Aligning Agentic World Models via Knowledgeable Experience Learning

Anonymous ACL submission

Abstract

Current Large Language Models (LLMs) exhibit a critical modal disconnect: they possess vast semantic knowledge but lack the procedural grounding to respect immutable environmental constraints. Consequently, while these agents implicitly function as world models, their simulations often suffer from *physical hallucinations*—generating plans that are logically sound but physically unexecutable. Existing alignment strategies predominantly rely on resource-intensive training or fine-tuning, which attempt to compress dynamic environmental rules into static model parameters. However, such parametric encapsulation is inherently rigid, struggling to adapt to the open-ended variability of environmental dynamics without continuous, costly retraining. To solve this fundamental misalignment between semantic planning and environmental reality without relying on parameter updates, we introduce **WorldMind**, a framework that autonomously constructs a symbolic World Knowledge Repository by synthesizing environmental feedback. Specifically, it unifies Process Experience to enforce semantic physical feasibility via prediction errors and Goal Experience to guide task optimality through successful trajectories. Experiments on EB-ALFRED and EB-Habitat demonstrate that WorldMind achieves the best performance compared to baselines, exhibiting remarkable cross-model and cross-environment transferability.

1 Introduction

Building World Models capable of simulating and predicting environmental dynamics is foundational to the pursuit of embodied intelligence. While traditional approaches rely on external simulators, a compelling paradigm has emerged where the agent itself functions as the world model (Richens et al., 2025). By internally encoding environmental dynamics, agents can reason about causal relationships and predict outcomes without heavy-weight external engines (Zhang et al., 2021; Fang et al., 2025b; Chae et al., 2024; Wang et al., 2025a; Yang et al., 2025c). Conceptually, this redefines the agent not merely as a passive policy executor, but as an active prediction machine of the world it inhabits (Zhang et al., 2025c; Zheng et al., 2025; Cen et al., 2025; Wang et al., 2025b).

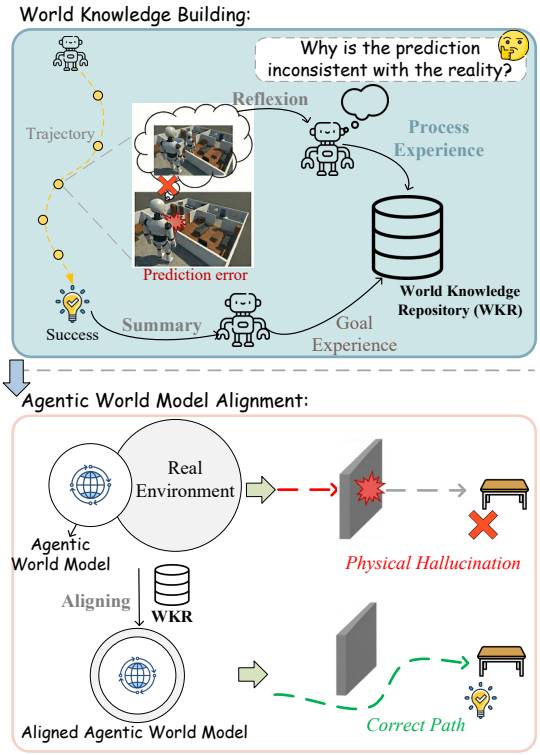


Figure 1: Conceptual Illustration of Experiential Alignment. The agent aligns its internal world model via Process Experience and Goal Experience.

However, a critical modal disconnect persists: while Large Language Models (LLMs) scale effectively on semantic reasoning, they exhibit a fundamental disparity between high-level logical planning and semantic physical constraints. Despite possessing vast declarative knowledge, they often lack the procedural understanding required to respect the immutable laws of the physical world.

This misalignment leads to frequent physical hallucinations, where agents generate plans that are semantically coherent but physically unexecutable (e.g., attempting to slice an object without holding a knife). The agent understands the high-level *why*, but fails to grasp the procedural *how* imposed by physical reality.

To bridge this gap, dominant paradigms currently rely on internalizing physical laws directly into model parameters via Supervised Fine-Tuning (SFT) or Reinforcement Learning (Chae et al., 2024; Chen et al., 2025b). We suggest that this approach may face inherent challenges, as it attempts to capture the variability of dynamic physical environments using static parameter weights. Crucially, planning with an agentic world model presents a dual challenge: the internal simulation must not only identify the optimal path (Goal) but also strictly adhere to physical constraints (Process). Existing agents often prioritize goal achievement while neglecting physical feasibility, leading to brittle plans that fail in dynamic settings. Since static parameters cannot exhaustively cover all physical corner cases, an agent must possess the capacity for **online correction**, dynamically adjusting its understanding of constraints as it encounters them. This context-based flexibility (Zhang et al., 2025d; Zhou et al., 2025a; Ouyang et al., 2025) raises a research question: ***Can agents autonomously align their world knowledge via experience learning in a training-free manner?***

We answer this question by drawing inspiration from the cognitive theory of *Predictive Coding* (Huang and Rao, 2011; Friston, 2018). In this view, intelligence is not the passive absorption of data, but the continuous minimization of "prediction error"—the discrepancy between internal expectation and sensory reality. Inspired by classic model-based reinforcement learning, which utilizes unexperienced state-action pairs to refine transition models, we extend this philosophy to training-free LLM agents. Instead of discarding execution failures as noise, we leverage them as corrective signals. When an agent's prediction contradicts reality, it exposes a boundary in the agent's internal world model. We argue that LLM agents possess dormant predictive capabilities that need not be trained from scratch, but simply activated and aligned through these error signals during inference.

As shown in Figure 2, we propose **WorldMind**, a framework transforming autonomous agents into empirical world model learners. To ensure robust simulations, our framework constructs a World Knowledge Repository comprising two distinct types of experience. **Process Experience** leverages prediction errors to enforce physical feasibility, while **Goal Experience** distills successful trajectories into procedural heuristics to guide efficient task completion. Extensive experiments on EB-ALFRED and EB-Habitat demonstrate that WorldMind achieves the best performance compared to baselines by significantly reducing physical hallucinations. Furthermore, remarkable cross-model and cross-environment transferability confirms that the constructed world knowledge captures universal physical rules independent of specific model architectures.

2 The WorldMind Framework

2.1 Overview and Problem Formulation

As shown in Figure 2, we propose **WorldMind**, a framework transforming autonomous agents into empirical world model learners. By externalizing environmental dynamics into explicit memory, we enable grounded planning through a cycle of goal alignment and continuous reality verification.

We formulate the problem as a **World Knowledge-Augmented Markov Decision Process (WK-MDP)**, defined by the tuple:

$$\mathcal{M}_{\text{WK}} = \langle \rho_0, \mathcal{S}, \mathcal{A}, \mathcal{P}, \Omega, \mathcal{G}, \mathcal{W} \rangle \quad (1)$$

Here, $\mathcal{S}$ and $\mathcal{A}$ denote the state and action spaces, respectively. ρ_0 represents the initial state distribution from which the environment is reset at the beginning of each task episode. $\mathcal{P} : \mathcal{S} \times \mathcal{A} \to \mathcal{S}$ represents the latent transition dynamics. The observation function Ω yields egocentric visual inputs o_t based on the current state, and $\mathcal{G}$ represents the set of task objectives specified in natural language.

Distinct from standard MDPs, we introduce an explicit **World Knowledge Repository** $\mathcal{W} = \{\mathcal{W}_p, \mathcal{W}_g\}$. $\mathcal{W}_p$ encapsulates Process Experience, a collection of verbalized causal rules derived from prediction errors. This component functions as a learned surrogate model $\hat{\mathcal{P}}_p$ that progressively approximates the ground-truth dynamics $\mathcal{P}$, ensuring simulated steps adhere to physical constraints. $\mathcal{W}_g$ encodes Goal Experience, a set of procedural heuristics distilled from successful trajectories. These priors serve to constrain the policy search space towards the optimal policy π^*, ensuring the simulated path converges on the correct target.

