Synergistic Multi-Robot Knowledge Aggregation for Energy-Sustainable Embodied Autonomy

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***Abstract*—This paper explores the critical energy demands arising from the integration of artificial intelligence and robotics, forming embodied AI (EAI) systems. It presents an examination of current learning paradigms' energy footprints and introduces "collective learning" as a novel approach to significantly reduce the energy consumption associated with EAI skill acquisition. The discussion within this paper models the dynamics of skill knowledge transfer and compares various learning paradigms, highlighting how collective knowledge sharing across EAI agents minimizes energy expenditure and accelerates learning efficiency. The presented analysis emphasizes the potential of this paradigm shift for achieving more energy-sustainable and scalable robotic intelligence.**

I. Introduction and Motivation

The convergence of artificial intelligence (AI) and robotics has given rise to a new class of intelligent physical agents known as Embodied AI (EAI) systems. These agents are capable of perceiving, reasoning, learning, and acting in dynamic physical environments. From autonomous vehicles and robotic arms to household service bots and industrial cobots, EAI systems are expected to undertake a wide array of tasks that require both physical embodiment and cognitive intelligence [1].

With the anticipated growth in the deployment of EAI systems across industries, logistics, healthcare, and households, the collective computational and mechanical energy demand associated with these agents is poised to rise exponentially. Unlike traditional AI systems that operate in abstract or simulated environments, embodied systems must continuously interact with the real world, making their energy expenditure a critical bottleneck to scalability and sustainability [2].

Traditional AI frameworks often treat intelligence as a purely symbolic process decoupled from physical embodiment. While such classical AI (CAI) paradigms offer valuable insights into data-driven decision-making, they fail to address the energetic implications of learning and action in real-world physical spaces [3]. In contrast, EAI systems must expend energy not only during computation and communication but also during movement, exploration, and real-time interaction with their environments.

This distinction introduces a profound shift in how energy consumption is distributed across different phases of intelligence. Energy is not only consumed during the inference or training of AI models but also during the physical execution of tasks, interaction with sensors and actuators, and communication with other agents or infrastructure [4]. As a result, energy sustainability becomes a multi-dimensional challenge encompassing both computational and mechanical domains.

Existing machine learning models, such as deep neural networks, have demonstrated remarkable success in static or simulated environments. However, these models are notoriously data-hungry and require substantial retraining when task variations are introduced. In the context of EAI, this limitation becomes problematic, as retraining often involves physical re-execution of tasks, thereby significantly increasing motion-related energy costs [5].

Furthermore, the reliance on centralized cloud infrastructure for training and updating models introduces additional layers of energy consumption, particularly from data transmission, distributed processing, and cooling in data centers. The combination of on-device processing and cloud offloading creates a hybrid computational model, which further amplifies the challenge of managing energy across different system layers [6].

As more robots operate concurrently within factories, hospitals, and homes, the duplication of learning efforts across agents becomes not only inefficient but also energetically wasteful. When each agent learns independently, the cumulative energy spent across all robots for learning similar tasks becomes prohibitive, both from an economic and environmental perspective [7].

This inefficiency calls for a rethinking of learning paradigms in EAI. A promising solution lies in collective knowledge sharing, where multiple agents can communicate and leverage each other's learning experiences. Such paradigms, if designed effectively, can reduce redundant exploration, accelerate skill acquisition, and minimize the computational and physical energy spent per agent [8].

The concept of collective learning introduces a synergistic mechanism in which agents not only share learned policies or models but also restructure their own learning trajectories based on peer insights. This transforms learning from a solitary endeavor into a collaborative process where experience and knowledge become distributed commodities within a robotic ecosystem [9].

In such a setting, agents can be organized into knowledge-sharing networks, where learned skills propagate both laterally across agents and hierarchically across tasks. This form of social intelligence allows the robotic collective to adapt, generalize, and evolve more efficiently than isolated systems. The implications for energy sustainability are profound: shared knowledge reduces the number of physical trials required per agent, thereby decreasing overall system energy usage [10].

