Knowledge Evolution for Lifelong Embodied AI: A Survey

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The resilience of life lies not in permanence, but in its capacity for constant evolution and adaptation—an enduring dialogue between the self and a changing world. Yet in the realm of Embodied Artificial Intelligence (Embodied AI), research remains largely grounded in static models, designed for fixed tasks or environments, unresponsive to the flux of real-world complexity. In this survey, we propose a knowledge evolution cycle for lifelong Embodied AI, inspired by memory mechanisms in neuroscience. This cycle consists of three core stages: active data collection, knowledge consolidation, and knowledge refinement. We examine how embodied agents can actively explore their environment, integrate and store new knowledge both in-parameter and in-context, and refine their models to ensure scalability and generalization over time. Unlike previous surveys focused on models or benchmarks, we frame lifelong Embodied AI as a dynamic process of continual knowledge evolution. Through this perspective, we provide a comprehensive overview of the field, highlight open challenges, and outline promising directions toward building self-evolving, autonomous embodied agents.

CCS Concepts: • **General and reference → Surveys and overviews**; • **Computing methodologies → Artificial intelligence**; *Robotic planning*; *Vision for robotics*; *Natural language processing*.

Additional Key Words and Phrases: Embodied AI, Lifelong Learning

1 Introduction

Current Embodied AI research often relies on one or multiple pre-trained models, each specialized for a unique task. This approach is effective when the agent operates in a fixed environment with consistent observations, such as fixed lighting conditions, uniform object arrangement, and other stationary factors. However, it falls short when the environment changes or when the agent needs to update its knowledge or acquire new skills. For instance, a home assistant robot must adapt to modifications in the household environment, learn new recipes, adjust to the owner's preferences, and even develop its own evolving personality. In such dynamic settings, a lifelong learning agent becomes essential.

We explore the challenge of lifelong Embodied AI and draw inspiration from neuroscience. In biological systems, the brain filters perceptual information based on previous experiences [47, 50], processes it through short-term memory in the hippocampus, and subsequently transfers it to the cerebral cortex with enhanced efficiency and abstraction [39, 53, 85]. Similarly, Artificial Intelligence (AI) knowledge evolution over a lifetime can follow a similar process, progressively refining and consolidating learned representations as experience accumulates. As illustrated in Figure 1, we introduce a knowledge evolution cycle within the lifespan of an Embodied AI agent, which is initialized by models pretrained on human-curated data and then iterates through active data collection, knowledge consolidation, and knowledge refinement. **Active data collection** refers to an agent autonomously acquiring data to get familiar with new environments, enhance existing skills or develop new ones. During the **knowledge consolidation phase**, the embodied agent learns from the collected data, encoding knowledge either within its model parameters or organizing it

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in an external storage as in-context memory for future querying. Finally, in the **knowledge refinement phase**, the model is optimized to improve efficiency in time and storage, preventing resource overgrowth on edge devices, and to enhance generalization, reducing the risk of performance degradation during iterative evolution.

Existing surveys on Embodied AI contributed to collect and summarize Embodied AI tasks and one-off decision-making models [38, 101, 187], or the continual learning in the Large Language Models (LLMs) era [142, 166], or mainly discuss the Embodied AI in the context of LLMs agent [151, 167, 182], Vision-Language-Action (VLA) agent [105, 112]. Unlike previous surveys that focus on specific models, training strategies, or benchmarks, our work takes a broader perspective by framing Embodied AI through the lens of knowledge evolution. The content is organized as follows. In Section 2, we review two types of Embodied AI foundation models that have gained attention in recent years, forming the basis for lifelong agents. Section 3 covers data sources and active collection strategies. Knowledge consolidation based on incoming data is covered in Section 4. Finally, Section 5 discusses strategies for improving model efficiency and enhancing generalization before initiating the next evolution cycle. Building on the key topics outlined above, we aim to provide a brief review of research that advances the long-term goal towards developing self-evolving Embodied AI capable of lifelong autonomy and generalization. An overview of the survey structure is illustrated in Figure 2.

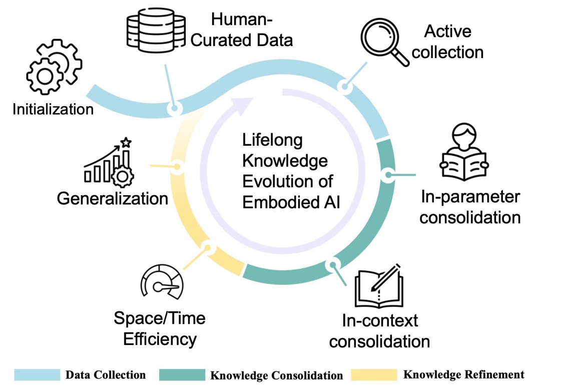

Fig. 1. The knowledge evolution process for lifelong Embodied AI. The embodied agent begins with an initialization, providing essential capabilities for active interaction with the environment. It then iterates through a cycle of **data collection**, **knowledge consolidation**, and **knowledge refinement**.

Our survey includes papers from peer-reviewed journals, conferences, and preprint archives such as arXiv to capture the latest advancements in this rapidly evolving field.

2 Embodied Agent Initialization

For lifelong knowledge evolution in embodied agents, a strong initialization serves as a crucial foundation to effectively bootstrap the evolutionary process. As illustrated in Figure 3, two primary branches of Embodied AI models—commonly referred to as VLA models—demonstrate significant potential in fulfilling this role.

The first branch follows a modular design powered by the strong reasoning ability of LLMs [6, 52, 115, 155]. Interaction between the model and its environment is typically mediated through a script-based interface or supplemented by additional policy modules to execute natural language instructions. For instance, works proposed in [59, 60, 90, 99] design prompt-based policies that guide LLMs in generating executable control codes, enabling interaction with vision models or low-level robotic controllers in a zero-shot manner. Among them, Code as Policies [90] introduces a framework where pre-trained language models are prompted to generate executable robot control code directly from natural language instructions. The approach treats policies as programs, leveraging structured API calls to perception and control modules, enabling interpretable and generalizable behavior without any model fine-tuning. Instruct2Act [59] also formulates robot policy generation as code synthesis via large language models, but with an emphasis on multi-modal instructions, including textual and visual references. By combining perception models (*e.g.,* SAM, CLIP) and predefined action libraries, it maps high-level goals to end-to-end executable programs without requiring additional training.