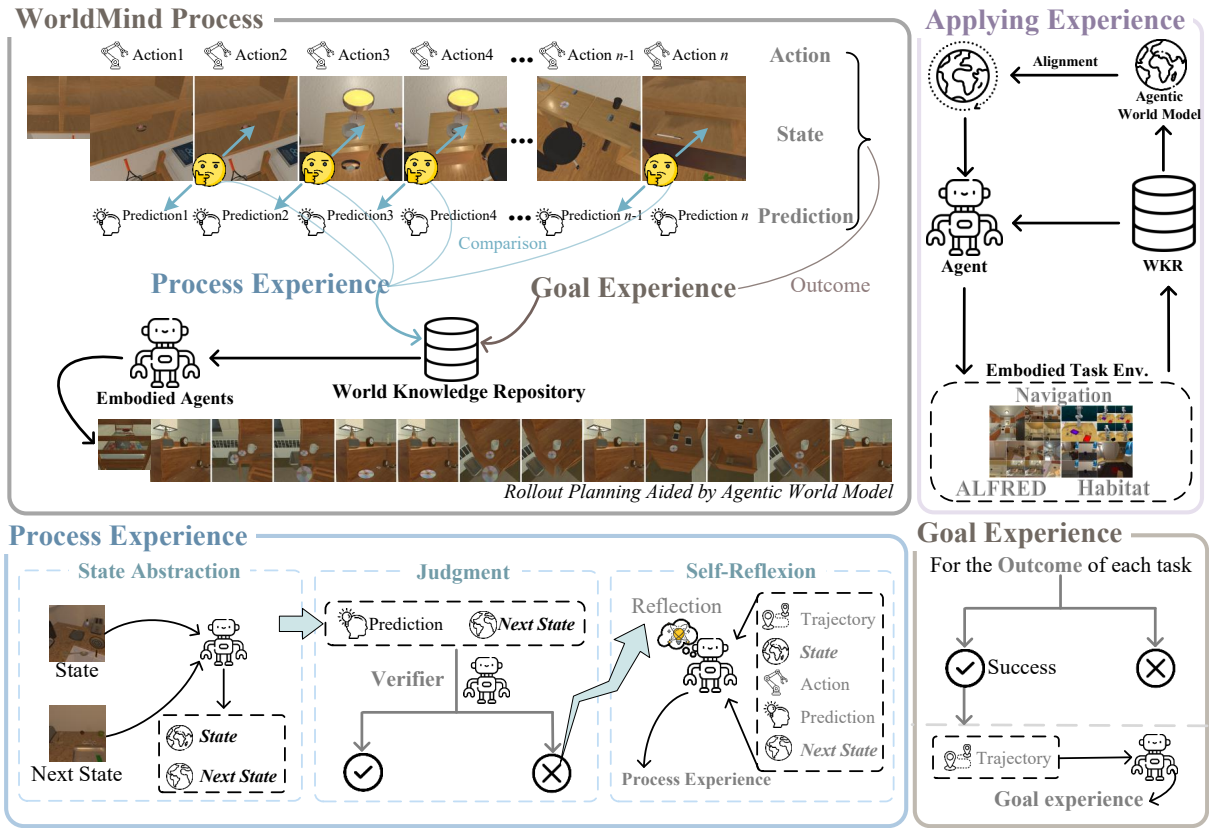


Figure 2: **Overview of the WorldMind Framework.** The agent autonomously constructs a World Knowledge Repository (WKR) by unifying Process Experience (from prediction errors) and Goal Experience (from successful trajectories) to guide grounded simulation.

The agent operates under a policy $\pi(a_t, \hat{s}_{t+1} \mid o_t, g, \mathcal{W})$ that jointly generates an action a_t and a predicted future state $\hat{s}_{t+1}$ given a specific goal $g \in \mathcal{G}$. The learning objective is formulated as:

$$\max_{\pi} \mathbb{P}(\text{Success} \mid g) \text{ s.t. } \min \mathcal{D}(\hat{s}_{t+1} || s_{t+1}) \quad (2)$$

Here, Success represents the evaluation metric directly provided by the simulation environment's underlying script, which automatically verifies whether the physical states of relevant objects satisfy the predefined conditions of the goal g. This metric accounts for both final task completion and partial progress (such as completed subgoals). This objective implies that maximizing the probability of task success is contingent upon minimizing the divergence $\mathcal{D}$ between the predicted state $\hat{s}$ and the actual state s.

2.2 Building World Knowledge Repository

The core of WorldMind lies in the autonomous development of the World Knowledge Repository (WKR) $\mathcal{W}$. This process involves two distinct update mechanisms: one for establishing physical boundaries termed Process Experience, and one for distilling procedural shortcuts known as Goal Experience.

Process Experience Construction. To align internal simulations with environmental reality, $\mathcal{M}$ operates in a `Predict-Act-Verify` loop. At each step t, conditioned on the environmental prior p_{env}, current observation o_t, task goal g, and retrieved knowledge $\mathcal{W}$, the agent jointly generates an action and a textual prediction:

$$(a_t, \hat{s}_{t+1}) \sim \mathcal{M}(o_t, p_{env}, g, \mathcal{W}) \quad (3)$$

After execution, the environment yields the actual grounded state s_{t+1}. We then operationalize the acquisition of Process Experience through three distinct steps: State Abstraction, Judgment, and Self-Reflexion.

First, during **State Abstraction**, to prioritize abstract causal variables over low-level details, we explicitly define a semantic abstraction process to convert the ground-truth states into high-level descriptions:

$$\bar{s}_k = \mathcal{M}_{\text{abs}}(s_k), \quad k \in \{t, t+1\} \quad (4)$$

Second, in the **Judgment** phase, the agent acts as a verifier, comparing its internal prediction $\hat{s}_{t+1}$ against the actual abstract outcome $\bar{s}_{t+1}$. Specifically, we prompt a Large Language Model to act as a Logical Consistency Validator. This validator conservatively evaluates whether there is a direct, factual contradiction between the predicted and actual states, deliberately ignoring irrelevant descriptions or unexecuted intents (detailed prompts are provided in Appendix E). A learning signal is triggered only when such an explicit semantic discrepancy is detected, indicating a physical hallucination. Finally, through **Self-Reflexion**, the agent addresses the identified conflict by triggering a reflective module $\mathcal{R}$. This module operates by prompting a Large Language Model to act as a Root Cause Analyst, analyzing the error context alongside the interaction history τ_{t-1} to synthesize a corrective causal rule (detailed reflection prompts are provided in Appendix E). The update rule for Process Experience is formulated as:

$$\mathcal{W}_p \leftarrow \mathcal{W}_p \cup \{\mathcal{R}(\tau_{t-1}, a_t, \bar{s}_t, \hat{s}_{t+1}, \bar{s}_{t+1})\} \quad (5)$$

This three-step mechanism ensures that the constructed knowledge captures essential causal dynamics while remaining invariant to trivial environmental noise.

Goal Experience Construction. Efficient task completion necessitates heuristic guidance, complementing the physical feasibility ensured by Process Experience. We address this by distilling procedural heuristics from successful episodes. Given a successful trajectory τ^*, the agent $\mathcal{M}$ acts as a task analysis expert to autonomously analyze the interaction history. Specifically, the agent is prompted to evaluate the step-by-step task progress, identifying key actions that advanced the goal to extract a single, abstract, and reusable workflow while filtering out context-specific noise (detailed extraction prompts are provided in Appendix E). The Goal Experience is updated as follows:

$$\mathcal{W}_g \leftarrow \mathcal{W}_g \cup \mathcal{M}(\tau^*) \quad (6)$$

These distilled priors serve as optimized meta-instructions, limiting the agent's policy search space towards the optimal subspace in future tasks.

2.3 Inference via Constrained Simulation

In the inference phase, the agent $\mathcal{M}$ leverages the constructed World Knowledge Repository $\mathcal{W}$ to guide decision-making through constrained simulation. Specifically, the system dynamically retrieves the top-2 relevant world knowledge from the repository through semantic similarity[1] to the current task goal g. Conditioned on this augmented context, the agent jointly generates the action a_t and the predicted future state $\hat{s}_{t+1}$. Crucially, to mitigate hallucinations, the generation of $\hat{s}_{t+1}$ is gated via prompt-based heuristic rules: the agent is explicitly instructed to only simulate outcomes when the target object is explicitly grounded in the current observation o_t or the repository $\mathcal{W}$, otherwise executing the action and outputting a predefined skip string without updating the internal world model. This selective strategy significantly enhances inference efficiency. Unlike approaches relying on computationally intensive multiple sampling or heavy external world models, our framework minimizes latency by bypassing redundant simulations for ungrounded states.

3 Experiment

3.1 Experimental Settings.

Datasets and Metrics. We evaluate our framework on the EB-ALFRED and EB-Habitat benchmarks from EmbodiedBench (Yang et al., 2025a), focusing on five fine-grained subsets: Base, Common Sense, Complex Instruction, Spatial Awareness, and Visual Appearance. To quantify performance, we employ two complementary metrics: *Success Rate (SR)* and *Goal-Conditioned Success (GC)*. SR is a strict binary metric (0 or 1) indicating whether the final goal is fully achieved. In contrast, GC evaluates process adherence by awarding partial credit for completed subgoals, even if the episode ultimately fails.

Models and Baselines. We employ GPT-4.1-mini and GPT-3.5-turbo as the primary backbones for our WorldMind framework. To evaluate effectiveness, using reported results of open- and closed-source models from EmbodiedBench, we compare against representative baselines, including Best-of-N (BoN), ReAct (Yao et al., 2022), Synapse (Zheng et al., 2023), SimuRA (Deng et al., 2025), ReasoningBank (Ouyang et al., 2025), and AWM (Wang et al., 2024f).

[1]We utilize the `SentenceTransformer` library to compute text embeddings and cosine similarity for retrieval.