This paper proposes a formal analysis of the energy implications of various learning paradigms in EAI, including isolated learning, incremental learning, transfer learning, and collective learning. Through dynamic modeling of knowledge acquisition and empirical simulation of learning scenarios, we demonstrate that collective learning offers significant reductions in energy consumption, particularly as the number of agents and tasks scales.

By framing energy sustainability as a fundamental design constraint for EAI, this research aims to shift the paradigm from isolated skill learning to collaborative knowledge aggregation. We contend that the future of scalable, energy-conscious embodied intelligence depends not just on optimizing individual agents but on fostering emergent behaviors through cooperative learning architectures.

II. Energy Expenditure in Embodied AI Systems

The operation of Embodied AI (EAI) agents introduces a multifaceted energy profile that includes computation, mechanical action, and communication. To understand the systemic implications of deploying EAI systems at scale, it is crucial to decompose energy usage into distinct categories. We define three primary expenditure domains: Computation and Communication Expenditure (CCE), Basal Energy Expenditure (BEE), and Motion and Interaction Expenditure (MIE).

CCE encompasses all energy used in planning, learning, data processing, and inter-agent communication. As the complexity of AI models grows, especially with deep learning architectures like transformers, the computational requirements for training and inference have become disproportionately energy intensive [3]. Moreover, energy consumed in transmitting large data volumes across networks adds to this burden, especially in cloud-dependent architectures [6].

BEE refers to the foundational energy needed to keep a robot operational. This includes maintaining idle states, powering sensors and embedded controllers, and running minimal background processes required for proprioception and system awareness. For aerial drones, this also involves constant thrust generation to maintain altitude; for mobile ground robots, BEE includes locomotion control even when stationary [4].

MIE accounts for the energy consumed when executing a task that involves movement or manipulation. Unlike simulated models, physical robots must invest real energy to perform pick-and-place actions, navigate terrain, or apply force to objects. The amount of energy consumed is highly dependent on task complexity, robot morphology, and environmental resistance [12].

To formalize the total energy cost E_τ associated with learning and executing a skill τ, we follow the formulation introduced in prior studies on energy modeling in embodied systems. The minimum theoretical energy E^* represents the optimal motion cost for a perfectly known trajectory, and the actual energy expenditure is given by:

$$E_\tau = E_\tau^* + E_{\text{BEE}} + E_{\text{CCE}} + E_{\text{MIE}}$$

This equation underscores that even the most efficient agents cannot avoid baseline physical energy demands, while poor learning strategies can exacerbate the remaining components significantly.

Recent studies have shown that while computational energy costs dominate traditional AI applications, in EAI systems, the MIE and BEE contributions are equally significant. In autonomous vehicles, for instance, the energy spent simply to gather training data via on-road driving may surpass the cost of model inference itself [13]. Similarly, service robots in household settings must re-learn task variants due to dynamically changing environments, leading to redundant physical exploration [14].

Compounding this is the fact that EAI agents often require continuous learning. Unlike static models trained once and deployed, EAI systems experience concept drift—changes in task specification or context—which requires them to frequently retrain or adapt their models. Each retraining cycle reactivates all energy-intensive components, including data acquisition and action execution [5].

Figure 1 presents a visual overview of the energy flow in an EAI agent, demonstrating how energy is distributed across components during both the learning and deployment phases. It illustrates that while the core skill may have a fixed energy cost, poor reuse of knowledge can inflate total consumption through repeated computation and unnecessary physical trials.