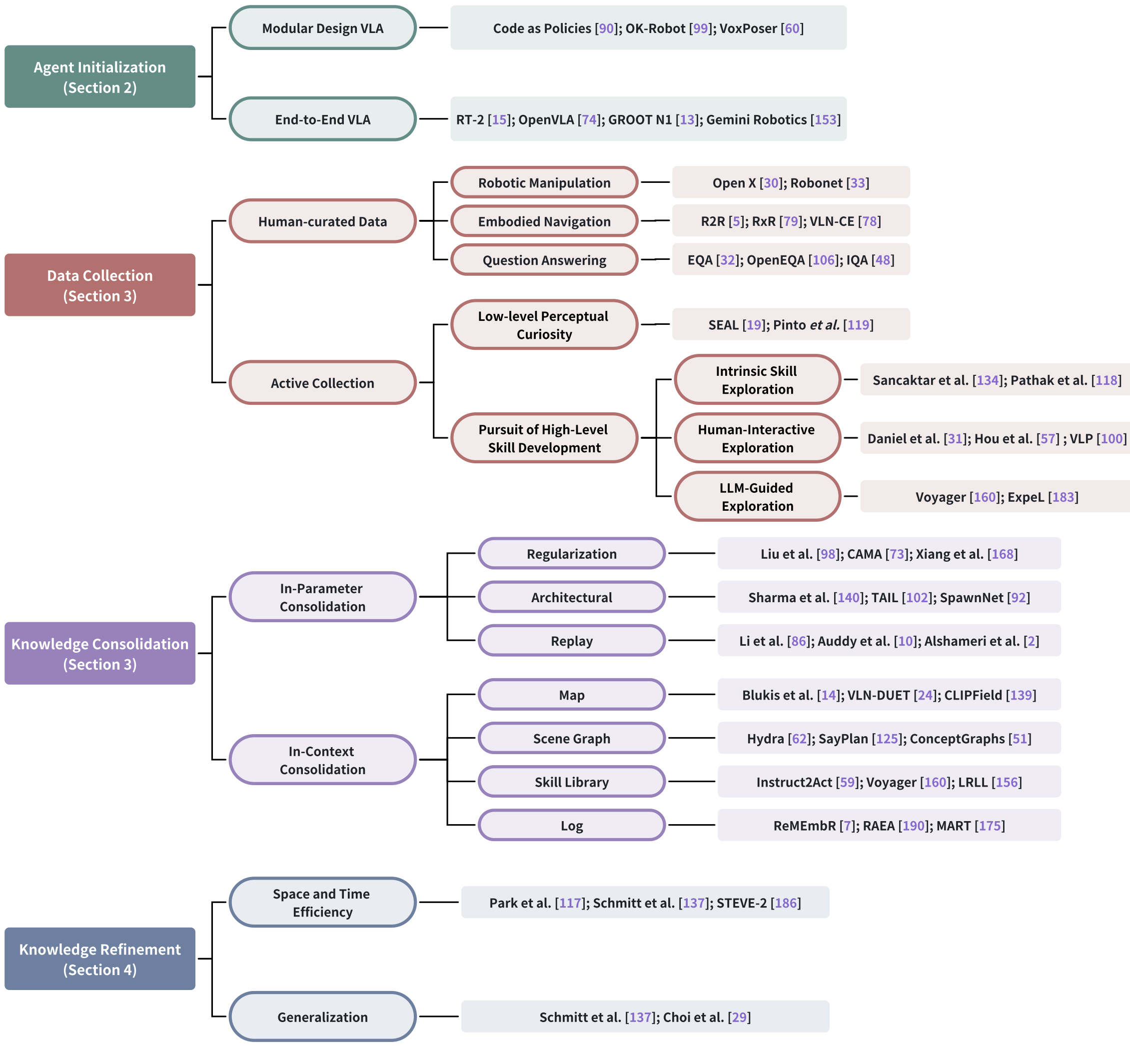

Fig. 2. Overview of the survey structure.

Extending this principle, OK-Robot [99] integrates navigation planner and supports harder compositional Embodied AI tasks. VoxPoser [60] introduces a novel intermediate abstraction of manipulation plans by generating 3D spatial value maps that represent action affordances across the environment; these are derived from vision-language API outputs and passed to model-based planners. These models are valued for their flexibility and interpretability, as they often produce explicit intermediate outputs. While modular design offers these benefits, it can introduce significant overhead during lifelong updates. When the model's capabilities become insufficient, each module requires a separate update strategy, making the process costly and difficult to manage.

The second branch follows an end-to-end design, which aims to equip embodied agents with capabilities for perception, reasoning, and action in a single model. While models such as PaLM-E [37] and SayCan [16] adopt an end-to-end training

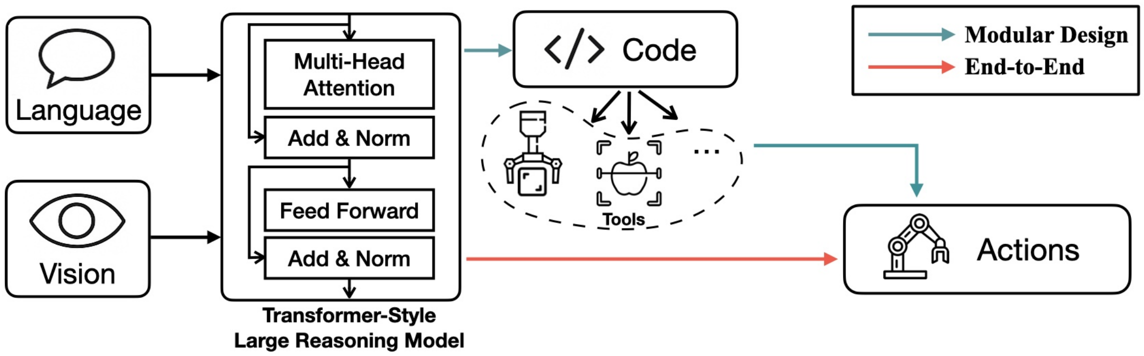

Fig. 3. **Embodied Agent Initialization Strategies.** Initial VLAs are designed in a modular fashion, relying on the strong coding capabilities of LLMs and a predefined set of functional tools. However, to support increasingly diverse Embodied AI tasks and enable more dynamic control, recent research is shifting toward end-to-end VLA approaches.

paradigm for processing multimodal inputs and output high-level sub-tasks, which require additional task-specific controllers. We consider these set of execution architectures to be not fully end-to-end, as they do not directly output robot control parameters. Subsequent research has advanced this concept by enabling direct robot control within unified frameworks. For instance, RT-2 [15] is trained jointly on web-scale vision-language data and robotic demonstrations, representing robot actions as language tokens. This allows the model to map multimodal inputs directly to executable actions using a single Transformer-based architecture. Building on this foundation, OpenVLA [74] adopts a similar tokenized action representation but enhances performance across diverse tasks and embodiments by leveraging a large corpus of real-world robotic demonstrations and efficient training strategies. Despite these improvements, integrating planning and motion control into a single model can introduce latency and execution bottlenecks. To address this, GROOT N1 [13] proposes a slow-fast system: a dual-system architecture where a slow, reasoning-focused component (System 2) utilizes a vision-language model (VLM) for high-level planning, while a fast control component (System 1) employs a Diffusion Transformer for low-latency motion execution. The model is also trained on a mixture of data sources—including action-less videos—allowing it to generalize effectively and benefit from broader supervision. Similarly, Gemini Robotics [153] adopts the two-system design, with a particular emphasis on rapid adaptation to novel tasks. Although these models streamline the perception-to-action optimizable pipeline and demonstrate strong empirical performance, their effectiveness still depends heavily on access to large and diverse training datasets, which remains a key challenge for broader adoption.

3 Data Collection

Data is the fundamental driver of modern AI models, shaping their learning, adaptation, and decision-making processes. For lifelong Embodied AI, data collection is not merely a passive, preprocessing step building on human-curated data (Section 3.1) but an active process (Section 3.2) that shapes the agent's knowledge evolution over time.

3.1 Human-Curated Data

Human-curated data refers to data in which humans actively provide annotations and demonstrations, typically to establish essential foundational abilities before the system begins autonomous learning. In this section, we provide a brief summary of some key Embodied AI tasks and data collection devices. While these tasks and devices are often introduced during the initialization of embodied models, they also play a crucial role throughout the continuous evolution of lifelong Embodied AI. Understanding these foundational tasks is essential for grasping the broader landscape of Embodied AI research.

3.1.1 Robotic Manipulation. Manipulation tasks have received significant attention in the research community, as they play a central role in Embodied AI. These tasks range from fundamental actions of robot arms such as grasping [18, 34, 40] and pouring [89, 135] to more complex and compositional tasks such as object rearrangement [12, 69, 179] and general daily manipulation [30, 33, 66, 67, 72, 144].