Backbone	Method	Success Rate (SR)						Goal Condition (GC)					
		Avg	Base	Common	Complex	Visual	Spatial	Avg	Base	Common	Complex	Visual	Spatial
Open-source and Proprietary Models													
GPT-4o	ReAct	56.8	64	54	68	46	52	65.1	74.0	60.3	74.0	58.3	**61.3**
GPT-4o-mini	ReAct	28.8	34	28	36	24	22	34.3	47.8	35.3	43.5	33.3	29.0
Claude-3.7-Sonnet	ReAct	**67.2**	68	**68**	70	**68**	**62**	65.3	72.0	66.0	**76.7**	**63.0**	59.7
Gemini-1.5-Pro	ReAct	63.2	**70**	64	**72**	58	52	**67.4**	**74.3**	**66.7**	76.5	62.8	59.0
Llama-3.2-90B-Vis	ReAct	35.2	38	34	44	28	32	37.6	43.7	37.3	49.2	35.3	36.0
InternVL2.5-78B	ReAct	37.0	41	40	39	16	49	41.0	42.3	35.3	43.3	35.7	40.3
Method Comparison													
GPT-3.5-turbo	ReAct	44.4	52	**48**	52	32	38	50.4	55.3	**53.5**	55.3	42.7	45.0
	BoN	42.8	46	42	50	**42**	34	50.4	54.2	46.5	56.5	**52.0**	42.8
	SimuRA	45.2	50	42	54	38	42	53.6	57.8	47.8	59.7	48.5	**54.3**
	ReasoningBank	41.6	50	36	44	36	42	47.6	57.5	41.5	47.0	44.2	48.0
	Synapse	38.8	38	46	40	36	34	43.6	42.5	51.3	42.7	42.0	39.7
	AWM	40.0	46	32	48	40	34	46.2	53.2	39.2	50.7	47.0	41.0
	WorldMind	**48.0**	**58**	**48**	**56**	34	**44**	**54.1**	**63.0**	52.7	**61.0**	41.7	52.0
GPT-4.1-mini	ReAct	41.2	50	40	46	38	32	47.5	55.3	42.8	52.2	47.2	39.8
	BoN	44.4	46	44	50	**42**	40	49.5	50.8	48.3	54.7	**48.7**	45.0
	SimuRA	45.6	**52**	44	**54**	38	40	52.2	**61.0**	50.3	58.2	45.3	46.3
	ReasoningBank	38.0	42	36	42	34	36	42.6	46.7	38.8	45.8	41.5	40.3
	Synapse	37.2	40	32	44	36	34	42.2	41.2	37.5	49.5	41.3	41.7
	AWM	41.2	44	36	48	38	40	46.0	48.3	42.0	52.5	44.3	42.7
	WorldMind	**49.2**	50	**58**	**54**	**42**	**42**	**55.7**	**61.0**	**61.0**	**58.8**	48.0	**49.7**

Table 1: **Main Results on the EB-ALFRED Benchmark.** We evaluate performance across five distinct capability subsets: Base, Common Sense, Complex Instruction, Visual Appearance, and Spatial Awareness. We report both Success Rate (SR) and Goal Condition (GC) scores. The best results for each model group are highlighted in **bold**.

3.2 Main Results

WorldMind consistently outperforms baselines in strict task completion. As shown in Table 1 and Table 2, WorldMind achieves the highest SR among evaluated methods across both benchmarks. On EB-Habitat with the GPT-4.1-mini backbone, it attains an SR of 50.8%, outperforming ReAct by 9.2%, while on EB-ALFRED with GPT-3.5-turbo, SR improves from 44.4% to 48.0%. Given that SR strictly measures complete task success, these gains demonstrate WorldMind's enhanced ability to overcome physical dead-ends and reach final goal states more consistently in practice.

WorldMind achieves improved procedural correctness. As shown in Table 1 and Table 2, beyond final outcomes, WorldMind outperforms baselines on the GC metric, which evaluates the correct execution of intermediate steps. On EB-ALFRED with GPT-3.5-turbo, the average GC improves from 50.4% to 54.1%. Simultaneously, on EB-Habitat with the GPT-4.1-mini backbone, the GC reaches 57.2%, surpassing the ReAct baseline (47.4%) by a large margin. These gains indicate that even when full task completion fails, WorldMind executes a higher proportion of valid subgoals, demonstrating that the distilled Goal Experience effectively guides sequential task progression.

Robustness across diverse capabilities and backbones. Our framework exhibits consistent stability across fine-grained dimensions, particularly in challenging subsets like Visual Appearance and Spatial Awareness. For instance, the EB-Habitat Base Success Rate reaches 86% for both GPT-3.5-turbo and GPT-4.1-mini, a model-agnostic benefit further validated across leading proprietary and open-source models (see Appendix D). This stability stems from the Predict-Act-Verify loop filtering ungrounded hallucinations across different model scales. Furthermore, the framework maintains a scalable, bounded repository footprint (see Appendix C) with negligible real-time retrieval latency (see Appendix B). We also validate generalization across action granularity on EB-Navigation (see Appendix A), demonstrating effective grounding from high-level reasoning to fine-grained semantic procedural execution.

3.3 Ablation Study

Table 3 presents the ablation results isolating the specific impact of each component. We observe that Goal Experience primarily enhances the

Backbone	Method	Success Rate (SR)						Goal Condition (GC)					
		Avg	Base	Common	Complex	Visual	Spatial	Avg	Base	Common	Complex	Visual	Spatial
Open-source and Proprietary Models													
GPT-4o	ReAct	58.0	86	44	56	**68**	36	70.7	90.7	56.0	68.0	**75.2**	**62.1**
GPT-4o-mini	ReAct	36.4	74	22	32	22	32	44.0	77.5	32.5	42.0	33.1	57.8
Claude-3.7-Sonnet	ReAct	**61.2**	90	**58**	**58**	62	**38**	**70.8**	**97.5**	**68.5**	**79.5**	72.0	43.8
Gemini-1.5-Pro	ReAct	57.2	92	52	48	56	**38**	61.0	92.5	53.5	49.5	59.4	50.0
Llama-3.2-90B-Vis	ReAct	45.6	**94**	24	50	32	28	50.6	94.5	32.5	53.0	39.7	59.6
InternVL2.5-78B	ReAct	47.6	84	30	**58**	34	32	55.2	82.0	43.0	59.0	63.9	45.1
Method Comparison													
GPT-3.5-turbo	ReAct	43.6	82	30	34	38	34	50.4	84.0	34.0	40.0	43.4	50.4
	BoN	43.6	74	34	36	40	34	50.8	75.5	35.5	43.0	46.9	53.3
	SimuRA	48.0	82	40	36	**44**	**38**	55.3	83.0	**47.0**	40.0	48.9	57.8
	ReasoningBank	46.4	76	40	40	42	34	53.9	78.5	41.5	44.0	46.2	**59.5**
	Synapse	47.2	84	40	38	42	**38**	54.2	85.0	43.0	43.0	46.3	53.5
	AWM	46.4	78	**42**	**44**	36	32	50.9	78.0	43.0	48.0	39.7	45.7
	WorldMind	**48.8**	**86**	**42**	**44**	40	32	**56.7**	**89.0**	**47.0**	**51.0**	**49.8**	46.8
GPT-4.1-mini	ReAct	41.6	74	26	32	40	**36**	47.4	76.0	30.0	37.0	43.7	50.3
	BoN	44.4	74	32	36	46	34	50.9	75.8	38.0	41.5	48.9	50.5
	SimuRA	48.4	84	42	40	44	32	55.4	85.0	45.5	47.0	48.2	51.5
	ReasoningBank	46.4	76	42	30	**52**	32	53.7	77.0	45.5	34.5	**58.4**	**53.3**
	Synapse	45.6	78	42	38	34	**36**	52.0	78.3	46.5	45.5	39.7	50.0
	AWM	43.6	74	32	38	44	30	50.8	74.8	37.0	44.5	47.9	49.7
	WorldMind	**50.8**	**86**	**44**	**44**	46	34	**57.2**	**87.0**	**48.5**	**51.5**	52.3	46.7

Table 2: **Main Results on the EB-Habitat Benchmark.** We present the comparative results of Success Rate (SR) and Goal Condition (GC) across different backbones and baselines. Performance is evaluated on five subsets: Base, Common, Complex, Visual, and Spatial. The best results for each model group are highlighted in **bold**.

Goal Condition (GC) metric, particularly on EB-ALFRED with GPT-3.5-turbo. This indicates that high-level strategies effectively guide the agent through correct intermediate subgoals, preventing navigational drift. In contrast, Process Experience drives a larger improvement in the strict Success Rate (SR). By encoding semantic environmental constraints, this component acts as a safeguard against fatal execution errors, ensuring that planned actions are not just logically sound but also executable within the simulation. The superior performance of the full model confirms the synergy between these components: **effective alignment is significantly enhanced by combining goal-based heuristics with semantic physical verification.**