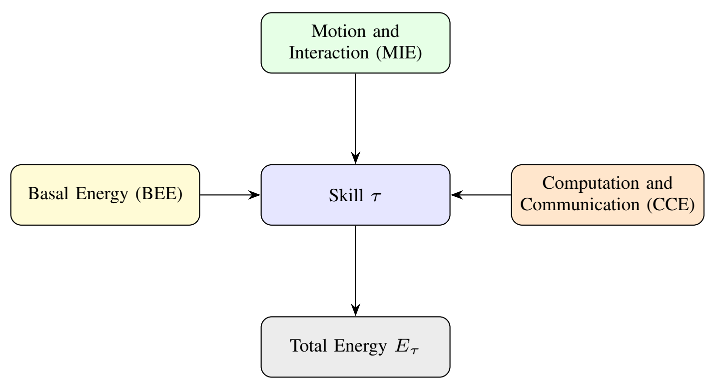

Fig. 1. Energy components contributing to total cost E_τ for skill execution.

In addition to robot-specific energy, there is also a non-negligible overhead associated with manufacturing and maintaining EAI systems. While not directly modeled here, the carbon footprint and material costs of producing robot hardware and GPUs contribute to the broader sustainability concern [15]. As the robot population scales, these indirect energy costs accumulate rapidly.

A particularly underexplored area is the energy cost of communication during multi-agent coordination. When multiple EAI agents work in the same environment, they must frequently share state information, learned policies, or sensory data. These transmissions, especially over wireless links, contribute significantly to CCE and can create network congestion that increases latency and energy waste [10].

To make EAI systems truly scalable, reducing any one of the energy dimensions alone is insufficient. Instead, integrated strategies that promote data-efficient algorithms, motion-efficient hardware, and communication-aware learning architectures must be employed. This comprehensive perspective is necessary for developing future-proof systems that can adapt without depleting energy reserves or exceeding infrastructure capacity.

In the next section, we propose that the key to achieving such efficiency lies not only in optimization of individual agents, but in the design of learning paradigms that encourage inter-agent cooperation and knowledge reuse. We introduce the concept of collective learning as a viable alternative to energy-intensive isolated learning, and establish the framework for analyzing its energetic impact.

III. Collective Learning: A Paradigm Shift

As the deployment of Embodied AI (EAI) systems becomes increasingly widespread, a key limitation of conventional learning approaches emerges: inefficiency i n energy and time due to redundant isolated learning processes. Most existing agents are trained independently, often learning similar or identical skills with no cross-agent benefit. This siloed methodology leads to cumulative energy waste and slower system-wide skill acquisition.

Collective Learning (CL) offers a fundamental departure from these legacy approaches by introducing a framework where robots actively share, disseminate, and build upon each other's acquired knowledge. Inspired by social learning in biological systems, CL promotes distributed intelligence and mutual adaptability, transforming a collection of individual learners into an interconnected, energy-efficient collective [8].

In isolated learning (IsL), each agent begins from scratch, expending energy on both exploration and repeated failure, even if another agent has already mastered the skill. Incremental learning (IL) mitigates some of this waste by allowing a single agent to build on previously learned skills over time. Transfer learning (TL) extends this by transferring knowledge across different tasks or agents, but often without continuous synchronization [5].

CL, however, unifies t hese c oncepts u nder a cohesive model. In CL, each agent is a node in a knowledge-sharing network, capable of bi-directional communication and contextual model updates. Skill learning is no longer a solitary endeavor but a distributed process where knowledge is replicated, modified, and improved collectively across the agent population [10].

From an energy standpoint, CL significantly reduces redundant exploration. When one robot learns an optimal trajectory or skill model, others can adapt or reuse that knowledge directly, avoiding costly motion replays. This decreases Motion and Interaction Expenditure (MIE) and Computation and Communication Expenditure (CCE) per agent [12].

Additionally, by shortening the time each agent spends learning, the system also reduces Basal Energy Expenditure (BEE). Agents spend less time idling or executing fallback procedures between trial episodes. For swarms or factories with dozens of robots, the compounding energy savings from CL become substantial [14].

The mechanics of CL can be modeled using graph-based representations where each node corresponds to an EAI agent and edges represent communication or knowledge transfer channels. These edges can carry weights that reflect trust, skill similarity, or bandwidth constraints. The propagation of knowledge through such a graph evolves over time as agents learn new skills or refine existing ones [9].