The evolution of teleoperation devices for data collection has seen significant progress, particularly in terms of usability and efficiency. Early approaches relied on joysticks [95, 145], followed by VR devices [9, 63, 180], and twin-arm systems [185]. The latest advancement is the Universal Manipulation Interface (UMI) [27], which provides flexibility enabled by wireless connectivity, allowing the capture of long and complex robot end-effector trajectories. For whole-arm manipulation, AirExo [43] provides a low-cost exoskeleton solution for data collection. To facilitate continuous and scalable data collection, RoboTurk [107] introduced a crowdsourcing platform as a solution.

3.1.2 Embodied Navigation. The data collection for embodied navigation still largely relies on simulation environments, such as Habitat-Sim [149], VirtualHome [122], and IsaacLab [111], with human annotators' keyboard or joystick control. The tasks range from object-goal navigation [20] and point-goal navigation [164] to more advanced multimodal tasks such as path-aligned vision-language navigation (VLN) [5, 25, 78, 79] and goal-oriented VLN [123, 189]. A new trend in this category involves manipulation tasks during navigation, such as OK-Robot [99] and SayPlan [125]. However, the data used in these works is often not publicly available, as it is heavily dependent on the specific scene and the configuration of the mobile robots. More recently, benchmarks combining manipulation with embodied navigation on humanoid robots have gained attention, such as Humanoidbench [138].

3.1.3 Embodied Question Answering. Beyond the aforementioned goal-driven tasks, knowledge-driven tasks require strong reasoning abilities supported by world knowledge. These tasks are typically framed as embodied question-answering challenges. One notable subcategory is Episodic-Memory Question Answering (EMQA), where an agent must develop an understanding of the environment from its episodic memory to answer queries, such as "Where is my smartphone?". Data for these tasks are typically obtained through crowdsourced annotations [106, 150] or generated from predefined templates [168]. Another subcategory, Active Embodied Question Answering (AEQA), requires agents to engage in further exploration and interaction with the environment to retrieve the necessary information [32, 36, 48].

3.2 Active data collection

Lifelong Embodied AI agents are expected to continually learn and adapt by interacting with their environment. A key to this adaptability is active data collection, where an agent autonomously gathers new experiences rather than relying solely on a fixed training set. By actively selecting which data to collect, the agent can identify gaps in its knowledge, focus on informative experiences, and thereby improve its competencies more efficiently. This process is crucial in domains like navigation, manipulation, and perception, where an embodied agent must cope with open-ended scenarios and evolving tasks. For example, a household robot may roam to map unseen rooms, experiment with objects to learn their properties, or ask for help when encountering an unfamiliar task. Active data collection thus enables continual improvement in perception and reasoning by closing the loop between experience and learning.

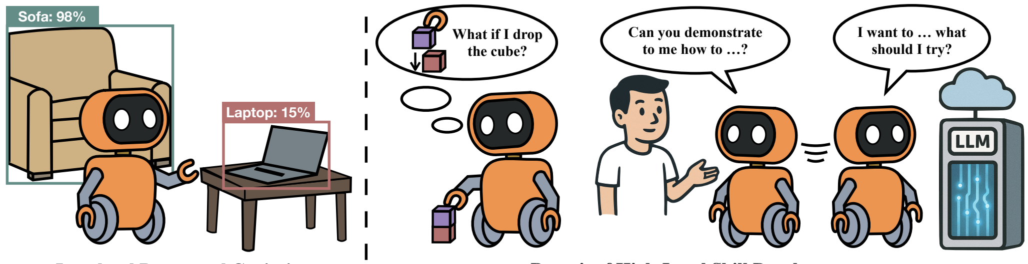

Fig. 4. **Active Data collection.** Active data collection methods can be categorized based on their underlying driving forces. These methods may be motivated by low-level perceptual curiosity or by the pursuit of high-level skill development. In the context of skill development, further categorization can be made based on the source of guidance.

We discuss active data collection strategies in existing Embodied AI literature, driven either by **low-level perceptual curiosity** or the pursuit of high-level skill development. For high-level skill development, we further break down them based on the source of guidance for a more detailed discussion. We identify three prominent sub-categories in current works: (a) **intrinsic skill exploration**, (b) **human-interactive exploration**, and (c) **LLM-guided exploration**. While many traditional strategies rely on additional policy modules, some advanced approaches—particularly those that leverage LLMs—can be adapted directly to VLA models discussed in Section 2.

3.2.1 Low-level Perceptual Curiosity. Perceptual curiosity refers to an agent's intrinsic drive to efficiently explore and get familiar with its environment, primarily to improve its sensory understanding. The agent actively collects data (*e.g.,* images, sensor readings) to build a richer spatial memory of the world or to obtain more informative samples that enhance its perceptual models. In lifelong Embodied AI, this is crucial for an agent that may enter new environments or encounter novel objects curiosity encourages it to seek out new information rather than passively observe.

This low-level exploration is often formulated as an **intrinsic reward maximization** problem in reinforcement learning. Common formulations of this intrinsic reward include: area of coverage [21, 77], semantic uncertainty [19, 22, 114]. In Active Neural SLAM [21], the agent's global policy is trained to set waypoints maximizing unexplored area. In Semantic Curiosity [22], the reward is higher when the agent's object recognition is inconsistent across viewpoints, prompting it to investigate those spots further. Other approaches build intrinsic rewards from learned model uncertainty or disagreement. For instance, SEAL [19] closes the action-perception loop by using a 3D semantic map as both a training signal and reward. The agent leverages a perception model pre-trained on internet images, and then learns an exploration policy that moves around to improve that model. Crucially, observations are labeled in a self-supervised way via 3D consistency (if an object looks the same from multiple views, it reinforces the label). This eliminates manual labeling. SEAL demonstrates that by just moving around in training environments, an agent can significantly improve its instance segmentation performance, which in turn leads to better navigation, such as object-goal navigation. This result exemplifies how low-level curiosity-driven exploration directly enhances perception and even downstream task performance.

Not all approaches rely on learned rewards; some use **rule-based strategies** for active data collection when appropriate [80, 119]. Pinto *et al.* [119] has a robotic arm that performs a series of predefined physical interactions with objects (pushing, poking, grasping), collecting images before and after each interaction. By doing so, the robot gathers a diverse dataset of object views and contexts, which is then used to train a more robust visual representation. Another example is Lamanna *et al.* [80], who uses symbolic planning to devise experiments for learning object properties. Their system would, say, plan to roll a ball to test an object's weight or push a cup to see if it is attached to a surface, thereby actively uncovering properties that static observation cannot. Such approaches highlight that even without fancy learning algorithms, an embodied agent can be programmed to systematically probe its environment for new data.

3.2.2 Pursuit of High-level Skill Development. While exploring for better perception is necessary, lifelong agents must also acquire new skills and behaviors as their tasks evolve. High-level active data collection is about an agent proactively seeking experiences or feedback that help it learn novel tasks or improve complex skills beyond its existing capabilities. In contrast to low-level perceptual curiosity (which might memorize a scene or learn object appearances), this involves learning policies and competencies - for example, learning how to open a door, how to navigate to a goal efficiently, or how to perform a new household chore. Crucially, the agent needs to recognize its own skill gaps and then actively gather the data needed to fill those gaps. This may involve setting new goals for itself, practicing through trial and error, or even querying the environment or humans for guidance. High-level active learning thus enables an agent to evolve its capabilities over time, rather than being limited to the skills it was initially programmed or trained on.

Intrinsic Skill Exploration

In intrinsic skill exploration, the agent itself generates goals for new skills, analogous to how children engage in open-ended play. Here, intrinsic motivation (curiosity, novelty-seeking, mastery drive) operates not just at the perceptual level but at the task level. The agent might ask: what new behavior can I learn that I have not tried before? or can I achieve a more challenging goal than I currently can? The methods often extend ideas from curiosity to more structured behaviors, encouraging the agent to practice progressively more complex skills without external rewards.

