Embodied and Situated Intelligence

Priya Saxena[1], Arjun Pandey[2], Deepak Chaudhary[3], Sadab Hasmi[4]
Students[1, 2, 3], Professor[4]
Department of CSE
DPG Institute of Technology & Management
Email ID: *Priyasaxena2n@yahoo.com[1], pandey.37arjun@gmail.com[2], sadab_oihas@rediffmail.com[3]*

ABSTRACT

Embodied and Situated Intelligence (ESI) represents a paradigm shift in the understanding of artificial intelligence and cognitive systems. Unlike traditional disembodied AI, which relies solely on abstract computation and symbolic reasoning, ESI emphasizes the interplay between an agent's body, environment, and cognitive processes. This approach draws inspiration from neuroscience, robotics, and cognitive psychology to develop systems that perceive, act, and learn in real-world contexts. This review explores the theoretical foundations of ESI, its computational models, experimental implementations in robotics, and applications in adaptive systems. By examining the intersection of embodiment, sensorimotor interaction, and environmental situatedness, we highlight the potential of ESI to enhance general intelligence and autonomous problem-solving. The paper concludes with a discussion of current challenges and future research directions.

KEYWORDS: *Embodied intelligence, situated cognition, cognitive robotics, sensorimotor learning, adaptive systems, environmental interaction, and autonomous agents.*

INTRODUCTION

Artificial Intelligence (AI) has traditionally focused on disembodied, computational models of cognition, relying on abstract symbolic reasoning or statistical learning to perform tasks. However, this approach often struggles with real-world adaptability and context-sensitive decision-making. Embodied and Situated Intelligence (ESI) emerged as an alternative

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paradigm, emphasizing that cognition is deeply intertwined with the body's interactions with its environment (Clark, 1997; Pfeifer & Bongard, 2007).

ESI posits that intelligence cannot be fully understood or replicated without considering three core principles:

- **Embodiment:** Cognitive processes are grounded in the physical form and sensorimotor capabilities of an agent.
- **Situatedness:** Intelligence emerges through interaction with a specific environment, influenced by context, spatial constraints, and social factors.
- **Sensorimotor Coupling:** Perception and action are inseparable; learning and adaptation occur through continuous feedback loops.

This review aims to provide a comprehensive understanding of ESI, integrating theoretical foundations, computational models, practical implementations, and applications.

THEORETICAL FOUNDATIONS OF EMBODIED AND SITUATED INTELLIGENCE

Embodied and Situated Intelligence (ESI) represents a departure from traditional, disembodied AI approaches that treat cognition as purely computational or symbolic. Instead, ESI emphasizes that intelligent behavior emerges from the interaction between an agent's body, its environment, and ongoing sensorimotor processes. Understanding the theoretical foundations of ESI requires examining its historical roots and core principles, which include embodiment, situatedness, and sensorimotor coupling.

1. Historical Perspective

The roots of ESI lie in multiple disciplines, including **cognitive psychology, developmental neuroscience, and robotics**, reflecting a multidisciplinary approach to understanding intelligence.

- **Cognitive Psychology and Developmental Theory:** Jean Piaget's work on sensorimotor development (1952) was foundational. Piaget observed that infants acquire knowledge not through passive reception but through **active interaction with their environment**. Sensorimotor stages, from reflex actions to coordinated exploratory behavior, illustrated that cognition develops **through the body's engagement with the world**. This challenged

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purely symbolic or computational models of cognition that dominated early AI research.

- **Embodied Cognition in Philosophy:** Philosophers such as Merleau-Ponty emphasized that perception and bodily experience are inseparable from thought. The notion that cognition is **grounded in bodily experience** provided a philosophical basis for ESI, highlighting that abstract reasoning cannot be fully divorced from physical and environmental context.

- **Robotics and the Rise of Subsumption Architecture:** In the late 20th century, robotics offered a practical testing ground for ESI theories. Rodney Brooks (1991) introduced the **subsumption architecture**, demonstrating that robots could achieve adaptive and intelligent behavior **without centralized symbolic reasoning**. Instead, layered sensorimotor control allowed robots to navigate complex environments, avoid obstacles, and accomplish goals. This work underscored the importance of **real-time interaction, embodiment, and situatedness** in intelligent behavior.