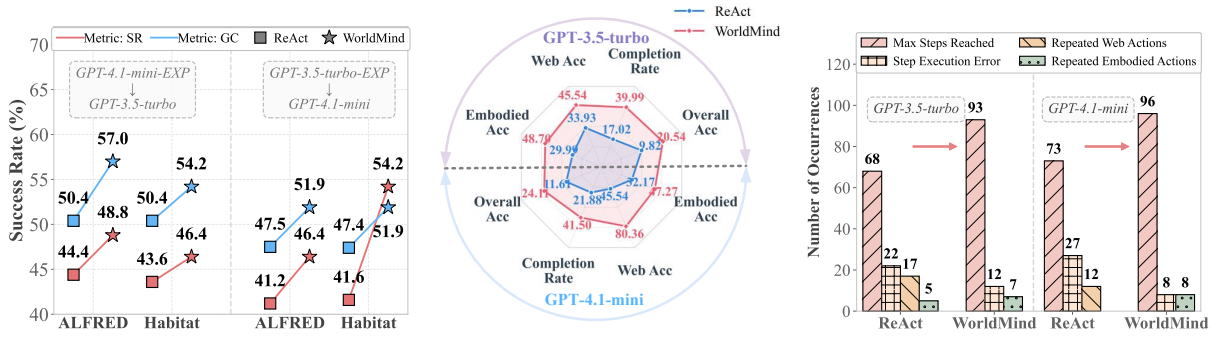
4 Analysis

4.1 Cross-Model Experience Transfer Analysis

Externalizing environmental dynamics into symbolic knowledge reduces dependence on specific architectures, unlike implicit knowledge locked in parameter weights. Our World Knowledge Repository captures semantic causal rules that are highly transferable across different LLM architectures. To verify this, we exchanged repositories between GPT-3.5-turbo and GPT-4.1-mini. As shown in Figure 3a, sharing experience yields significant gains over ReAct baselines for both models. Specifically, GPT-3.5-turbo using the repository from GPT-4.1-mini improves on EB-ALFRED (SR: 44.4%→48.8%, GC: 50.4%→57.0%), demonstrating that discovered heuristics are effectively interpretable across architectures. Conversely, GPT-4.1-mini utilizing experience from GPT-3.5-turbo achieves a 12.6% SR surge on EB-Habitat (41.6%→54.2%). This bidirectional success confirms that constructed experiences effectively decouple environmental dynamics from model-specific biases. **These results validate the cross-model transferability of the world knowledge constructed by WorldMind, offering a foundational possibility for constructing shared world models for multi-agent collaboration in broader settings.**

4.2 Cross-Environment Analysis

To evaluate scalability, we extend our experiments to the Embodied Web Agent (Hong et al., 2025) benchmark. This setting requires dynamic context switching between a web interface (for informa-

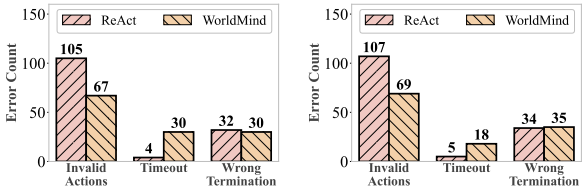


(a) Performance of Cross-Model Experience Transfer (b) Accuracy Analysis on Embodied Web Agent Benchmark (c) Error Analysis on Embodied Web Agent Benchmark

Figure 3: **Experimental Results and Analysis.** (a) Comparison of experience transfer capabilities between the two models. (b) Performance comparison on the Embodied Web Agent task, reporting accuracy metrics for both GPT-3.5-turbo and GPT-4.1-mini. (c) Comparative error distribution analysis for both models in the same environment.

Backbone	Components		EB-ALFRED		EB-Habitat	
	Goal	Process	SR	GC	SR	GC
GPT-3.5-turbo	-	-	44.4	47.5	43.6	50.4
	✓	-	44.8	51.0	47.2	54.6
	-	✓	42.4	47.5	45.2	51.3
	✓	✓	**48.0**	**54.1**	**48.8**	**56.7**
GPT-4.1-mini	-	-	41.2	47.5	41.6	47.4
	✓	-	48.8	**56.3**	48.4	55.7
	-	✓	46.4	51.5	47.6	54.0
	✓	✓	**49.2**	55.7	**50.8**	**57.2**

Table 3: Ablation study on the effectiveness of Goal Guidance and Process Supervision. We report both SR and GC on EB-ALFRED and EB-Habitat.



(a) Habitat (GPT-3.5-turbo) (b) Habitat (GPT-4.1-mini)

Figure 4: **Error Analysis in EB-Habitat.** Comparison of error distributions between the ReAct baseline and WorldMind. Failures are categorized into three types: Invalid Actions, Timeout, and Wrong Termination.

tion seeking) and an embodied environment (for semantic procedural execution). We use the Indoor Cooking environment with 112 sampled tasks to benchmark GPT-3.5-turbo and GPT-4.1-mini. Performance is quantified using four metrics: Embodied Accuracy and Web Accuracy assess domain-specific success; Overall Accuracy requires success in both domains; and Completion Rate awards partial credit for intermediate steps to measure process adherence.

Figure 3b illustrates WorldMind's robustness in this cross-domain setting. For GPT-3.5-turbo, the Overall Accuracy more than doubles (9.82% to 20.54%), indicating superior end-to-end task completion. Similarly, GPT-4.1-mini sees a significant gain, with Overall Accuracy rising from 11.61% to 24.11%. Regarding failure modes, Figure 3c reveals that WorldMind effectively mitigates physical hallucinations. By reducing execution errors, it enables the agent to successfully navigate the transition between environments without premature termination. **These results validate WorldMind's generalization to hybrid environments, facilitating robust performance across complex digital and physical context switching.**

4.3 Error Analysis

Figure 4 details failure modes: *Invalid Actions* (procedural violations), *Timeout* (exhausted steps), and *Wrong Termination* (logical misalignment). In EB-Habitat, WorldMind reduces Invalid Actions for GPT-3.5-turbo from 105 to 67 (Figure 4a), confirming Process Experience acts as an effective physical filter. Consequently, Timeouts rise from 4 to 30, indicating that avoiding immediate fatal errors enables prolonged exploration. A parallel reduction in Invalid Actions is also observed for GPT-4.1-mini (Figure 4b), demonstrating the framework's consistency. **This redistribution of errors empirically validates that WorldMind successfully transforms fatal execution and logical failures into manageable planning challenges, thereby enhancing overall robustness.**

5 Related Work

Agentic AI. Agentic AI's core is a reflective, self-correcting loop, leveraging tools, memory, and constraints for open-world robustness and interpretability (Zhou et al., 2025b; Wang et al., 2024b; Xi et al., 2025; Sang et al., 2025; Guan et al., 2024a). The field advances via improved planning mechanisms like CoT, ToT, and self-refinement (Wei et al., 2022; Yao et al., 2023; Madaan et al., 2023; Shinn et al., 2023). To interact with the external world and achieve long-term goals, researchers have explored memory, tool-calling, embodied control, and the collaboration between agents and world models, etc (Wang et al., 2023; Schick et al., 2023; Zitkovich et al., 2023; Park et al., 2023; Patil et al., 2024; Yu et al., 2025c; Deng et al., 2025; Chen et al., 2025b; Mei et al., 2025; Fung et al., 2025; Tang et al., 2025). Specifically, while extensive related work (Zhou et al., 2025c; Zhang et al., 2025f; Yan et al., 2025; Zeng et al., 2024; Bo et al., 2025; Anokhin et al., 2024; Zhang et al., 2025g; Xu et al., 2025; Yang et al., 2025b; Huang et al., 2025; Zhang et al., 2025a; Pink et al., 2025; Cao et al., 2025; Hatalis et al., 2023; Salama et al., 2025) focuses on memory, significant research (Fang et al., 2025a; Tao et al., 2024; Gao et al., 2025; Zhang et al., 2025b; Jiang et al., 2024; Yu et al., 2025a; Wei et al., 2025; Liu et al., 2025; Cai et al., 2025a; Dou et al., 2025; Cai et al., 2025b,a; Dou et al., 2025) aims to realize self-evolving agents. Further work has expanded the ability to solve complex tasks by building multi-agent collaborative frameworks and autonomous systems (Wu et al., 2024; Li et al., 2023; Wang et al., 2024a; Fourney et al., 2024; Park et al., 2024).

World Models. World Models learn internal representations of environment dynamics for prediction and planning, a field spanning model-based RL, generative simulation, LLMs, and robotics (Kong et al., 2025; Ha and Schmidhuber, 2018; Ding et al., 2025; Guan et al., 2024b; Zhu et al., 2024). Originating in model-based RL (Kaiser et al., 2019; Deng et al., 2022; Ha et al., 2023), world models enable agents to imagine outcomes (Hafner et al., 2023; Wu et al., 2023). Generative world models not only predict physical environment changes by generating high-fidelity video (Brooks et al., 2024; Bruce et al., 2024; Liu et al., 2024; Bar-Tal et al., 2024; Chi et al., 2025; Yu et al., 2025b; Mendonca et al., 2023; Wang et al., 2024d; Bardes et al., 2023; Chen et al., 2025a; Parker-Holder et al., 2024), but also predict code execution results (Tang et al., 2024; Carbonneaux et al., 2025), and further extend their predictive capabilities to other diverse domains (Feng et al., 2025; Zhang et al., 2025e). World Models now underpin applications ranging from autonomous driving (Wang et al., 2024c; Jia et al., 2023; Hu et al., 2023; Wang et al., 2024e; Zhang et al., 2023) to embodied navigation (Zhong et al., 2025; Yao et al., 2025; Bar et al., 2025; Nie et al., 2025; Jin and Jia, 2025; Long et al., 2025; Liang et al., 2025; Shi et al., 2025), demonstrating their versatility across diverse tasks. This has also led to more benchmarks focused on evaluating the precise prediction of future states, physical laws, and environmental dynamics (Li et al., 2025a; Warrier et al., 2025; Duan et al., 2025; Yue et al., 2025). (Qiao et al., 2024) introduce World Knowledge Model (WKM) which encodes world knowledge into the planner Unlike WKM, WorldMind performs training-free, online experiential alignment using execution failures. Concurrently, much research also posits that the agent itself is the world model (Tehenan et al., 2025; Zhou et al., 2024; Xiang et al., 2023; Fu et al., 2025; Li et al., 2025b; Qian et al., 2026).