One approach is through automatic curriculum learning: the agent self-adjusts the difficulty or targets of tasks it practices, to continually push its boundaries. For example, Intrinsically Motivated Goal Exploration Processes [44] provide a framework where an agent samples goals for itself (*e.g.,* reaching certain positions or manipulating objects into certain configurations) and learns to achieve them, gradually increasing difficulty as easier goals become mastered. This process results in a self-generated curriculum, through which the agent gradually acquires a broader range of skills. Another example is the work by Sancaktar *et al.* [134] on curious free-play in object manipulation. They use a structured world model with relational biases as an internal simulator. The agent plans sequences of actions that will lead to novel states in this world model (*i.e.,* "planning for novelty" inside its own learned simulation). By doing so, the agent in a block manipulation environment starts with simple behaviors (tapping or moving a block) and on its own progresses to more complex ones (stacking two blocks, then flipping a block, *etc.*). Importantly, this self-driven exploration was interaction-rich - the agent actively engaged with objects early and often, rather than wandering aimlessly. The outcome was remarkable: after training on state-transfer data collected in an entirely intrinsic exploration phase, the agent could solve multiple downstream manipulation tasks zero-shot, even in new settings with more objects than before. This illustrates how intrinsic skill exploration allows an agent to acquire and generalize high-level skills by bootstrapping on its prior knowledge.

Another line of work uses self-supervised multi-model disagreement to drive skill learning. For instance, Pathak *et al.* [118] have explored training an ensemble of forward models and using the regions of state-action space where these models disagree as targets for exploration. The idea is that disagreement signals high uncertainty about the consequences of actions - a gap in the agent's understanding of the dynamics - so it should practice there. Such techniques have been applied in navigation and manipulation, encouraging an agent to attempt actions where its predictors are unsure, thus learning new transitions and skills. The general insight is that an agent can self-identify what it does not know how to do and then focus practice on those failure cases until they become successes.

Human-Interactive Exploration

Not all high-level learning needs to be solitary. Often, an embodied agent can actively seek external information to accelerate skill acquisition - for example, by asking a human teacher for demonstrations, preferences, or evaluations, or by querying the environment (*e.g.,* asking "what is this object?" in a simulated QA setting). This sub-category includes active learning from humans and other strategies where the agent guides its data collection via questions or requests. The hallmark of these approaches is that the agent recognizes a knowledge or skill gap that it likely cannot bridge alone, and thus takes initiative to obtain guidance.

A line of work has looked at how robots can request demonstrations or adjust human teaching to improve learning. Hou *et al.* [57] allow a robot to actively guide the human teacher during demonstrations. For example, if all demonstrations so far have shown a task from one angle or in one context, the robot might reposition itself or prompt the human to demonstrate in a new context, thus balancing the data. The robot essentially says "show me something different because I am overfitting to what you showed before." This active curriculum for the human teacher results in a more robust policy learned from those demonstrations. Similarly, Cakmak *et al.* [17] leveraged human-designed and hard-coded questions to enable robots to interact with humans for informative data gathering.

Another branch of this category is preference-based learning for skill optimization. Rather than assuming a fixed reward function, an agent can interact with a human to learn the reward or goal criteria for a task. Daniel *et al.* [31] implemented this by having a robot query a human by demonstrating different behaviors and asking for expert ratings. By intelligently choosing which queries to make, the agent learns an accurate reward model with fewer queries than passive observation. This addresses the knowledge gap in "what should I do?" through minimal human feedback. More recently, vision-language preference learning (VLP) [100] for robotics uses humans to choose which of two attempted behaviors is better for a given command. The agent actively tests different strategies and asks the human to pick the preferred outcome. Over time, the agent learns a reward function aligned with human intent, enabling it to perform complex manipulation tasks that satisfy human preferences (like how hard to squeeze an object, *etc.*). Importantly, the agent chooses the most informative comparisons to show the human (active query selection), which speeds up convergence. Similarly, gathering an universal prior from human feedback [35] has been explored for dexterous manipulation, where the robot queries humans on what successful grasps or tool uses look like, and distills those into a prior it uses across tasks.

LLM-Guided Exploration

A very recent trend (2022-2025) in Embodied AI is to incorporate high-level knowledge and reasoning systems, such as LLMs, to guide an agent's exploration. These approaches still fall under active data collection - the agent is deciding what actions to take to learn - but the decision is informed by an abstract understanding or memory rather than just raw curiosity. The motivation is that LLMs contain a wealth of prior knowledge and can perform reasoning, which an embodied agent can exploit to make exploration more directed and efficient. We can think of this as the agent asking not a human, but an internalized internet-scale mentor or using its accumulated memory to decide what experiences to gather next.

A notable example is Voyager [160], the researchers design the first LLM-powered lifelong embodied agent. Voyager operates in the game Minecraft as an open-ended world. Instead of naive exploration, Voyager uses GPT-4 [115] to continually propose new goals, generate action plans, interact with the environments, and record the outcomes. It maintains an automatic curriculum of skills: each time it achieves something (*e.g.,* "craft a wooden pickaxe"), it logs that skill in a skill library and then asks the LLM to suggest a next objective slightly beyond its current capabilities. In this way, it intelligently sequences tasks from easy to hard, always exploring something novel but achievable. Voyager also uses an iterative prompting mechanism: when an attempt fails, it feeds the error and environment feedback back into GPT-4, which then refines the plan. This closes the loop between experience and learning, where the agent improves through trial-and-error, guided by the reasoning capabilities of the LLM. The results have been striking: Voyager actively learned dozens of skills on its own and achieved progress in the game far faster than a standard RL agent with better generalization.

Another example is ExpeL [183], which combines an embodied agent with LLMs differently. Instead of updating the LLM's weights, ExpeL has the agent autonomously generate and store experiences as natural language. When facing a new problem, the agent can query its accumulated textual memory or use the LLM to reason over those experiences to make an informed decision. This effectively means the agent is actively collecting not just raw data, but knowledge snippets in human-readable form. As it faces more tasks, its library of experiences grows, and so does its performance - experiments showed a consistent improvement as ExpeL's agent accumulated more experience and could "recall" past insights to handle new challenges. This kind of approach highlights that active data collection need not be low-level trial-and-error only; it can involve high-level abstraction and learning from past knowledge. The agent identifies what it did not know in earlier tasks, learns a lesson, and actively applies it later.

3.3 Discussion

As humans continue to provide annotations for fundamental tasks, the amount of data they can collect will eventually reach a limit. To adapt to dynamic environmental changes and personalized customer requirements, active data collection becomes essential in lifelong Embodied AI. However, current research in this area remains limited. Most existing approaches are tailored to specific tasks, such as area exploration, question answering or interaction with a predefined set of objects. These methods typically optimize for task-specific objectives rather than developing a generalizable framework. In addition, some of these strategies require specialized policy module designs, adding complexity to the overall embodied agent architecture. With the advances in LLMs and their integration in embodied agents, the LLM-driven active data collection strategies offer a promising direction. However, a key challenge lies in how the LLMs can effectively identify the agent's current capability gaps and generate informative, context-aware questions based on this understanding. More research is needed to address this issue.

4 Knowledge Consolidation

Lifelong embodied agents will be exposed to online streams of knowledge due to the open-ended nature of the real world. The key challenge for such an agent will be acquiring new knowledge without forgetting the old one. We have identified works that could potentially overcome this challenge and have categorized them according to whether the new knowledge is stored in the model's parameters through optimization (4.1) or outside (4.2), *i.e.,* using external memory.