Figure **??** compares the four paradigms: IsL, IL, TL, and CL. Unlike the others, CL demonstrates dense inter-agent communication and knowledge reuse, leading to a dynamic feedback-rich environment where agents rapidly converge to optimal behaviors.

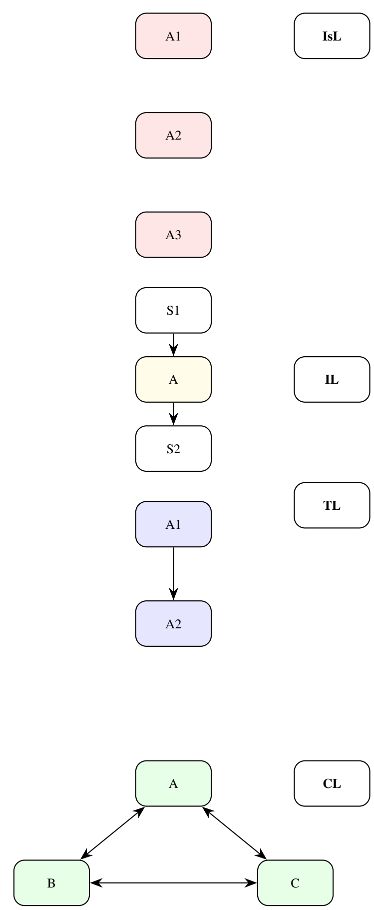

Fig. 2. Vertical view of agent learning paradigms: IsL, IL, TL, and CL.

Implementing CL at scale introduces challenges such as communication bottlenecks, inconsistent models, and synchronization latency. However, recent advances in federated learning, graph neural networks, and decentralized control make these concerns increasingly addressable in real-world deployments [16].

In a collective learning system, skill models can be periodically synchronized using averaging techniques, while learned experiences can be abstracted into transferable embeddings or subpolicies. These representations are more compact than raw data and are ideal for energy-constrained communication systems like wireless mesh networks [1].

Perhaps the most profound implication of CL is its alignment with energy-aware system design. Rather than optimizing learning locally, CL considers the energy dynamics of the entire agent network. Decisions about who learns what and when are driven by minimizing total system energy, not just individual success rates [15].

In summary, CL transforms the learning architecture of EAI systems into an emergent, scalable, and energy-conscious process. The next section delves into how we model the knowledge dynamics underlying CL, including mathematical formulations of skill complexity reduction, convergence rate, and learning synergy across agents.

IV. Skill Acquisition Dynamics and Knowledge Reuse

Understanding how EAI agents acquire and refine skills is essential for optimizing collective learning systems. Unlike traditional agents that treat each task as an isolated challenge, collective learning enables shared context, reducing the learning curve for related tasks. This section formalizes the concepts of skill complexity, similarity clustering, and dynamic knowledge reuse.

We begin by defining a s kill u niverse $S = \{s_1, s_2, \dots, s_{NS}\}$, where NS is the total number of discrete skills relevant to the operational domain. Each skill s_j is associated with a complexity c_j, representing the number of episodes or trials required for an agent to learn it satisfactorily under isolated conditions [1].

To capture semantic and operational similarities among tasks, skills are grouped into K clusters $Z_k \subset S$, each containing N_Z similar skills. For example, household tasks like "sweeping" and "vacuuming" might reside in the same cluster, whereas "driving" and "object recognition" would be distinct. Within each cluster, we denote $\zeta_k \subset Z_k$ as the subset of skills already learned by one or more agents [9].

The premise of reuse is formalized using a remaining knowledge function $\bar{\sigma}_{j,k}(n) \in [0,1]$, which models the fraction of skill $s_{j,k} \in Z_k \setminus \zeta_k$ that still needs to be learned after n trial episodes. We use:

$$\bar{\sigma}_{j,k}(0) = \begin{cases} 1 & \text{if } \zeta_k = \emptyset \\ e^{-\delta N_{\zeta_k}} & \text{otherwise} \end{cases}$$

Here, δ controls how strongly prior knowledge reduces the initial learning burden.