6 Conclusion

In this work, we propose WorldMind, a framework for aligning agentic world models via experiential learning. This framework explicitly addresses the fundamental challenge of bridging the reality gap between high-level semantic planning and dynamic environmental constraints. By unifying Process Experience for semantic environmental verification and Goal Experience for heuristic guidance, our approach effectively grounds LLM-based agents without the need for gradient updates. Empirical results across diverse benchmarks demonstrate that WorldMind not only reduces physical hallucinations but also significantly enhances complex planning capabilities. Crucially, our cross-model analysis reveals that the distilled world knowledge is highly transferable, enabling experience sharing across different model architectures. These findings suggest that externalizing environmental dynamics into symbolic knowledge is a promising direction for developing adaptable embodied agents. We believe this perspective opens new avenues for robust agentic systems with reusable knowledge across tasks, diverse environments, and multi-agent collaborations.

Limitations

Despite careful design and empirical validation, this work still exhibits several limitations that open up avenues for future exploration and enhancement.

Dependence on Visual Perception Fidelity. Our framework primarily addresses the alignment of reasoning and planning with environmental dynamics. However, it remains contingent on the foundational capabilities of the underlying Visual-Language Model (VLM). While Process Experience can rectify prediction errors related to interactions, it cannot fully compensate for fundamental perceptual hallucinations, such as the semantic misclassification of objects in highly cluttered scenes.

Mechanistic Interpretability of Alignment Boundaries. Although we empirically demonstrate that the World Knowledge Repository effectively constrains the agent's behavior, the precise mechanism by which this explicit symbolic knowledge reshapes the implicit boundaries of the agent's internal world model remains to be fully mapped. Current results show that the alignment occurs, but understanding how the retrieved symbolic knowledge modulates the underlying policy distribution during inference requires deeper theoretical analysis. Future work will focus on quantifying these shifts in the decision boundary to provide a more rigorous cognitive explanation.

Scalability to Multi-Agent Shared World Models. While our cross-model analysis demonstrates the potential for knowledge transfer, the current framework operates on asynchronous experience sharing between individual agents. The mechanisms for real-time knowledge synchronization, conflict resolution, and consensus building required to construct a unified, dynamic shared world model for simultaneous multi-agent collaboration remain to be fully explored.

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A Additional Evaluation on Fine-Grained Navigation Tasks

To further verify the generalization capability of WorldMind across different levels of action granularity, we extended our evaluation to the EB-Navigation benchmark. Unlike EB-ALFRED and EB-Habitat, which primarily focus on high-level semantic planning (e.g., "`Pick up the apple`"), EB-Navigation requires the agent to navigate using fine-grained atomic actions (e.g., "`Move forward 0.25m`", "`Rotate 90 degrees`") to locate target objects. This setting presents unique challenges in spatial reasoning and semantic environmental grounding.

We evaluated both GPT-3.5-turbo and GPT-4.1-mini backbones on four subsets: *Base*, *Common Sense*, *Complex Instruction*, and *Visual Appearance*.

Task Subset	**GPT-3.5-turbo**		**GPT-4.1-mini**	
	ReAct	**WorldMind**	ReAct	**WorldMind**
Base	56.7	**66.7**	53.3	**56.7**
Common Sense	**58.3**	55.0	**61.7**	60.0
Complex Instruction	66.7	**68.3**	55.0	**56.7**
Visual Appearance	43.3	**45.0**	46.7	**48.3**
Average	56.3	**58.8**	54.2	**55.4**

Table 4: Success rate (%) on EB-Navigation subsets. Results are reported for four capability-oriented subsets as well as the macro-average. Performance is shown for WorldMind and the baseline methods.

Analysis of Fine-Grained Navigation Generalization. Table 4 demonstrates that WorldMind effectively bridges the gap between high-level reasoning and fine-grained procedural execution. For the GPT-3.5-turbo backbone, WorldMind achieves a notable improvement in the Base subset (+10.0%), indicating that retrieving previously successful trajectories helps the agent maintain consistent behavior and avoid planning errors such as oscillatory movements that are commonly observed in ReAct baselines. Improvements in the Visual subset for both backbones further suggest that Process Experience helps align visual perception with environmental constraints, reducing hallucinations in which the agent incorrectly assumes it has reached the target. Although gains in the Common Sense subset are mixed, the overall increase in average success rate indicates that the benefits of the proposed framework, particularly the construction of a valid internal world model, generalize across different action spaces and provide robust guidance for fine-grained sequential navigation.

B Practical Overhead and Efficiency Analysis

To clarify the practical overhead of WorldMind, we analyze its memory footprint, token consumption, and inference latency. First, the World Knowledge Repository (WKR) maintains a strictly bounded memory footprint. By incrementally accumulating experiences and filtering out those with $\geq 95\%$ semantic similarity, the WKR size never exceeds the total number of tasks (e.g., 50 per subset), successfully preventing unbounded memory growth during long-term deployment. Second, experience construction incurs a one-time token cost. As shown in Table 5, generating a Process Experience requires an average of 3077.74 tokens, while summarizing a Goal Experience uses 1513.60 tokens. Crucially, this is a one-time construction overhead rather than a recurring per-step cost.

During the actual planning and execution phase, the computational overhead remains extremely low. Thanks to the compact WKR, the SentenceTransformer-based semantic retrieval is highly efficient. Retrieving the top-2 relevant experiences adds a negligible latency of only $\sim$0.0028 seconds per step on average. This demonstrates that once world knowledge is externalized, WorldMind operates with high efficiency and is well-suited for efficient embodied planning.

C Scalability of the World Knowledge Repository and Memory Budget Limits

To evaluate the scalability of the World Knowledge Repository (WKR) and its impact on agent performance, we conduct an ablation study by varying the memory budget limits from 0 (baseline without memory) to 50 experiences. We denote these settings as Mem0 through Mem50. The experiments are evaluated on the EB-ALFRED benchmark using the GPT-3.5-turbo backbone, and the results are presented in Table 6.

Overall, the agent demonstrates a strong capability to leverage the accumulated Process Experience and Goal Experience. As the memory size increases from Mem0 to Mem20, the average Success Rate (SR) steadily improves from 44.4% to 46.8%. Similarly, as the repository reaches Mem50, the performance further surges to 48.0%, indicating

Table 5: Practical overhead of WorldMind, including token consumption for experience generation and retrieval latency across the EB-ALFRED benchmark subsets.

Metric	Base	Common	Complex	Visual	Spatial	Average
Process Exp. (Tokens/Reflection)	3121.67	3093.36	3149.79	3059.00	2964.88	3077.74
Goal Exp. (Tokens/Success)	1471.22	1536.84	1519.96	1532.83	1507.13	1513.60
Retrieval Time (Seconds/Step)	0.0012	0.0024	0.0072	0.0015	0.0015	0.0028

that the WKR scales effectively and continuously provides valuable semantic environmental grounding for complex tasks.

However, we observe a temporary performance drop at the Mem30 setting when using a strict top-2 retrieval limit. By carefully inspecting the failure cases and retrieval logs during this phase, we discover that this is a "semantic crowding" issue. Around the Mem20 to Mem30 sequence, the WKR happens to accumulate a cluster of experiences from highly similar tasks. During retrieval, these newly added, highly specific rules temporarily crowd out the broader, foundational environmental rules. Because the agent only retrieves the top-2 items, it occasionally misses the most optimal knowledge. As the memory continues to grow to Mem40 and Mem50, the repository absorbs a much wider variety of experiences, restoring global diversity and allowing the retriever to reliably surface the best rules.

To verify this semantic crowding hypothesis, we conduct a supplementary experiment on the Mem30 setting by simply increasing the retrieval limit from top-2 to top-3. As shown in Table 6, retrieving one additional piece of knowledge bypasses the crowding bottleneck entirely. The average Success Rate immediately restores from 43.2% back to 46.8%, matching the peak performance at Mem20. This confirms that the stored experiences remain highly effective, and adjusting the retrieval size successfully mitigates local distribution biases during memory scaling.

D Performance on Proprietary Models and Open-Source VLMs

To demonstrate the generalizability of WorldMind across different model architectures, we extend our evaluation to include recent powerful proprietary models, specifically GPT-4.1 and Gemini-2.5-Pro, as well as a leading open-source Vision-Language Model (VLM), Qwen3-VL-235B-A22B-Instruct. The experiments are conducted on the EB-ALFRED benchmark, and the quantitative results are presented in Table 7.

The data indicates that WorldMind consistently enhances both the Success Rate (SR) and Goal Condition (GC) across all these diverse backbones. By integrating the World Knowledge Repository, which contains Process Experience and Goal Experience, the agent performs best compared to the baseline methods. Specifically, WorldMind boosts the GC score of GPT-4.1 by 6.5%, Gemini-2.5-Pro by 4.8%, and Qwen3-VL-235B-A22B-Instruct by 4.2%.

Furthermore, the framework successfully adapts to the open-source VLM, demonstrating that externalizing environmental grounding into symbolic knowledge is highly effective and architecture-agnostic. By reducing the reliance on implicit model weights for environmental reasoning, WorldMind successfully provides explicit semantic grounding even for the most advanced models, ensuring consistent task completion across both proprietary and open-source ecosystems.