4.1 In-parameter knowledge consolidation

When training on new data, neural networks face the challenge of catastrophic forgetting [108, 127], where performance in previously learned tasks is severely degraded after learning a new one. In embodied domains, this forgetting largely limits the reliability of the agent for applications in lifelong scenarios. The continual learning community has proposed several methods to approach this challenge. Traditionally, CL methods are classified into three broad categories:

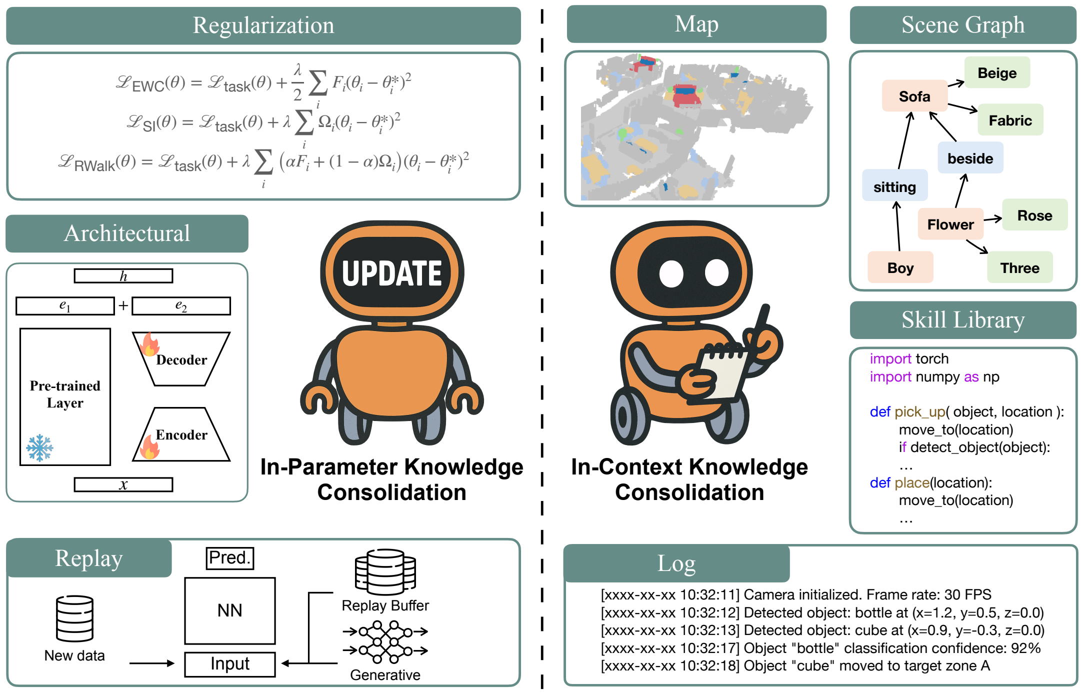

Fig. 5. **Knowledge Consolidation.** Knowledge can be consolidated in two ways: in model parameters or in context-similar to how humans take notes.

regularization-based (constraining parameter updates to preserve old knowledge), architectural or parameter-isolation methods (adding or modifying model structure to separate or preserve knowledge), and replay-based methods (revisiting past data or synthetic data to refresh the model's memory).

4.1.1 *Regularization approaches.*

Regularization approaches incorporate additional terms to the loss function to preserve previous knowledge. These approaches can be highly efficient with regard to storage and GPU memory during inference, but may require more computational resources for extra forward passes or computations during training. Despite their memory efficiency, they often do not achieve the best performance relative to other approaches.

A common strategy is functional regularization through knowledge distillation, which helps the model retain knowledge from previous tasks by guiding it to replicate past behaviors [87]. Liu *et al.* [98] propose a teacher-student architecture with selective knowledge distillation for robotic grasping detection, where the student learns from the teacher to preserve previous knowledge while adapting to new tasks. This method uses residual feature connections to enhance performance. Li *et al.* [84] address continual multi-task learning for dexterous soft-hand manipulation via policy distillation, a form of functional regularization. The expert RL policies for different object rotations are distilled into a single evolving student policy. A distillation loss preserves the behavior of earlier experts, acting as a regularizer on the policy outputs, consolidating knowledge in the student's weights. Additionally, a small memory of example trajectories is used to further mitigate forgetting. The distilled policy achieves versatile in-hand manipulation across object shapes, demonstrating that knowledge distillation can effectively consolidate multiple controllers into one continually learned policy. CAMA [73] stores logit predictions for each task in a replay buffer and incorporates them into an offline distillation regularization term during subsequent tasks. A key contribution of this approach is its dynamic updating of stored logits based on the agent's confidence, ensuring that past knowledge remains relevant as new data streams in, outperforming task-dependent methods.

Another prominent direction involves weight protection, *i.e.,* important parameters are protected while learning new tasks [176]. A classic method in this area is Elastic Weight Consolidation (EWC) [76], which approximates the importance of each parameter through the Fisher information matrix. Following this approach, Xiang *et al.* [168] propose finetuning large language models with embodied experiences from world models. This method utilizes a virtual household simulator to gather diverse embodied knowledge, encompassing both goal-oriented planning and random exploration. These experiences are used to finetune the models, enabling them to reason and act in physical environments, such as object tracking and goal completion. The method incorporates EWC to preserve general knowledge and Low-Rank Adaptation (LoRA) to enhance training efficiency. Piqué *et al.* [120] introduce EWC to continually re-tune a neural controller for a soft robot arm under changing payloads. By constraining weight updates with an EWC penalty, the robot adapts to material degradation or external loads without forgetting the base control policy. Experiments show that this EWC-based controller outperforms naive fine-tuning (SGD) in tracking accuracy under continuously changing conditions, marking a first step for CL in soft robot control. Yadav *et al.* [170] investigate Synaptic Intelligence (SI) [176] regularization (an improvement over EWC that estimates parameter importance online during training) for sequential learning of image-based manipulation tasks using offline reinforcement learning. This study combines an offline RL algorithm (SAC+CQlearning) with SI to protect weights important for earlier tasks. Results indicate that sequential task learning does yield forward transfer, *i.e.,* new tasks are learned faster by leveraging prior skills. However, while SI mitigates forgetting of past manipulation skills, it provides only limited improvement in forward knowledge transfer, highlighting a gap in leveraging prior knowledge in these settings.

Hybrid methods that combine both functional regularization and weight protection are also emerging. For example, AirLoop [46] integrates methods from Memory Aware Synapses [1] with distillation to provide additional parameter protection. It introduces three techniques for lifelong loop closure detection: Relational Memory Aware Synapses (RMAS), which preserves relationships between descriptors by tracking parameter importance based on similarity changes; Relational Knowledge Distillation (RKD), which minimizes discrepancies in descriptor similarity across environments; and a Similarity-Aware Memory Buffer, which stores past images and samples triplets based on similarity.

Lastly, regularization can guide optimization trajectories to prevent interference with previously learned tasks [103], as demonstrated in LLfN [94]. This paper introduces a framework for mobile robots to continuously improve navigation in new environments. LLfN utilizes a classical initial planner and learns a complementary policy that enhances navigation over time. To mitigate catastrophic forgetting, it employs Gradient Episodic Memory [103], a regularization-based approach that constrains gradient updates to avoid increasing the loss on previously seen tasks. During training, the robot dynamically stores key state-action pairs and adjusts new gradients based on those computed from past experiences. LLfN is implemented on a physical robot with limited computational resources, demonstrating the robot's ability to navigate across multiple environments while retaining previously acquired knowledge.

4.1.2 *Architectural approaches.*

Architectural approaches allocate dedicated parameters to each task, mitigating interference. As new tasks arrive, additional parameters—such as adapters [41, 58]—can be introduced, expanding the neural network's parameters. These approaches often yield a high performance, but lead to increased GPU memory usage and computational costs as the number of tasks grows in the iterative evolution cycle. The approach to addressing this issue is further discussed in the Knowledge Refinement Section. Furthermore, some strategies in this line rely on predefined or inferred task identities to route the data to the corresponding task parameters (*e.g.,* [174]), which may limit their applicability.

