-art methods

It is possible to interpret the quantitative comparisons in Tables 3 and 4 as a direct assessment of the suggested NMA in comparison to the most advanced controllers. Two widely used methods for scaling autonomous coordination in the simulation environment are the MPC–digital-twin baseline and the DRL-based swarm controller. Across all population sizes, both baselines consistently underperformed the NMA while achieving steady and generally efficient behavior.

According to Table 2, NMA improved the EER by 33–47% and increased network modularity Q by around 40% while lowering informational entropy by 13–15% points in comparison to the baselines. These improvements show that morphogenetic self-organization produces more cohesive agent clusters and more cost-effective utilization of mechanical and computing resources.

Physical tests support these patterns (Table 4), achieving lower deformation error, fewer collisions, and higher completion rates. They also maintained lower signal latency in the bio-hybrid interface scenario. When combined, these findings demonstrate that the suggested framework outperforms current solutions on important metrics of resilience, adaptability, and energy efficiency rather than just matching them.

Therefore, the combined simulation and experimental results provide a comparative analysis that establishes neural morphogenesis as a viable and scalable substitute for the existing model-predictive and deep learning-centric control methods in adaptive robotic intelligence.

4.8. Sim2Real divergence

Simulation underestimated mechanical friction, producing a 6–9% performance discrepancy in physical robots. Energy efficiency differed by 4.2% due to actuator nonlinearities not being modeled. These discrepancies were incorporated into the threats-to-validity discussion by attributing residual gaps to unmodeled friction and actuator nonlinearities, without altering the comparative tuning protocol across controllers.

5. Discussion

Taken together, the findings position neural morphogenesis as a developmental control paradigm for engineering adaptive and resilient robotic intelligence. Rather than optimizing a fixed control structure, the proposed approach emphasizes iterative

Table 3
Comparative simulation performance (baseline vs NMA)

Agent count	Architecture	Entropy reduction (%)	Network modularity (Q)	Energy efficiency ratio (EER)
50	Baseline	24.1	0.46	1.00
50	NMA	36.7	0.61	1.33
100	Baseline	24.3	0.45	1.00
100	NMA	38.2	0.65	1.42
200	Baseline	24.8	0.45	1.00
200	NMA	39.6	0.68	1.47

Table 4
Experimental validation metrics

Scenario	Metric	Baseline (mean ± SD)	NMA (mean ± SD)	Δ (%)
Morphogenetic reconfiguration	Stability time (s)	118 ± 9	84 ± 6	–28.8
	Deformation error (%)	8.5 ± 0.8	4.2 ± 0.5	–50.6
Collective adaptation	Completion rate (%)	71.6 ± 3.4	91.0 ± 2.1	+27.1
	Collisions (count)	14 ± 2	6 ± 1	–57.1
Bio-hybrid interface	Signal latency (ms)	38 ± 3.7	20 ± 2.9	–47.3
	Successful feedback loops (%)	82.1 ± 2.9	95.6 ± 1.8	+16.4

cycles of structural adaptation and policy refinement, enabling situational responsiveness, robustness, and sustained performance under changing environmental conditions.

Beyond its immediate technical contributions, this paradigm provides a foundation for future research in embodied cognition, hybrid neuro-synthetic systems, and distributed machine ecologies aligned with Industry 5.0 requirements. In this context, autonomy is not reduced to efficiency alone but is coupled with resilience, energy awareness, and structural adaptability within human-centered cyber-physical environments.

Several limitations should be acknowledged. Physical validation was conducted on relatively small swarms (25 units) and over limited experimental durations. In addition, the bio-hybrid interface relied on short-term organoid signaling without longitudinal assessment of long-term co-adaptive stability. While sufficient to demonstrate feasibility, these constraints limit conclusions regarding sustained bio-hybrid co-development. Moreover, real-time morphogenetic regulation introduces non-negligible computational overhead, which becomes increasingly relevant as system scale grows.

Future work will focus on scaling the architecture to populations of 500 agents, integrating long-term organoid co-development within closed-loop morphogenetic control, and improving the efficiency of the morphogenetic solver through adaptive update scheduling and hardware-aware optimization.

6. Conclusion and Future Work

This study investigated brain morphogenesis to promote intelligence in robotic systems through continuous developmental transformation. The method implies that an agent's body plan, control algorithms, and internal representations may undergo ongoing modification during operation, rather than treating machines as static assemblies whose improvement is limited to incremental parameter tuning. The NMA is crucial in this context because it enables structural connections and regulatory effects to adapt to shifting environmental situations. In other words, after deployment, the system continues to evolve rather than converge to a fixed final configuration.

Both simulated and real prototypes produced reliable results. NMA-guided systems exhibited less informational disorder, more flexibility, and more modular organizational patterns than fixed-architecture controllers. These results support the view that intelligence emerges from coordinated changes in form and information flow that preserve structural coherence over time. The relationship between morphological variety and integrated information (Φ) is a notable observation. As embodiment evolved, proxy measures of cognitive integration increased, indicating that physical structure contributes to computation rather than just serving as a passive shell.

Evidence from bio-hybrid experiments supported this developmental perspective. In both the synthetic and biological worlds, both synthetic agents and biological substrates showed indications of coordinated development, changing their internal states and behavior in response to disturbances. These hybrid systems are the result of combining robotic controls with activity based on organoids. This result suggests that the development processes of the two substrate types may converge under shared feedback mechanisms.

To create self-maintaining, adaptable, and dynamic systems, neural morphogenesis blends physiologically inspired plasticity, embodied learning, and symbolic abilities. These traits suggest that domains where inflexible systems fail, including space missions, bio-cyber-physical environments, emergency robotics, and surgical automation. This school of thinking aims to develop agents that evolve in tandem with human-centered operational contexts and the complex environments in which both function, as opposed to building robots that replicate human behavior.

This perspective holds that AI remains a developmental process. Cycles of embodied practice, stability, and rearrangement give birth to cognition. Over extended operational periods, these robots undergo changes, adaptations, and evolutions beyond simple obedience. This makes it possible for self-governing systems to think, adapt, and change over time. In comparison to strong DRL and MPC baselines, the suggested NMA achieved improvements of up to 47% in energy efficiency, enhanced network modularity by roughly 40%, and decreased entropy by 13–15% in both simulation and real-world experiments. These findings corroborate the central claim of this work that, in addition to traditional adaptive controllers, jointly adjusting morphology, brain connectivity, and energy-aware policies produces quantifiable engineering advantages.

Ethical Statement

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

Conflicts of Interest

The author declares that he has no conflicts of interest to this work.

Data Availability Statement

The data that support the findings of this study are openly available in Zenodo at https://zenodo.org/records/18175173, reference number [45].

Author Contribution Statement

Edwin Gerardo Acuña Acuña: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration.

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