Learning is modeled as a first-order dynamical system:

$$\dot{\bar{\sigma}}_{j,k}(n) = -f_{j,k}(N_{\zeta_k})\bar{\sigma}_{j,k}(n)$$
$$\Rightarrow \bar{\sigma}_{j,k}(n) = \bar{\sigma}_{j,k}(0) \cdot e^{-f_{j,k}(N_{\zeta_k})n}$$

where $f_{j,k}$ represents the rate of knowledge acquisition, and is positively correlated with the size of ζ_k, the set of similar, already learned skills.

To enhance this rate further, collective learning introduces an additional multiplier through shared experience. Let m be the number of agents and γ be the inter-agent learning coefficient. In this setting, knowledge propagates with:

$$\dot{\bar{\sigma}}^{CL}_{j,k}(n) = -\left[h_{j,k}(N_{\zeta_k}, m) + \gamma A \odot B\right] \bar{\sigma}^{CL}_{j,k}(n)$$

where A is the inter-agent adjacency matrix, B scales similarity across clusters, and $\odot$ denotes element-wise multiplication. This model captures both horizontal (across agents) and vertical (across tasks) knowledge propagation.

In this framework, each agent benefits not only from its own history but also from a distributed knowledge base evolving in real time. The rate function $h_{j,k}$ is defined as:

$$h_{j,k}(N_{\zeta_k}, m) = \alpha \cdot (\eta m N_{\zeta_k} + 1) / (1 - \beta_k)$$

where α is a baseline learning rate, η reflects reuse efficiency, and β_k encodes cluster similarity.

This dynamic accelerates convergence towards the learning threshold ϵ, below which a skill is considered mastered. For instance, with $\bar{\sigma}_{j,k}(n) < 0.01$, agents halt further trials, saving unnecessary motion and computation. Figure 3 illustrates this exponential decay across learning paradigms.

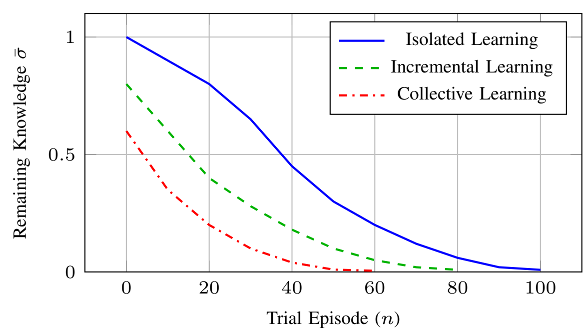

Fig. 3. Remaining knowledge decay across paradigms: collective learning enables faster convergence.

Through this model, it becomes evident that the complexity c_j of learning any skill is no longer a fixed property. Instead, it becomes a function of cluster knowledge and agent interaction density. By leveraging prior skill knowledge, both within and across agents, the system significantly compresses learning time and energy.

In conclusion, the dynamical model of remaining knowledge enables quantifiable analysis of energy savings and learning efficiency across paradigms. It lays the mathematical foundation for evaluating the cost-benefit trade-offs of collective learning. The next section leverages this formalism to simulate learning scenarios and compare energy consumption across paradigms under varying agent and skill configurations.

V. SIMULATION STUDY AND ENERGY CONSUMPTION ANALYSIS

To evaluate the effectiveness of various learning paradigms in terms of energy consumption and skill acquisition efficiency, we simulate a robotic environment wherein a group of EAI agents is tasked with learning a comprehensive skill set. Our objective is to quantify the learning time and energy demands for four paradigms: Isolated Learning (IsL), Incremental Learning (IL), Transfer-Integrated Learning (TIL), and Collective Learning (CL).