A line of work investigates the usage of parameter-efficient fine-tuning methods (PEFT). For new manipulation, several studies have demonstrated the effectiveness of adapter-based methods. For example, Sharma *et al.* [140] introduce adapters to bridge the gap between frozen pretrained vision models and task-specific fine-tuning. By strategically inserting lightweight adapter modules into different layers of a pretrained model, the method enables adaptation to new manipulation tasks without compromising the model's original capabilities. Similarly, TAIL [102] proposes a parameter-efficient framework for adapting large pretrained decision-making models to new control tasks via imitation learning. Leveraging lightweight adapter techniques, their LoRA-based variant can achieve superior post-adaptation performance while mitigating catastrophic forgetting and maintaining plasticity in continual learning settings. For motion control tasks, Przystupa *et al.* [121] investigate PEFT techniques for adapting transformer-based policies to diverse robot morphologies. A key distinction from generic lifelong learning methods is its focus on morphology shifts, where late-layer adaptations outperform full fine-tuning while maintaining computational efficiency—a critical advantage for real-world deployment.

Regarding works other than standard PEFT methods, SpawnNet [92] propose a two-stream architecture that combines frozen pretrained visual features with a learnable convolutional stream for continual skill acquisition. The method mitigates catastrophic forgetting by leveraging dense spatial descriptors from self-supervised vision transformers and fusing them with task-specific features via adapter layers. Compared to conventional lifelong learning methods, SpawnNet demonstrates superior cross-instance generalization in both simulated and real-world robotic tasks. Rusu *et al.* [132] adapt Progressive Neural Networks [131] for sim-to-real policy transfer in vision-based control tasks. The architecture employs lateral connections between independently trained network columns, allowing the real-world policy to retain low-level visual features and high-level strategies learned in simulation while incrementally adapting to new inputs. To learn task-specific policies from human demonstrations, FLAIR [23] introduces a hybrid architecture-replay approach for learning from heterogeneous human demonstrations. The method constructs policy mixtures from a growing set of prototypical strategies while using contrastive learning to distill shared and strategy-specific rewards.

Visual prompt tuning is used in CONPE [75] for new navigation tasks. Specifically, the method leverages CLIP's vision-language model for zero-shot adaptation in embodied agents. By employing contrastive learning to create a pool of domain-specific visual prompts, CONPE dynamically combines them via guided attention to generalize across unseen environments. Unlike conventional lifelong learning, this approach decouples representation learning from policy training, enabling state-of-the-art zero-shot performance in navigation and manipulation tasks with 50% fewer samples than baselines. Its modular design and interpretable attention mechanism make it particularly scalable for non-stationary visual conditions.

In the direction of hypernetworks, Auddy *et al.* [10] propose a hypernetwork that generates the weights of a trajectory-learning neural ODE for each new skill. Rather than modifying the policy network directly, the hypernetwork produces task-specific parameters, effectively isolating knowledge by task while consolidating meta-knowledge in its own weights. The approach enables retention of long sequences of learned motions without rehearsal. By combining a larger meta-model with a continuous-time neural ODE solver, the method achieves superior retention of robotic skills compared to prior continual learning approaches, making it well-suited for incremental learning from physical demonstrations.

4.1.3 *Replay approaches.*

Replay-based methods typically maintain a memory buffer containing a subset of previously encountered data or model states to store and replay past experiences during the learning process [128, 136, 172]. This family of approaches is widely regarded as the most effective approach for mitigating catastrophic forgetting, offering key advantages such as straightforward implementation, high adaptability to various tasks, and robust performance.

In the context of Embodied AI, replay-based methods extend beyond conventional approaches in notable ways. First, some methods leverage memory not only during training but also during inference. For example, Yang *et al.* [171] introduce a novel approach for continual robot learning without explicit task boundaries or identifiers. The method leverages an episodic memory system that enables both experience replay during training and retrieval-based adaptation during testing, allowing robots to rapidly restore previously learned skills when facing familiar scenarios. The authors demonstrate the effectiveness of this approach at mitigating catastrophic forgetting across multiple manipulation benchmarks while maintaining modest memory requirements.

Other works have explored diverse replay strategies: Li *et al.* [86] used a diversity-aware buffer using 3D augmentation to maximize sample diversity for incremental grasping tasks, while Alshameri *et al.* [2] applied adversarial experience replay to strategically select training data to promote complementary specialization between different end-effectors for incremental dual-arm grasping. LOTUS [159] constructs an ever-growing library of reusable sensorimotor skills by identifying recurring patterns in demonstrations using the open-vocabulary vision models DINOv2 and incremental clustering techniques. Mendez-Mendez *et al.* [109] mitigate forgetting in task and motion planning by replaying all past data.

While replay-based methods have been demonstrated to be effective in lifelong learning, they face notable limitations, including memory constraints and data privacy concerns. These challenges have prompted researchers to explore alternative approaches, particularly those leveraging generative models [143]. The literature on generative replay for lifelong Embodied AI is scarce, but an opportunity. Some pioneering works include the one by Auddy *et al.* [10] that we have discussed at the end of the last subsection, and Zhao *et al.* [184], who combine replay and distillation to improve lifelong RL for robotic manipulation. Instead of naively replaying old transitions, they distill past experiences into a highly compressed form: a generative model produces synthetic data that retains the essential dynamics of earlier tasks. A Fréchet Inception Distance (FID) loss enforces that the distribution of generated experiences matches the original, ensuring realism. During new task learning, the policy is trained on both current data and these distilled past experiences, and a policy distillation step (based on model uncertainty) further transfers knowledge forward. This hybrid of replay and regularization achieved higher success rates on a robot arm task sequence with a fraction of the buffer size, outperforming standard experience replay methods. This work illustrates how robotic CL can benefit from compressing memory (to save storage) and using distillation losses (to retain behaviour) at once. This architecture not only substantially reduces memory requirements but also maintains competitive performance, offering a viable alternative to traditional replay methods.

4.2 In-context knowledge consolidation

In Embodied AI tasks, a common method for integrating external knowledge from multiple modalities is in-context usage. This approach involves dynamically retrieving relevant knowledge and appending it to the model's input. This allows knowledge to be stored externally in a sustainable manner for lifelong task executions while maintaining strong interpretability. This section explores knowledge consolidation by examining common external data modalities and their integration in embodied agents, ranging from spatial memory, skill knowledge, to temporal facts.

4.2.1 Map.

Early embodied navigation systems often integrate traditional SLAM techniques, such as occupancy grid maps or topological maps, to track explored areas and support localization [113, 154, 163]. These maps typically include only geometric or metric information without rich semantic annotations, and operate over a closed set of recognizable object categories when semantics are later added [133, 173]. With the increasing focus on modularized solutions in Embodied AI research, maps are gradually adopted in embodied navigation tasks, including path-aligned instruction following [3, 4, 24, 162], interactive instruction following [14, 110], and goal-oriented embodied navigation [124, 169, 178]. Representatively, Blukis *et al.* [14] study 3D semantic maps in an interactive instruction following task. In their system, the agent incrementally builds a voxel-based semantic map that records the object class present in each 3D cell, along with an observability mask, its current inventory, and pose. Then, they are input into a transformer-style model for decision-making. Another type of map is the topological map, which is used, for instance, in VLN-DUET [24]. This model constructs the topological map from the agent's observations. Nodes in the map correspond to visited locations and store visual and semantic features, while edges indicate connectivity. The coarse-scale global map and a fine-scale local view are encoded by a dual-scale graph model jointly. This dual-scale map representation enables the agent to plan long-range trajectories guided by the instruction while grounding to local visual observations. Later, BEVBERT [3] extends this concept to include the metric map for richer in-context map information.