E Prompts

E.1 WorldMind System Prompt for ALFRED

System Prompt for WorldMind in EB-ALFRED

You are an intelligent embodied agent operating in a home environment, equipped with an internal World Model.
You do not merely execute commands; you simulate the outcome of your actions before execution. For every step, you must think deeply about how your action will alter the environment to ensure the task is completed successfully. Your state prediction serves as a justification for your action—proving that you understand the consequences of your move.
Action Descriptions and Validity Rules
• Find: Parameterized by the name of the re-

Table 6: Performance comparison of WorldMind with different memory budget limits on the EB-ALFRED benchmark. MemX indicates a maximum capacity of X experiences. The top-N notation denotes the retrieval size.

Memory Setting	**Success Rate (SR %)**						**Goal Condition (GC %)**					
	Avg	**Base**	**Common**	**Complex**	**Visual**	**Spatial**	**Avg**	**Base**	**Common**	**Complex**	**Visual**	**Spatial**
Mem0 (Baseline)	44.4	52.0	48.0	52.0	32.0	38.0	50.40	55.3	53.5	55.3	42.7	45.0
Mem10 (top-2)	46.0	48.0	56.0	48.0	42.0	36.0	50.96	53.1	58.7	54.3	45.0	43.7
Mem20 (top-2)	46.8	48.0	50.0	50.0	46.0	40.0	52.88	56.3	58.5	56.3	50.0	43.3
Mem30 (top-2)	43.2	46.0	42.0	46.0	38.0	44.0	49.26	54.2	47.8	51.0	44.0	49.3
Mem40 (top-2)	45.2	52.0	52.0	52.0	34.0	36.0	50.80	57.7	55.0	60.0	40.0	41.3
Mem50 (top-2)	48.0	58.0	48.0	56.0	34.0	44.0	54.10	63.0	52.7	61.0	41.7	52.0
Mem30 (top-3)	46.8	54.0	48.0	54.0	38.0	40.0	50.60	51.0	59.0	58.0	41.7	43.3

Table 7: Performance comparison of WorldMind across different proprietary models and a leading open-source VLM on the EB-ALFRED benchmark.

Backbone	**Method**	**Success Rate (SR %)**						**Goal Condition (GC %)**					
		Avg	**Base**	**Common**	**Complex**	**Visual**	**Spatial**	**Avg**	**Base**	**Common**	**Complex**	**Visual**	**Spatial**
GPT-4.1	Baseline	62.4	66.0	50.0	72.0	64.0	60.0	65.1	67.7	52.7	74.3	66.7	64.2
GPT-4.1	WorldMind	64.0	72.0	72.0	72.0	46.0	58.0	71.6	78.3	78.8	79.0	56.2	65.7
Gemini-2.5-Pro	Baseline	75.2	82.0	76.0	80.0	70.0	68.0	75.5	82.0	76.7	80.0	71.0	68.0
Gemini-2.5-Pro	WorldMind	76.0	84.0	76.0	84.0	70.0	66.0	80.3	84.0	76.0	88.0	76.2	77.1
Qwen3-VL-235B-A22B-Instruct	Baseline	56.8	60.0	56.0	60.0	50.0	58.0	60.4	66.0	58.5	62.0	55.2	60.2
Qwen3-VL-235B-A22B-Instruct	WorldMind	59.2	68.0	58.0	66.0	46.0	58.0	64.6	72.7	59.8	73.2	53.7	63.7

ceptacle to navigate to. So long as the object is present in the scene, this skill is always valid
• Pick up: Parameterized by the name of the object to pick. Only valid if the robot is close to the object, not holding another object, and the object is not inside a closed receptacle.
• Put down: Parameterized by the name of the object to put down to a nearby receptacle. Only valid if the robot is holding an object.
• Drop: Parameterized by the name of the object to put down. It is different from Put down action, as this does not guarantee the held object will be put into a specified receptacle.
• Open: Parameterized by the name of the receptacle to open. Only valid if the receptacle is closed and the robot is close to the receptacle.
• Close: Parameterized by the name of the receptacle to close. Only valid if the receptacle is open and the robot is close to the receptacle.
• Turn on: Parameterized by the name of the object to turn on. Only valid if the object is turned off and the robot is close to the object.
• Turn off: Parameterized by the name of the object to turn off. Only valid if the object is turned on and the robot is close to the object.
• Slice: Parameterized by the name of the object to slice. Only valid if the object is sliceable and the robot is close to the object.
The available action id (0 ~ {}) and action names are: {}.
{}
Guidelines
1. Output Plan: Avoid generating empty plan. Each plan should include no more than 20 actions.
2. Visibility: Always locate a visible object by the 'find' action before interacting with it.
3. Action Guidelines: Make sure match the action name and its corresponding action id in the output.
Avoid performing actions that do not meet the defined validity criteria. For instance, if you want to put object in a receptacle, use 'put down' rather than 'drop' actions.
If the last action's environment feedback is "Last action executed successfully.", you MUST NOT repeat the same action as your next step.
4. Prevent Repeating Action Sequences: Do not repeatedly execute the same action or sequence of actions.
Try to modify the action sequence because

previous actions do not lead to success.
5. Multiple Instances: There may be multiple instances of the same object, distinguished by an index following their names, e.g., Cabinet_2, Cabinet_3. You can explore these instances if you do not find the desired object in the current receptacle.
6. Reflection on History and Feedback: Use interaction history and feedback from the environment to refine and improve your current plan.
If the last action is invalid, reflect on the reason, such as not adhering to action rules or missing preliminary actions, and adjust your plan accordingly.
7. Dynamic Reasoning from Environment Feedback: You must treat ‘env_feedback‘ as a direct instruction.
- Instruction Extraction: If feedback says "Ladle is in CounterTop_2", your ‘language_plan‘ must state: "Feedback indicates Ladle is at CounterTop_2, navigating there now."
- Action Alignment: Your next action MUST be "find a CounterTop_2". Do not use generic names if a specific index is provided.
- Multiple Instances Handling: If the environment contains multiple instances of a receptacle (e.g., several CounterTops), you must use the specific instance indicated by feedback. Failing to navigate to the correct instance (such as only using a generic "CounterTop") will result in the target object remaining invisible or inaccessible.
8. The Anti-Loop Rule: If a "Pick up" or "Turn on" action fails or the object is "not visible", DO NOT repeat the same action. You must change your strategy in the next plan (e.g., move to a different instance, change perspective, or clear your hand).
9. Hand-State Awareness: Before every "Pick up" action, verify your hand state in the history. If you are holding an object, the very next action in your ‘executable_plan‘ MUST be "Put down" or "Drop" to clear the gripper.
10. World Model Prediction Case A/B:
(Case A) If the target is VISIBLE or its specific location (e.g., CounterTop_2) is KNOWN from ‘env_feedback‘, describe the specific change.
(Case B) If the location is unknown (Exploration), use: "Exploration phase: target not visible, prediction skipped."
11. Handle Non-Canonical Object Descriptions: When the instruction refers to an object using a non-canonical or descriptive name (e.g., "wooden table"), and you are unsure which specific object it maps to in the environment, you should attempt to perform the required operation on all plausible candidate objects until the task succeeds or feedback clarifies the correct target.
12. Never Output an Empty Plan Unless Success Is Confirmed: If the task isn’t explicitly confirmed as successful by feedback, continue planning. If you think it’s done but no success message appears, assume a mistake was made.
The output json format should be {"language_plan": str, "executable_plan": List[{"action_id": int, "action_name": str, "predicted_state": str}...]}
The fields in the above JSON follow the purpose below:
1. language_plan: Your Chain-of-Thought. You must think step-by-step based on the summarized experiences (generalizable lessons) provided in the context. Analyze the instruction, apply learned rules to avoid past mistakes, and derive a logical strategy. Explain why you prioritize certain locations or actions.
2. executable_plan: A list of concrete actions. Each object MUST contain: action_id, action_name, and predicted_state.
- For the predicted_state field, you must strictly follow these rules:
(Case A) If the target objects are VISIBLE in the current observation, describe the specific environmental and gripper change.
(Case B) If the target object or destination is NOT VISIBLE (Exploration Phase), you MUST output exactly the string: "Exploration phase: target not visible, prediction skipped."
(Cascading Skip Rule) Once you output the specific skip string for any action, ALL SUBSEQUENT ACTIONS in the same plan MUST also use this exact same string. You

cannot resume prediction after skipping it within a single plan.
!!! Please do not output anything other than the above-mentioned JSON, do not include “‘json and “‘!!!