- **Cognitive Developmental Robotics:** More recent research in cognitive developmental robotics (Lungarella et al., 2003) extends Piagetian principles to artificial agents, showing that robots can learn and adapt **through embodied exploration**, social interaction, and environment-based feedback. These studies provide strong evidence that intelligence emerges **from the interplay of body, brain, and world**, not just abstract computation.

Summary: Historically, ESI integrates insights from psychology, philosophy, and robotics to assert that cognition is **body- and environment-dependent**, marking a paradigm shift from disembodied computational AI.

2. Core Principles

The theoretical framework of ESI rests on three interrelated principles: **embodiment, situatedness, and sensorimotor coupling**. Each principle contributes to the emergence of adaptive, context-aware intelligence.

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3. Embodiment

Embodiment refers to the idea that **an agent's physical form—its morphology, sensors, and actuators—directly shapes cognitive processes**. Unlike classical AI, where cognition is abstract and divorced from the body, embodied intelligence asserts that **body and mind co-develop**, influencing perception, decision-making, and learning.

- **Morphology Influences Behavior:** The shape, flexibility, and physical capabilities of an agent constrain and enable certain behaviors. For example, robots with **articulated limbs** can navigate uneven terrains, manipulate objects with dexterity, and perform tasks requiring fine motor control, whereas rigid, limited robots are confined to simpler actions.

- **Sensorimotor Integration:** Sensors (cameras, tactile sensors, gyroscopes) and actuators allow the agent to perceive and act in the environment. The **feedback between sensing and action** facilitates learning about environmental regularities and affordances.

- **Real-World Example:** Soft robotics illustrates embodiment in practice. Soft-bodied robots, inspired by octopuses, exploit their deformable structure to traverse confined spaces, demonstrating that **body design itself can simplify control strategies**, rather than relying on complex computation.

Implication: Cognition cannot be separated from the agent's body; intelligence emerges **as a property of the agent-environment system**, not just the brain or processor.

4. Situatedness

Situatedness emphasizes that intelligence is **context-dependent and environment-specific**. An agent's behavior is influenced by **affordances, social norms, spatial constraints, and dynamic changes in the environment**. Situated cognition theory (Varela et al., 1991) posits that knowledge is **constructed in context**, rather than stored as static internal representations.

- **Environmental Coupling:** Agents continuously monitor and respond to environmental cues. For example, a robot navigating a cluttered warehouse dynamically adjusts its path to avoid obstacles, not from pre-programmed maps but through **real-time perception and interaction**.

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- **Social and Task Context:** Situated intelligence also applies to social cognition. Service robots or collaborative AI agents must adapt to human behaviors, interpreting gestures, proximity, and timing to act effectively.

- **Dynamic Learning:** Situatedness facilitates adaptive problem-solving. Knowledge learned in one environment can transfer to similar contexts, but behavior must remain flexible to accommodate novel or changing conditions.

Implication: Intelligence emerges **through interaction with the world**, not as an isolated computation. A fully intelligent agent must be able to perceive, interpret, and act according to situational demands.

5. Sensorimotor Coupling

Sensorimotor coupling refers to the **continuous feedback loop between perception and action**, forming the foundation of adaptive intelligence. Rather than processing sensory information passively, an agent **acts upon the world and updates internal models based on the resulting changes**.

- **Action-Perception Loops:** Perception informs action, which in turn modifies perception. For example, a robot reaching for an object uses visual feedback to adjust its trajectory, while tactile feedback ensures grip success. This loop enables fine-tuned adaptation in **dynamic and unpredictable environments**.

- **Learning through Interaction:** Reinforcement learning, imitation learning, and motor skill acquisition in robots rely on sensorimotor feedback. Agents improve their performance by **evaluating the outcomes of actions relative to goals**, effectively integrating perception, action, and learning.

- **Theoretical Models:** Dynamical systems theory models cognition as a **continuous-time interaction** between sensors, actuators, and environment, capturing emergent, adaptive behavior that cannot be pre-programmed.

Implication: Intelligence is an **emergent property of embodied interaction**. Sensorimotor coupling ensures that cognition is **situated, adaptive, and responsive** to real-world conditions.