Initially, the use of maps is limited to explicit representations with fixed semantic labels. Since 2023, the rise of vision-language large pretrained models [96, 115, 152] along with semantic neural rendering [71, 146, 188] has brought attention to relatively semi-implicit spatial memory, valued for its open-vocabulary querying capabilities. Robotics research, exemplified by works such as CLIPField [139], has begun integrating semi-implicit maps into more complex Embodied AI tasks. This line of work encodes vision-language features into 3D space and enables view-dependent feature rendering. These features support complex spatial relation understanding even in a zero-shot manner. It becomes particularly helpful for subgoal localization in embodied navigation tasks. Additionally, the map modality has gained traction in manipulation tasks, as demonstrated in works like VoxPoser [60] and novel object pick-and-place [141]. In particular, VoxPoser [60] proposes a trajectory planning strategy based on the strong spatial knowledge in large vision-language models. Given the observations and language instruction, the VLM is responsible for recognizing the end-effector affordances and composing 3D value maps using its generated codes. The value maps are treated as the source for further end-effectors' trajectory planning. The full pipeline supports zero-shot manipulation.

4.2.2 Scene Graph.

Scene graphs [8, 62, 130] provide a structured memory of the environments that supports efficient query, update, and encoding. They are primarily used in high-level task planning or question answering rather than detailed trajectory planning. Hydra [62] is a real-time spatial perception system that incrementally builds a layered 3D scene graph as the robot explores. In Hydra, the environment is represented at multiple levels (*e.g.,* objects, places, or rooms). As the robot moves, a local Euclidean Signed Distance Function (ESDF) is computed around the agent; a topological graph of places is extracted from it, and places are then grouped into rooms. This continuously updated graph stores nodes for objects and regions and edges for spatial relations. The system also performs loop-closure optimization over the graph to maintain global consistency.

Since the advancement in LLMs, scene graphs have become a widely adopted modality for complex Embodied AI tasks. For instance, SayPlan [125] presents a scalable framework for grounding task plans generated by LLMs in expansive, multi-room, and multi-floor environments using 3D Scene Graphs. The approach leverages the hierarchical nature of scene graphs to enable semantic search, allowing LLMs to identify task-relevant subgraphs from a collapsed representation of the full graph. To manage navigation, SayPlan integrates classical path planners, such as Dijkstra's algorithm, reducing the planning horizon and ensuring the feasibility of generated plans. Additionally, an iterative replanning pipeline refines initial plans using feedback from a scene graph simulator, correcting infeasible actions and avoiding planning failures. This combination of techniques allows SayPlan to generate grounded, executable plans for complex, long-horizon tasks in real-world settings. ConceptGraphs [51] extends the idea of scene graphs into the open-vocabulary regime by constructing object-centric 3D representations. ConceptGraphs utilizes outputs from 2D foundation models like CLIP to semantically embed segmented object regions, supporting flexible reasoning over novel objects and relationships. Due to their flexible graph structure, external knowledge graphs hold the potential to further enhance planning capabilities [70].

4.2.3 Skill library.

Skill libraries refer to collections of reusable behaviors or modules that the agent can invoke. Liang *et al.* [90] propose "Code as Policies", leveraging code-writing LLMs to generate robot controllers from language commands for manipulation tasks. Here, skills (*e.g.,* moving a gripper) are exposed as API calls, and the LLM composes them into Python programs. Given a few examples of command-to-code pairs, the LLM can generalize to new instructions: it writes functions or control loops that process perception outputs and call control primitives. For instance, an instruction like "move to object X and pick it up" is turned into code that locates the object (via a vision API), computes a grasp pose, and commands the arm. This uses the LLM's in-context knowledge of programming to perform spatial reasoning and parametric control. The advantage is its flexibility: it can generate complex, precise policies without task-specific training. Consecutive works, such as Instruct2Act [59], organizes the tools with a more structured hierarchy and broader tasks. OK-Robot [99] further includes a navigation tool stack, which extends the model's ability for compositional Embodied AI tasks, such as "move the Takis on the desk to the nightstand".

However, due to the inherent scalability limitations of human-designed libraries, LLM-driven approaches have taken over. In Voyager [160], researchers introduce a lifelong skill library evolution strategy fully driven by LLMs. Operating in the open-ended Minecraft environment, Voyager employs GPT-4 to autonomously generate goals, synthesize code-level skills, and test them through interaction with the environment. Successful behaviors are stored as reusable functions in a continually expanding skill library, enabling curriculum learning via self-discovery. This strategy also includes a retry-and-revise loop, where failed trials feed back into the prompt to improve skill synthesis, making learning iterative and self-correcting. More recently, this idea has been extended to robotic manipulation tasks [88, 156, 177]. For instance, LEAGUE++ [88] integrates LLMs with Task and Motion Planning (TAMP) and reinforcement learning to build a symbolic skill library that grows over time. The system autonomously decomposes complex instructions, grounds them to low-level controllers, and stores newly learned behaviors as reusable symbolic operators. Each new skill benefits from warm-start training initialized from semantically similar skills, facilitating efficient, continual skill acquisition and transfer to novel tasks. Similarly, Lifelong Robot Library Learning (LRLL) [156] introduce a dynamic memory mechanism and a goal proposal strategy guided by LLMs to extract skills from recent interactions. These skills are abstracted and organized into a library, enabling the agent to compose and adapt behaviors for new manipulation tasks. Importantly, the framework incorporates mechanisms to avoid catastrophic forgetting, ensuring stable accumulation of reusable motor programs across tasks. Another example is BOSS [177], which enables robots to discover new manipulation skills without external rewards. The agent begins with a set of primitive skills and interacts with the environment, while an LLM guides the creation and composition of new skills by suggesting meaningful subgoals. These emerging behaviors are incrementally added to the skill library, allowing the robot to generalize to zero-shot long-horizon tasks in household environments. The process supports unsupervised skill discovery with strong performance on previously unseen task compositions.

4.2.4 *Log data.*

Log-based knowledge consolidation uses an agent's experience history as memory. While differing in structure and purpose, recent systems share the common goal of transforming past observations and actions into reusable knowledge for downstream decision-making.

The way logs are captured and structured plays a critical role in how they can be reused. ReMEmbR [7] continuously records egocentric video streams as the robot navigates, pairing each segment with spatial and temporal metadata. These logs are transformed into a vectorized spatio-temporal memory by embedding visual segments and associating them with coordinates and timestamps. In contrast, RAEA [190] focuses on action-conditioned demonstrations for manipulation tasks, storing multimodal tuples of task instructions, sensory observations (*e.g.,* RGB-D frames), and action sequences. These are not explicitly temporally ordered but are instead organized as discrete strategy examples. MART [175] builds on expert-generated trajectories for compositional Embodied AI tasks and further distills them into key steps extracted from longer executions. This abstraction reduces memory size while preserving decision-relevant information, making the logs more interpretable and retrievable for downstream use.

Different systems adopt different retrieval paradigms depending on the nature of their memory representations. RAEA [190] retrieves demonstration episodes using dense multimodal encodings of the current state and task prompt, selecting similar entries to serve as in-context examples for a policy generator. This retrieval is similarity-based and deterministic. In contrast, MART [175] replaces similarity matching with a preference-trained MLLM retriever, which scores candidate trajectories by estimating their utility for the current task. The model is trained via preference learning on trajectory pairs with different success outcomes, enabling retrieval that is sensitive to task effectiveness. ReMEmbR [7] takes a more open-ended approach: it allows natural language queries to be interpreted by an LLM, which in turn invokes structured search functions (*e.g.,* text, spatial, temporal) to retrieve relevant log segments. This allows semantically grounded access over a large and unstructured log corpus.