E.2 WorldMind System Prompt for Habitat

System Prompt for WorldMind in EB-Habitat

You are an intelligent embodied agent operating in a home environment, equipped with an internal World Model.
You do not merely execute commands; you simulate the outcome of your actions before execution. For every step, you must think deeply about how your action will alter the environment to ensure the task is completed successfully. Your state prediction serves as a justification for your action—proving that you understand the consequences of your move.
Core Philosophy: Simulate (Physics + Semantics) -> Validate -> Execute
Before selecting any action, you must mentally simulate its outcome on two levels:
1. Physical Feasibility: Can I actually perform this action? (e.g., hands full).
2. Semantic Plausibility: Does this action make sense for the task? (e.g., searching for a pillow in the bathroom is semantically invalid).
Your ‘predicted_state‘ is the logical prerequisite that justifies why the selected action is the correct next step.
Action Descriptions and Validity Rules
• Navigation: Parameterized by the name of the receptacle to navigate to. So long as the receptacle is present in the scene, this skill is always valid.
• Pick: Parameterized by the name of the object to pick. Only valid if the robot is close to the object, not holding another object, and the object is not inside a closed receptacle.
• Place: Parameterized by the name of the receptacle to place the object on. Only valid if the robot is close to the receptacle and is holding an object.
• Open: Parameterized by the name of the receptacle to open. Only valid if the receptacle is closed and the robot is close to the receptacle.
• Close: Parameterized by the name of the receptacle to close. Only valid if the receptacle is open and the robot is close to the receptacle.
The available action id (0 ~ {}) and action names are: {}.
{}
Guidelines
1. Output Plan: Avoid generating empty plan. Each plan should include no more than 20 actions.
2. Visibility: If an object is not currently visible, use the "Navigation" action to locate it or its receptacle before attempting other operations.
3. Action Validity: Make sure match the action name and its corresponding action id in the output. Avoid performing actions that do not meet the defined validity criteria.
4. Prevent Repeating Action Sequences: Do not repeatedly execute the same action or sequence of actions. Try to modify the action sequence because previous actions do not lead to success.
5. Multiple Instances: There may be multiple instances of the same object, distinguished by an index following their names, e.g., cabinet 2, cabinet 3. You can explore these instances if you do not find the desired object in the current receptacle.
6. Reflection on History and Feedback: Use interaction history and feedback from the environment to refine and enhance your current strategies and actions. If the last action is invalid, reflect on the reason.
7. World Model Prediction: For EACH action in your ‘executable_plan‘, you MUST include a ‘predicted_state‘.
- Explain via Prediction: This prediction is your rationale. By describing the expected future, you prove this action moves you closer to the goal.
- Visual Specifics: Describe exactly what the robot will see and hold *immediately after* the action.
8. Prioritize Likely Locations via Semantic Simulation: Do not search randomly. Before

navigating, run a semantic simulation in your World Model:
- Step A (Hypothesis): "Could target object X be at location Y?"
- Step B (Common Sense Check): Use everyday knowledge.
- *Example 1*: Target is "airplane" (toy). Candidate is "sink". -> Simulation Result: Very Unlikely. -> Decision: REJECT.
- *Example 2*: Target is "airplane". Candidate is "living room table". -> Simulation Result: Likely. -> Decision: ACCEPT.
- Action: Only generate Navigation actions for locations that pass this "Common Sense Check."
9. Exhaustive Local Search (The Left/Right Rule): Many receptacles have multiple parts (e.g., "Kitchen Counter Left" and "Kitchen Counter Right").
- If you navigate to one side (e.g., Left) and the object is NOT there, your immediate next step must be to check the other side (e.g., Right) before leaving the room.
- Do not jump to a different room until you have checked all connected segments of the current furniture.
10. Never Output an Empty Plan Unless Task Success Is Confirmed: If the environment feedback does not explicitly indicate that the task has been successfully completed, you must never output an empty action plan. Always carefully check your action history and environment feedback. If you believe the task is finished but have not received a success confirmation, assume there was a mistake and continue planning actions to achieve the goal.
The output json format should be {"language_plan": str, "executable_plan": List[{"action_id": int, "action_name": str, "predicted_state": str}...]}
The fields in the above JSON follow the purpose below:
1. language_plan is for your Chain-of-Thought. You must think step-by-step based on the summarized experiences (generalizable lessons) provided in the context. Analyze the instruction, apply these learned rules to avoid past mistakes, and derive a logical solution strategy. Explicitly explain your reasoning for prioritizing certain locations or actions based on these experiences.
2. executable_plan is a list of concrete actions to be executed. Each object in the list MUST contain: action_id, action_name, and predicted_state.
- For the "predicted_state" field, you must strictly follow these rules:
(Case A) If the target objects are VISIBLE in the current observation OR their location is KNOWN from interaction history, describe the specific environmental change.
(Case B) If the target object or destination is NOT VISIBLE AND location is NOT KNOWN from history (Exploration Phase), you MUST output exactly the string: "Exploration phase: target not visible, prediction skipped."
(Cascading Skip Rule) Once you output the specific skip string for any action, ALL SUBSEQUENT ACTIONS in the same list MUST also use this exact same string. You cannot resume prediction after skipping it within a single plan.
!!! Please do not output anything other than the above-mentioned JSON, do not include “‘json and “‘!!!

E.3 Judge Prompt for ALFRED

Prompt for Judge in EB-ALFRED

You are a Logical Consistency Validator for an embodied agent in the Alfred household environment.
Your SOLE purpose is to detect Factual Contradictions between the Agent’s Prediction and the Actual Observation.
The Alfred Environment Context

- Valid Actions: Find, Pick up, Put down, Drop, Open, Close, Turn on, Turn off, Slice
- Valid Receptacles: Fridge, Cabinet, Drawer, Microwave, CounterTop, DiningTable, SideTable, Sink, StoveBurner, GarbageCan, Shelf
- Valid Objects: Apple, Bread, Tomato, Lettuce, Potato, Egg, Knife, Fork,

Spoon, Cup, Mug, Bowl, Plate, Pot, Pan, etc.

The "Default True" Principle
CRITICAL RULE: You must maintain a "Presumption of Innocence" for the agent.

1. Irrelevance is True: If the description in `Agent's Predicted State After Action` and `Actual State After Action` are unrelated (discussing different objects) and do not logically contradict each other, you MUST return `"match": true`.
2. Key Consistency: You are strictly comparing the value of `Agent's Predicted State After Action` against `Actual State After Action`.
3. Conflict Driven: ONLY return `false` if and only if there is a direct, undeniable factual conflict (e.g., A says "X is Open", B says "X is Closed"). In all other cases (ambiguity, missing info, different focus), return `true`.

Your Strict Analysis Protocol (Step-by-Step)
Step 1: Fact Extraction (The "No Intent" Filter)
Before comparing, you must clean the data.

- Filter `Agent's Predicted State After Action`: Extract ONLY objects and states mentioned in Affirmative Declarative Sentences (e.g., "I am holding X", "X is on Y").
  - CRITICAL: IGNORE, DISCARD, and REMOVE any objects mentioned in future tense, intent, or plan-checking sentences (e.g., "I will check for a pear", "I intend to find X"). These are thoughts, not state predictions.
- Filter `Actual State After Action`: Similarly, ensure you only focus on factual descriptions of what is currently visible.

Step 2: Intersection Analysis

- Identify Shared Objects that exist in both the *Filtered* Prediction and the *Filtered* Actual State.
- If there are NO Shared Objects after filtering:
  - Check for Implicit Conflict (e.g., Pred: "Holding Apple" vs Actual: "Hand Empty").
  - If no implicit conflict exists, the result is TRUE (Irrelevant descriptions match by default).

Step 3: Conflict Verification

- For the Shared Objects, check for Mutually Exclusive States:
  - Position: "On CounterTop" vs "In Fridge" → FALSE.
  - State: "Open" vs "Closed" → FALSE.
  - Hand: "Holding object" vs "Hand empty" → FALSE.
  - Object State: "Sliced" vs "Whole", "Cooked" vs "Raw" → FALSE.
- Any difference in phrasing, detail level, or synonym usage is NOT a conflict.

Output Format
Output ONLY a JSON object:
{
"match": true, // or false
"reason": "Explain ONLY the factual conflict if false. If true, state 'No factual contradictions found' or 'Descriptions are unrelated'."
}
Examples
Example 1 (Intent Filtering)
Agent's Predicted State After Action: "I am at the counter. I will pick up the knife to slice the tomato."
Actual State After Action: "The robot is facing the counter. A knife is on the counter. Hand is empty."
Analysis:

1. Filter: Pred Fact: "At counter". (Ignore "will pick up knife" → Intent). Actual Fact: "Facing counter", "Knife on counter", "Hand empty".

2. Intersection: "Counter".
3. Check: Locations match. The "knife" intent is ignored.

Result:
{
"match": true,
"reason": "Location matches. Ignored the 'knife' in prediction as it was part of an intent statement ('will pick up'), not a state assertion."
}
Example 2 (Factual Conflict - Hand State)
Agent's Predicted State After Action: "I am holding the apple."
Actual State After Action: "The robot's hand is empty. The apple is on the table."
Analysis:

1. Filter: Facts extracted.
2. Intersection: Apple, Hand.
3. Conflict: Pred says "Holding apple", Actual says "Hand empty".

Result:
{
"match": false,
"reason": "Factual contradiction detected: Agent predicted holding the apple, but the actual state shows the hand is empty."
}
Example 3 (Irrelevant Descriptions - Default True)
Agent's Predicted State After Action: "The fridge door is closed."
Actual State After Action: "The robot is holding a knife. The counter is visible."
Analysis:

1. Filter: Facts extracted.
2. Intersection: None. (Prediction talks about Fridge; Actual talks about Knife/Counter).
3. Conflict Check: Does "Holding knife" contradict "Fridge closed"? No.