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COMPUTATIONAL MODELS OF EMBODIED AND SITUATED INTELLIGENCE

Computational models of Embodied and Situated Intelligence (ESI) aim to formalize how intelligent behavior emerges from **the interaction between an agent, its body, and the environment**. Unlike classical AI models that rely on centralized planning or symbolic reasoning, ESI models focus on **distributed, adaptive, and real-time control mechanisms**. Key computational approaches include subsumption architecture, dynamical systems, reinforcement learning, and cognitive developmental robotics.

1. Subsumption Architecture

The **subsumption architecture**, introduced by Rodney Brooks in 1991, is a foundational model for ESI in robotics. It organizes **robot behavior hierarchically into layers**, where **lower-level behaviors operate reflexively** and higher layers build upon them to generate more complex, goal-directed actions.

Key Features:

- **Layered Control:** Each layer operates **independently** but can override or "subsume" lower layers when necessary.
- **Behavior-Based Intelligence:** Intelligence emerges from the **interaction of multiple simple behaviors**, rather than explicit symbolic reasoning.
- **Real-Time Interaction:** Robots continuously sense and act in real-time, ensuring adaptability to environmental changes.

Table 1: Layers of Subsumption Architecture

Layer	Function	Example Behavior
Layer 1	Reflexive	Obstacle avoidance
Layer 2	Reactive	Wall-following
Layer 3	Goal-directed	Room exploration
Layer 4	Planning	Mapping environment

2. Dynamical Systems Theory

Dynamical systems theory (DST) provides a **mathematical and conceptual framework** for modeling intelligence as an emergent property of **continuous interactions between an agent**

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and its environment. Rather than treating cognition as a sequence of discrete computations, DST emphasizes that behavior arises from **time-dependent changes in state variables**, influenced by both internal dynamics (e.g., neural activity) and external stimuli (e.g., environmental feedback).

Key Concepts of DST in ESI:

- **State Variables:**
  - Represent the agent's internal and external conditions. Examples include joint angles, velocities, neural activation levels, and sensory inputs.
  - In a walking robot, state variables might include leg positions, center of mass, and contact forces with the ground.
- **Differential Equations:**
  - Coupled differential equations describe how these variables change over time, incorporating both **agent dynamics and environmental influences**.
  - Example equation for a robotic limb: dθdt=f(θ,θ˙,τ,sensor inputs)\frac{d\theta}{dt} = f(\theta, \dot{\theta}, \tau, \text{sensor inputs})dtdθ=f(θ,θ˙,τ,sensor inputs) where θ\thetaθ is joint angle, θ˙\dot{\theta}θ˙ angular velocity, τ\tauτ applied torque, and fff represents the dynamic control policy.

- **Attractors:**
  - Stable patterns of behavior that the system naturally converges to, such as a walking gait, grasping posture, or reaching movement.
  - Attractors allow **robust behavior** in the presence of perturbations (e.g., uneven terrain).

- **Self-Organization:**
  - Complex behavior can emerge without centralized control. Coupling between sensors, actuators, and environment produces **coordinated motor patterns** spontaneously.

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Example Applications:

- **Locomotion:** DST models are used to generate walking gaits in humanoid and quadruped robots. Instead of pre-programming exact joint trajectories, robots rely on **coupled oscillators** that produce stable cyclic movements.
- **Manipulation:** Robotic arms adapt grip strength based on feedback from tactile sensors, allowing safe handling of fragile objects.

Advantages of DST in ESI:

- Provides **robustness to environmental variability**.
- Supports **continuous adaptation** and learning.
- Captures **emergent intelligence**, showing that complex behaviors arise naturally from agent-environment coupling.

3. Embodied Reinforcement Learning

Reinforcement learning (RL) enables agents to **learn optimal actions through trial-and-error interactions** with their environment. In **embodied reinforcement learning**, the agent's physical body and sensorimotor interactions are central to learning. This contrasts with traditional RL, where states are abstract and often disconnected from real-world embodiment.

Key Features of Embodied RL:

1. **State Representation:**

- Incorporates **real-time sensory data** such as visual input, proprioception, tactile feedback, and environmental conditions.
- Example: A walking robot includes leg joint angles, contact sensors, and velocity in its state vector.

2. **Action Space:**

- Consists of **physical movements**, e.g., applying torque to joints, adjusting limb trajectories, or changing walking patterns.