We define a simulation scenario $\phi = (N_S, N_K, m, \rho)$, where N_S is the total number of skills, N_K is the number of skill clusters, m is the number of EAI agents, and $\rho = [\alpha, \eta, \delta]$ captures learning parameters. For this study, we use $N_S = 512$, $N_K = 4$, and $m \in \{2, 4, 8, 16, 32, 64\}$. Each cluster Z_k contains $N_Z = 128$ skills [1].

Baseline parameters are chosen based on prior works and practical observations: $\alpha = 0.0461$ represents the base learning rate, $\eta = 0.1$ reflects knowledge reuse efficiency, and $\delta = 0.036$ controls the effect of prior knowledge on initial complexity [10]. Each skill trial episode is assumed to last $\Delta t = 60s$, with power demands from three energy domains: $P_{\text{BEE}} = 40W$, $P_{\text{MIE}} = 300W$, and $P_{\text{CCE}} = 1075.78W$ [4], [3].

The total energy per trial episode becomes:

$$e_0 = P_0 \cdot \Delta t = (P_{\text{BEE}} + P_{\text{MIE}} + P_{\text{CCE}}) \cdot 60 = 105 \text{ kJ}$$

For each paradigm, we compute the total number of episodes C_S required to master all N_S skills and multiply this by the number of agents m and the per-episode energy cost e_0. Table I summarizes the results.

Table I: Energy Use by Learning Paradigm ($N_S = 512$)

Type	C_S	Energy (MJ)	Savings
IsL	51200	322.56	baseline
IL	31488	198.16	38.6%
TIL	25856	162.31	49.7%
CL	12288	80.64	**74.9%**

As evident from the results, IsL consumes the most energy. Each agent must independently learn every skill from scratch, resulting in high C_S and cumulative energy costs. IL reduces redundant effort by enabling agents to build upon previously acquired skills within a cluster, cutting energy usage by 38.6%.

TIL provides further benefits by introducing inter-cluster transfer, allowing previously learned knowledge to support learning in new clusters. However, its effectiveness diminishes as the number of agents increases, due to knowledge dilution across multiple clusters [5].

CL delivers the most energy-efficient performance by facilitating continuous, bidirectional knowledge sharing among agents. Agents learn in parallel and share both intermediate knowledge and complete skills. The number of trials required to master new skills reduces significantly, resulting in total energy savings of nearly 75% compared to IsL.

Figure 4 plots the total energy consumption against the number of robots for each paradigm. While IL and TIL exhibit sublinear improvements, CL continues to outperform even as the agent count scales, demonstrating its resilience and scalability.

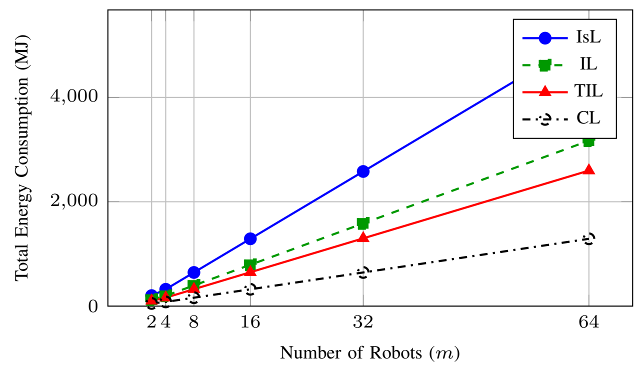

Fig. 4. Energy consumption vs. number of robots across learning paradigms.

Importantly, the relative performance of each paradigm shifts as more agents are introduced. In IL and TIL, knowledge sharing is constrained by the agent-to-cluster distribution, which weakens the transfer effect. In contrast, CL adapts fluidly by leveraging both intra- and inter-agent collaboration.

These results also highlight a key insight: energy efficiency in EAI systems is not merely a function of better hardware or algorithms but of systemic collaboration. The broader the knowledge base and the richer the sharing mechanisms, the more energy-efficient the system becomes [15].