For explicitly handling long-term history at scale, Bärmann *et al.* [11] propose a hierarchical episodic memory structure. The system organizes the agent's experience as a tree: leaf nodes store raw sensor data (*e.g.,* images, proprioception), while higher-level nodes abstract this data into symbolic events described in natural language. When a user submits a query, an LLM-based agent traverses the tree by dynamically expanding relevant nodes, allowing it to efficiently locate and retrieve information (*e.g.,* "When did the robot last see a soda can?"). This hierarchical representation enables scalable reasoning over months of accumulated data by collapsing redundant history into meaningful semantic units such as rooms, objects, or activities.

4.3 Discussion

The field of lifelong Embodied AI is still an emerging area, with limited research specifically focused on in-parameter knowledge consolidation. For example, much of the existing literature lacks rigorous evaluation and analysis of the computational requirements and performance, which are important in the context of Embodied AI due to the limited embedded resources. Recent works in the continual learning field [55, 157] suggest caring more about computational constraints, paving the way towards efficient algorithms that enable lifelong learning on embedded devices [54, 158].

Another key question is: where should the knowledge be stored? Similarly to humans, who do not retain all the information they encounter, lifelong embodied agents must balance in-parameter knowledge, which would be analogous to studying a subject, and in-context knowledge, which would be analogous to taking notes. A truly lifelong agent must intelligently decide which information is worth encoding into its parameters, *e.g.*, for fast and recurrent access, and which should be stored externally for retrieval later on. However, this critical decision-making process is largely absent in the current literature.

5 Knowledge Refinement

In the lifelong evolution cycle, the embodied agent continuously accumulates knowledge by increasing its in-context storage or expanding its model size. A critical challenge is how to manage this ever-growing knowledge and data within the constraints of limited edge resources, while maximizing knowledge retention to prevent model degeneration. Achieving this requires a balanced focus on improving both the space/time efficiency and the model's generalization capabilities. Fortunately, for in-parameter knowledge, we have several techniques that can potentially tackle this challenge, including knowledge distillation, model quantization, and network pruning. For in-context knowledge, we can refer to well-studied database compression techniques [116], which have been extensively studied; therefore, we will not elaborate on them further in this section.

5.1 Space and Time Efficiency

Model compression techniques effectively enhance both space and time efficiency for in-parameter knowledge. By reducing model size, these techniques enable faster computation and response while alleviating the computational and storage constraints commonly faced when deploying models on resource-limited devices.

5.1.1 Distillation. Knowledge distillation [49] reduces computational and memory overhead by transferring knowledge from a larger, complex teacher model to a smaller and more efficient student model. The student model is trained to mimic the teacher's behavior, supervised by teacher's soft labels [56], intermediate features [129], and more. In Embodied AI, research has focused on distilling perceptual knowledge[148] and decision-making strategies[29, 65, 137, 161, 186] into multitask embodied agents. For example, Sumers *et al.* [148] targets perceptual grounding by using a pretrained vision-language model to retroactively label trajectories, reducing human annotation while injecting task-relevant language cues into embodied agents. In the realm of decision-making, Schmitt *et al.* [137] combines teacher-based policy guidance with reward-driven learning so that student agents not only assimilate knowledge from the teacher but can exceed its performance. Similarly, Jain *et al.* [65] separates perception from planning via grid world training with terminal rewards, then distills that policy into a vision-based environment, reducing the burden of reward shaping. While past methods typically rely on multiple specialized agents or pretrained teachers, STEVE-2 [186] introduces a hierarchical knowledge distillation approach that consolidates multi-agent embodied tasks into a single multimodal model, thereby simplifying system complexity while retaining strong open-ended performance. In contrast to prior works focused on more straightforward or single-step knowledge distillation, MAGIC [161] introduces a meta-ability guided interactive chain-of-distillation framework that iteratively compresses large vision-and-language navigation models into smaller ones while preserving robust performance via multi-stage teacher-student feedback loops. Given the growing prominence of LLMs, there is increasing interest in transferring their embodied reasoning abilities into smaller, more resource-friendly policies. In this vein, DEDER [29] harnesses the generative and self-verification features of LLMs to distill embodied-relevant knowledge into compact models, specifically targeting interactive navigation and manipulation tasks.

5.1.2 Quantization. Network quantization can also refine knowledge and make models more compact. By reducing numerical precision, it lowers storage requirements and computational costs [64, 91, 97, 165]. Some hardware is also designed for quantized networks to enhance computational efficiency [83, 126, 147], which can benefit embodied agents. Recent studies have shown that quantization-aware training can preserve model performance even under aggressive bit reduction [28, 42, 64]. This technique has been effectively applied to fine-tune neural network-based control policies for robotics, enabling real-time deployment on low-power hardware without sacrificing task performance [117]. Specifically, Park *et al.* [117] proposes a quantization-aware imitation learning framework (QAIL+QBC) that improves policy robustness under low-bit precision, achieving up to 3.7× speedup and 3.1× energy savings while preserving decision accuracy in manipulation and driving tasks. Despite its advantages, quantization remains relatively underexplored in Embodied AI.

5.1.3 Pruning. Model pruning reduces model complexity by selectively removing parameters that contribute minimally to performance. Structured pruning eliminates entire convolutional filters or layers, leading to a more compact architecture, while unstructured pruning removes individual weights, enabling finer control over sparsity. Both techniques aim to balance accuracy and computational efficiency. There is a lack of studies on network pruning for Embodied AI. However, since LLMs are widely regarded as a mainstream foundation for new methods, advances in both structured [68, 104] and unstructured [181] pruning techniques for LLMs are also worth referencing.

5.2 Generalization

Keeping or even improving generalization is crucial for Embodied AI systems, enabling them to adapt to novel environments and unseen scenarios while preventing model degeneration during lifelong iterative evolution. Unlike training-time generalization which enhances a model's ability to adapt to unseen data through model design [26], or data augmentation [81], refinement-stage generalization focuses on preserving performance when reducing model complexity as first discussed in 1989 [82]. This principle remains applicable and is evident in advanced model compression techniques [29, 45, 61]. As models become more lightweight, their test performance initially improves but eventually declines. In Embodied AI research, knowledge distillation on decision-making policies [137] has been shown to significantly enhance data efficiency for further learning. In the study of distilling embodied-relevant knowledge from larger models [29, 161], and quantization work [117], the student model can achieve comparable or superior performance to their larger counterparts. However, the impact of model compression techniques on refining generalization remains largely unexplored in Embodied AI research, especially lack of studies in real-world embodied tasks.

5.3 Discussion

Research on knowledge refinement in Embodied AI is still in its early stages, particularly regarding iterative evolution cycles. While some recent efforts have explored optimizing space and time efficiency for embodied agents, such studies remain scarce. Notably, there has been little to no work specifically studying generalization and model degeneration for embodied agents. However, for lifelong embodied agents, effective knowledge refinement is essential to ensure sustainable operation on resource-constrained edge devices. Model refinement and optimization techniques, such as distillation and quantization, have gained significant attention in the context of LLMs — as highlighted in DeepSeek reports [52, 93]. Whether these methods can be seamlessly adapted to Embodied AI models or if there are unique challenges that remain difficult to address is an open question. This uncertainty highlights exciting opportunities for future research and exploration.

6 Conclusion

In this article, we propose a framework for the knowledge evolution of lifelong embodied AI, positioning existing research within this context and identifying potential gaps. Taking a deeper perspective, this framework addresses lifelong from two aspects: first, an outer loop that defines high-level lifelong evolution processes throughout the agent's lifespan, and second, the inner lifelong learning mechanism that consolidates incoming knowledge into the model's parameters. We hope the insights presented in this article will inspire valuable directions for future research.

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