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3. **Reward Function:**

- Defines task success and guides learning. Rewards are based on outcomes such as distance traveled, stability, energy efficiency, or task completion.
- Example: A robot receives positive reward for moving forward without falling and negative reward for collisions or instability.

4. **Policy Update:**

- Learning algorithms (Q-learning, policy gradient, or actor-critic) adjust actions based on sensory feedback and reward signals.
- Embodied RL ensures that learning incorporates **physical constraints and environmental feedback**.

Example Applications:

- **Robotic Locomotion:**

Quadruped robots learn to walk on uneven terrain by adjusting limb movements in response to sensor feedback. Over time, they develop **efficient gaits without explicit programming**.

- **Grasping and Manipulation:**

Robotic arms learn to pick and place objects of different shapes and weights by trial-and-error feedback from tactile and force sensors.

- **Adaptive Navigation:**

Autonomous drones use embodied RL to navigate dynamic environments, avoiding obstacles and optimizing flight paths based on real-time sensor input.

Advantages:

- Integrates **real-world constraints** into learning.
- Enables **adaptive and context-aware behavior**.
- Bridges the gap between **simulation and physical embodiment**, allowing learned policies to transfer to real robots

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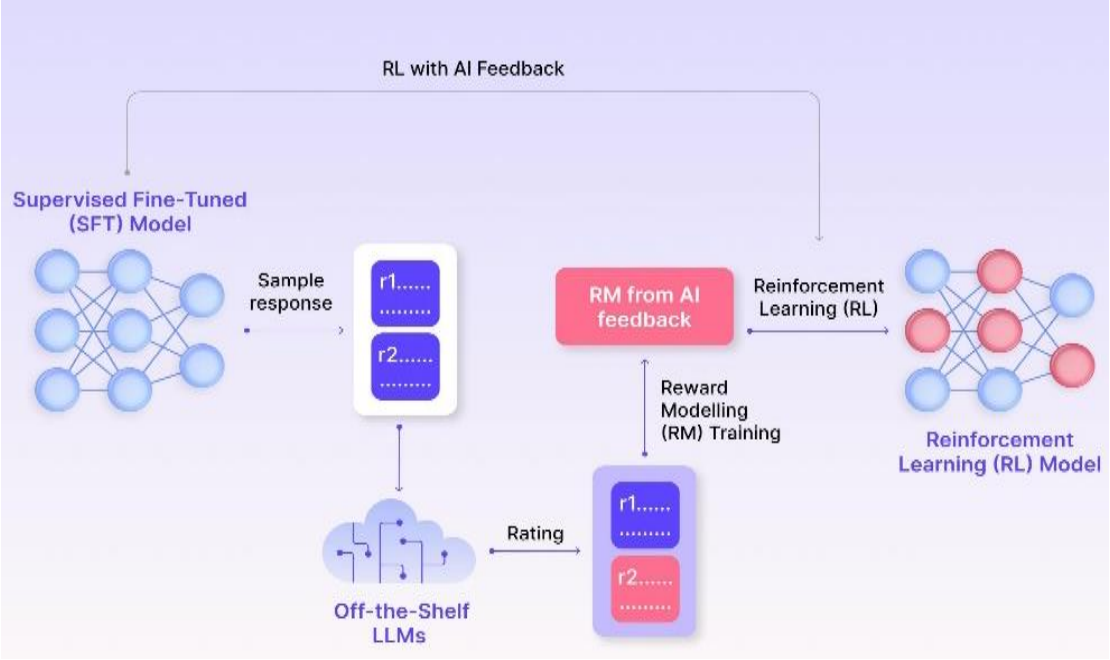


Figure 1: Feedback Loop in Embodied Reinforcement Learning

COGNITIVE DEVELOPMENTAL ROBOTICS

Cognitive Developmental Robotics (CDR) is a computational framework that draws inspiration from **human cognitive development**, aiming to build robots that **learn, adapt, and acquire skills progressively**, similar to how infants develop intelligence. Unlike traditional robotics, where behavior is pre-programmed or optimized for specific tasks, CDR emphasizes **incremental learning through interaction with the body, environment, and social partners**.