Moreover, the simulation validates the theoretical models introduced earlier. The exponential decay of remaining knowledge and the role of shared learning rates are mirrored in the reduced episode counts for CL. The convergence threshold $\epsilon = 0.01$ remains consistent across all paradigms, ensuring comparability.

In summary, our empirical analysis confirms that collective learning not only accelerates skill acquisition but also significantly reduces energy costs. The final section synthesizes these findings, discusses implications for future EAI deployment, and outlines open challenges for energy-aware multi-agent learning systems.

VI. IMPLICATIONS, LIMITATIONS, AND FUTURE DIRECTIONS

The findings of this study underscore a pressing shift in the design philosophy of Embodied AI (EAI) systems—from isolated, resource-intensive learning agents toward coordinated, energy-efficient collectives. The proposed collective learning (CL) paradigm not only accelerates skill acquisition but also demonstrates measurable reductions in energy consumption, critical for scaling intelligent robotic infrastructure.

A key implication is that EAI systems can no longer be evaluated solely based on accuracy, speed, or adaptability. Energy efficiency must become a first-class performance metric. In applications such as autonomous logistics, manufacturing, or healthcare, the cumulative energy demands of fleets of robots could rival those of entire data centers if unmanaged [2], [6].

Our results reveal that when learning paradigms incorporate structured knowledge reuse—especially under CL—the total number of physical trials and model updates decreases substantially. This implies not just energy savings, but also prolonged hardware life, reduced operational cost, and improved task reliability over time.

From an architectural standpoint, implementing CL demands a shift in both software and communication protocols. Agents must be equipped with mechanisms for storing, querying, and verifying shared knowledge. Real-time coordination, bandwidth-aware communication, and policy validation frameworks will be necessary to ensure that shared models remain coherent and trustworthy across agents [16], [8].

However, these advantages come with trade-offs. CL assumes relatively homogeneous agents capable of meaningful knowledge transfer. In real-world deployments, agents may differ in sensors, actuators, processing power, or local task priorities. Heterogeneity may reduce transferability, requiring additional effort to standardize representations or learn adaptable mappings [15].

Moreover, inter-agent communication is not free. In wireless environments, energy used in data transmission and synchronization can offset some of the savings from reduced computation and interaction. Protocol-level innovations like lightweight model distillation, selective sharing, or federated filtering may help mitigate these costs.

Another limitation lies in task generalization. While CL accelerates skill learning within and across clusters, it may falter when confronted with highly divergent or novel tasks for which no peer has useful experience. Ongoing research in few-shot learning and meta-reinforcement learning can support this edge case, making CL systems more robust [5].

Security and robustness are additional concerns. In adversarial or open environments, malicious agents could inject corrupt knowledge into the shared pool, degrading collective performance. Incorporating consensus mechanisms, trust scores, or cryptographic validation may be necessary for mission-critical applications.

Despite these limitations, the potential of CL remains transformative. By reframing learning as a cooperative, energy-aware activity, CL paves the way for more scalable and sustainable AI systems. Applications in warehouse robotics, multi-UAV surveillance, and autonomous vehicle fleets stand to benefit immensely from these principles [14].

From a policy perspective, organizations deploying EAI systems must now consider the collective energy footprint as part of regulatory compliance and sustainability goals. Metrics similar to Green AI benchmarks in NLP could emerge for robotics, requiring disclosure of energy use per task or per learning episode [3], [15].

Future research should focus on hybrid architectures that integrate CL with local adaptation. While collective memory provides a foundation, local refinement ensures contextual specificity. Combining shared embeddings with instance-specific fine-tuning could yield optimal performance with minimal energy waste.

In conclusion, collective learning marks a necessary evolution in how intelligent systems learn, scale, and conserve energy. It combines algorithmic efficiency with systemic sustainability, addressing core challenges of embodied autonomy. The synergy of distributed intelligence and resource-awareness may ultimately define the next generation of AI-augmented robotic ecosystems.

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