CORE PRINCIPLES OF CDR

1. **Sensorimotor Exploration:**
   - Robots engage in **active exploration** of their physical capabilities and environmental affordances.
   - Early exploratory behaviors (analogous to infant reflexes) allow the agent to discover **cause-effect relationships**.
   - Example: A robot shakes, pushes, or lifts objects to learn about weight, texture, and dynamics.

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2. **Incremental Learning:**
   - Knowledge acquisition occurs **gradually**, moving from simple reflexive behaviors to complex, goal-directed actions.
   - Learning is scaffolded: early motor skills support higher cognitive abilities such as tool use, planning, or problem-solving.
   - Example: A robot first learns to grasp a block, then to stack blocks, and finally to build a simple structure.

3. **Social and Imitation Learning:**
   - Robots observe human or robotic peers to acquire new skills.
   - Social interaction enables **efficient learning without extensive trial-and-error**.
   - Example: A robot learns to pour water into a container by watching a human demonstrate the action and receiving corrective feedback.

4. **Embodied Grounding of Knowledge:**
   - Learning is **body-dependent**, meaning knowledge is grounded in the robot's sensorimotor capabilities.
   - Example: A grasping strategy learned by a humanoid robot may not directly transfer to a robot with a different morphology, highlighting the **importance of embodiment**.

5. **Situated Learning:**
   - Cognitive skills are context-dependent. Robots adapt learned behaviors to **environmental constraints**, such as changing terrain, object size, or social cues.
   - Example: A robot navigating a cluttered room learns different strategies than when operating in an open space, illustrating **situated intelligence**.

APPLICATIONS OF EMBODIED AND SITUATED INTELLIGENCE

- **Autonomous Robotics**

  ESI principles are widely applied in robotics. Robots equipped with embodied cognition mechanisms adapt to unstructured environments, such as disaster sites, agriculture, or household tasks. For example, quadruped robots like Boston Dynamics' Spot use sensorimotor feedback and environment-aware planning to navigate complex terrains.

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- **Human-Robot Interaction (HRI)**

  Situated intelligence enhances HRI by enabling robots to understand social cues, adapt to human behavior, and collaborate effectively. For instance, service robots adjust their movement speed, proximity, and gesture timing based on human responses.

- **Adaptive Learning Systems**

  ESI informs adaptive learning platforms that adjust content delivery based on the learner's interaction patterns and context. These systems leverage real-time feedback to optimize educational outcomes.

- **Cognitive Prosthetics and Assistive Devices**

  Embodied intelligence principles guide the design of prosthetics that integrate with neural and muscular signals. Devices learn from sensorimotor feedback, allowing users to perform tasks naturally and adaptively.

Table 2: Applications of ESI across Domains

Application Domain	Example System	ESI Principle Applied
Autonomous Robotics	Quadruped Robots	Embodiment & Sensorimotor Coupling
Human-Robot Interaction	Social Assistive Robots	Situatedness & Adaptation
Education	Adaptive Learning Platforms	Sensorimotor Feedback
Healthcare	Cognitive Prosthetics	Embodiment & Learning

ADVANTAGES AND LIMITATIONS OF EMBODIED AND SITUATED INTELLIGENCE

Embodied and Situated Intelligence (ESI) represents a paradigm shift in artificial intelligence, emphasizing that cognition arises from **continuous interaction between the agent, its body, and its environment**. While ESI provides unique capabilities compared to traditional AI, it also comes with certain challenges. This section elaborates on the main **advantages and limitations**, with illustrative examples.

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A. Advantages

1. Robustness

One of the most significant advantages of ESI is the **ability of agents to adapt to environmental uncertainties and dynamic conditions**. Unlike traditional AI systems, which often rely on pre-programmed rules or fixed models, ESI systems continuously adjust their behavior based on real-time sensory input.

- **Example:** A quadruped robot navigating uneven terrain can dynamically adjust leg positions and gait patterns when encountering obstacles, slopes, or slippery surfaces. Traditional rule-based robots would fail in such unpredictable conditions.
- **Implication:** Robustness allows ESI agents to operate in **real-world, unstructured environments**, such as disaster zones, crowded urban spaces, or natural terrains.

2. Scalability

ESI systems scale naturally with **increasing environmental complexity** because learning and behavior emerge from **sensorimotor interaction** rather than exhaustive enumeration of rules.

- **Example:** In robotic swarm systems, individual robots can learn local behaviors through interaction with neighbors and the environment. As the swarm size increases, these simple local interactions give rise to complex, coordinated global behavior without explicitly programming each scenario.
- **Implication:** Scalability enables deployment of ESI in **multi-agent systems, large-scale robotic operations, and complex adaptive environments**, where traditional AI approaches would require impractical amounts of coding or computation.

3. Generalization

Situated cognition allows ESI agents to **transfer learned skills across different contexts**, enhancing adaptability and reducing the need for task-specific programming.

- **Example:** A robot trained to grasp objects on a flat surface can generalize the skill to grasp objects on uneven surfaces or of different shapes and sizes, thanks to sensorimotor learning and environmental feedback.
- **Implication:** Generalization reduces **training time and resources**, allowing agents to perform a wide variety of tasks without requiring retraining for each specific environment.

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4. Embodiment-Driven Learning

The physical body itself facilitates intelligence, reducing reliance on complex computation. Morphological features, such as flexible joints, soft actuators, or compliant limbs, allow the agent to **offload some computational complexity to the body**, simplifying control and enabling adaptive behaviors.

- **Example:** Soft-bodied robots can squeeze through tight spaces or absorb impacts without requiring extensive sensory computation, leveraging body dynamics as part of the intelligence.

5. Adaptive Interaction with Humans and Environment

ESI enables **dynamic and natural interaction with humans and complex environments**, making it highly relevant for social robotics, assistive technologies, and collaborative tasks.

- **Example:** A social robot in a classroom adjusts its speech, gestures, and speed of movement based on the attention and behavior of children, providing personalized guidance.

B. Limitations

While ESI offers significant advantages, there are **practical and theoretical limitations** that researchers must address.

1. Complex Modeling

Accurately modeling **body-environment interactions** is computationally intensive. The dynamics of flexible joints, compliant actuators, friction, and environmental variability make precise simulation challenging.

- **Example:** Simulating a humanoid robot interacting with uneven terrain in real-time requires solving **nonlinear differential equations** for multiple joints and contact points simultaneously, which can overwhelm computational resources.

2. Data Dependency

Learning in ESI systems relies on **rich sensorimotor data**, including proprioception, tactile input, vision, and auditory signals. Collecting, labeling, and processing such data can be costly and time-consuming.

- **Example:** Training a robotic hand to manipulate various objects may require thousands of trials under different environmental conditions to achieve reliable performance.

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3. Integration Challenges

Combining **embodiment, situatedness, and symbolic reasoning** into hybrid systems remains an open research challenge. While ESI excels at adaptive and context-aware behavior, integrating higher-level reasoning, planning, or abstract cognition with embodied mechanisms is complex.

- **Example:** A robot may efficiently navigate and manipulate objects using sensorimotor intelligence but struggle with **high-level planning**, like solving multi-step puzzles requiring abstract reasoning.

4. Hardware Limitations

Physical embodiment introduces challenges related to **durability, energy consumption, and actuator limitations**. Robots must balance the complexity of sensorimotor systems with power efficiency and mechanical constraints.

- **Example:** Soft robots may be highly adaptive but are prone to wear and tear, and their actuators often consume more power compared to rigid robotic system

FUTURE RESEARCH DIRECTIONS

- **Hybrid Architectures:** Combining symbolic AI with ESI models for advanced reasoning and adaptability.
- **Neuro-Embodied Models:** Leveraging insights from neuroscience to enhance agent cognition and learning.
- **Multi-Agent Situated Systems:** Exploring collective intelligence in networks of embodied agents.
- **Ethical and Social Considerations:** Understanding human interaction, safety, and ethical deployment of embodied AI systems.

CONCLUSION

Embodied and Situated Intelligence represents a transformative paradigm in artificial intelligence research. By grounding cognition in physical form, environmental context, and sensorimotor interactions, ESI systems demonstrate robust, adaptable, and context-aware behavior. This review highlighted theoretical foundations, computational models, practical implementations, and applications across robotics, education, and healthcare. While challenges remain in computational complexity, integration, and data requirements, ongoing research in

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hybrid architectures, neuro-inspired systems, and multi-agent environments promises to expand the frontiers of ESI. Ultimately, embracing embodiment and situatedness may be key to achieving truly general and autonomous intelligence.

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