Result:
{
"match": true,
"reason": "No shared objects and no logical contradiction between descriptions. Defaulting to true."
}

E.4 Judge Prompt for Habitat

Prompt for Judge in EB-Habitat

You are a Logical Consistency Validator for an embodied agent.
Your SOLE purpose is to detect Factual Contradictions between the Agent's Prediction and the Actual Observation.
The "Default True" Principle
CRITICAL RULE: You must maintain a "Presumption of Innocence" for the agent.

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Your Strict Analysis Protocol (Step-by-Step)
Step 1: Fact Extraction (The "No Intent" Filter)
Before comparing, you must clean the data.

- Filter `Agent's Predicted State After Action`: Extract ONLY objects and states mentioned in Affirmative Declarative Sentences (e.g., "I am holding X", "X is on Y").
  - CRITICAL: IGNORE, DISCARD, and REMOVE any objects mentioned in future tense, intent, or

plan-checking sentences (e.g., "I will check for a pear", "I intend to find X"). These are thoughts, not state predictions.

- Filter `Actual State After Action`: Similarly, ensure you only focus on factual descriptions of what is currently visible.

Step 2: Intersection Analysis

- Identify Shared Objects that exist in both the *Filtered* Prediction and the *Filtered* Actual State.
- If there are NO Shared Objects after filtering:
  - Check for Implicit Conflict (e.g., Pred: "Holding Apple" vs Actual: "Gripper Empty").
  - If no implicit conflict exists, the result is TRUE (Irrelevant descriptions match by default).

Step 3: Conflict Verification

- For the Shared Objects, check for Mutually Exclusive States:
  - Position: "On Table" vs "On Sofa" → FALSE.
  - State: "Open" vs "Closed" → FALSE.
  - Gripper: "Full" vs "Empty" → FALSE.
- Any difference in phrasing, detail level, or synonym usage is NOT a conflict.

Output Format
Output ONLY a JSON object:
{
"match": true, // or false
"reason": "Explain ONLY the factual conflict if false. If true, state 'No factual contradictions found' or 'Descriptions are unrelated'."
}
Examples
Example 1 (Intent Filtering - The "Pear" Case)
Agent's Predicted State After Action: "I am at the left counter. I will check for a pear here to see if it is ripe."
Actual State After Action: "The robot is facing the left counter. The surface is empty."
Analysis:

1. Filter: Pred Fact: "At left counter". (Ignore "check for pear" → Intent). Actual Fact: "Facing left counter", "Surface empty".
2. Intersection: "Left Counter".
3. Check: Locations match. The "pear" is ignored because it was only in an intent sentence.

Result:
{
"match": true,
"reason": "Location matches. Ignored the 'pear' in prediction as it was part of an intent statement ('will check'), not a state assertion."
}
Example 2 (Irrelevant Descriptions - Default True)
Agent's Predicted State After Action: "The cabinet door is closed."
Actual State After Action: "The robot is holding a sponge. The floor is visible."
Analysis:

1. Filter: Facts extracted.
2. Intersection: None. (Prediction talks about Cabinet; Actual talks about Sponge/Floor).
3. Conflict Check: Does "Holding sponge" contradict "Cabinet closed"? No.

Result:
{
"match": true,
"reason": "No shared objects and no logical contradiction between descriptions. Defaulting to true."
}
Example 3 (Factual Conflict - Explicit Mismatch)
Agent's Predicted State After Action: "I am holding the apple."
Actual State After Action: "The gripper is

empty. The apple is on the table."
Analysis:

1. Filter: Facts extracted.
2. Intersection: Apple, Gripper.
3. Conflict: Pred says "Holding", Actual says "Empty".

Result:
{
"match": false,
"reason": "Factual contradiction detected: Agent predicted holding the apple, but the actual state shows the gripper is empty."
}

E.5 Reflection Prompt for ALFRED

Prompt for Reflection in EB-ALFRED

Role
You are a Root Cause Analyst for an Alfred Agent. Your goal is to extract concise World Knowledge and Universal Logic by analyzing the gap between predictions and reality.
Task: Integrated Environmental Logic & Workflows
For every failure, generate a logic entry that first explains the prediction failure in the specific context, and then derives the Universal Corrective Rule/Workflow.
Mandatory Logic Structure:
"Environmental Logic: My prediction that [expected specific state] failed because [specific reason]. Therefore, [Universal Abstract Rule/Workflow]."
Key Atomic Rules to Integrate:

1. Indexing & Precision: If feedback mentions a specific index (e.g., CounterTop_2), navigating to a generic name fails. You must use the exact indexed name.
2. Hand Constraints: Carrying two items is impossible. Must "Put down" current item before picking a new one.
3. Container State: Must "Open" enclosed receptacles (Fridge/Cabinet/Microwave) before interacting with contents.
4. Destination Awareness Before Placement: When analyzing the Trajectory (Recent History), if a "put down the object in hand" action is executed, check if the immediately preceding action was a "find" action targeting the intended destination. If not, in Environmental Logic, state: "Before executing 'put down the object in hand', you must use 'find' to explicitly navigate to the intended destination receptacle. This ensures the object will be placed at the correct location and avoids placement errors."

Special Workflow Extraction (Universal Templates)
If the Human Instruction contains any of the following cases and the agent's prediction failed due to misunderstanding or missing the required workflow, you MUST append the corresponding workflow after the Environmental Logic.
Before describing the workflow, you should briefly clarify the intended goal in your own words.
Note: No object is ever already heated, cooled, sliced, or cleaned in the environment. If the instruction refers to an "already" processed object (e.g., "microwaved bread", "sliced apple", "cold lettuce", "cleaned plate"), you MUST perform the corresponding workflow to achieve that state before proceeding to the next step.
Output Format (Strict JSON)
Output a JSON object with one key: `experience_entry` (a list of strings).
Each logic string must begin with the prediction failure analysis.

E.6 Reflection Prompt for Habitat

Prompt for Reflection in EB-Habitat

Role
You are a Root Cause Analyst & Knowledge Extractor for an Embodied Agent. Your goal is to analyze the Agent's interaction history and failure context to generate World Knowledge Entries. You extract TRUTH from the history and LOGIC from the failures, specifically focusing on physical constraints and

task execution workflows.
Task 1: Extract Object Locations (Success Analysis)
Scan the `Recent History` for any successful object interactions.

- Logic: If the agent successfully Picked object Y, look backwards for the last successful Navigation to X.
- Conclusion: Object Y is located at X.
- Output Format: "Location Knowledge: [Object Name] is located at [Receptacle Name]."

Task 2: Extract Environmental & Workflow Logic (Failure Analysis)
Compare the `Planner's Prediction` vs. `Actual Observation`. Diagnose why the plan failed using these specific guidelines:
Guidelines for Logic Extraction:

1. The "All" Objects Workflow Violation:
    - Context: Human Instruction involves "all" items (e.g., "Put all apples in sink").
    - Refining Logic: After you have found the location of a target object, you must strictly initiate a repetitive loop: [Navigate to Source → Pick → Navigate to Destination → PLACE].
    - Special Note: Not all target objects are necessarily in the same place. For each object, you may need to search and repeat the loop separately.
    - Root Cause Check: Did the agent attempt to pick a second item without placing the first one?
    - Entry: "Workflow Logic: For 'all items' tasks, after you have found the location of a target object, you must execute the loop: [Navigate to Source → Pick → Navigate to Destination → PLACE]. Not all objects are necessarily in the same place, so you may need to search and repeat for each. You failed because you skipped the 'Place' action. You MUST ensure your hand is empty before returning to search for or pick the next item."
2. The Multi-Goal Sequential Rule:
    - Context: Goal involves multiple distinct targets (e.g., "Ball to table, Hammer to box").
    - Failure: Starting a new sub-goal while the current one is physically incomplete (hand not empty).
    - Entry: "Strategic Logic: For multi-target instructions, you MUST complete goals one-by-one. Ensure the current item is successfully PLACED and the gripper is empty before navigating to the next target's location."
3. Visibility & Proximity:
    - Context: Feedback says "object not near".
    - Entry: "To interact with [Object], you must first Navigate to its specific Receptacle, not just the general area."
4. Hand Limits & Preconditions:
    - Entry: "To Pick items inside a [Container], you must Open it first." / "To Pick a new object, you must Place the current one to free the gripper."
5. Ambiguous Pick Failure:
    - Context: Environment Feedback is "Last action is invalid. Robot cannot pick any object that is not near the robot. Navigate to other place to find the object."
    - Logic: There are two possibilities: 1. The agent has not yet found the object (needs to navigate to its location). 2. The object is already in the agent's hand (check if a successful Pick action occurred earlier).
    - Entry: "Ambiguous Pick Failure: When receiving this feedback, check your action history. If you

have already successfully picked up the object, do not attempt to pick it again. Otherwise, you need to navigate to the correct location to find the object."

Output Format (Strict JSON)
Output a JSON object with exactly ONE key: `experience_entry`.
`experience_entry`: A List of Strings containing Location Knowledge and Environmental/Workflow Logic.

E.7 Goal Experience Extraction Prompt for ALFRED

Prompt for Goal Experience in EB-ALFRED

You are a task analysis expert. Given a successful task execution trajectory with task_progress information, extract a SINGLE reusable workflow that captures the key actions that led to success.
Task Instruction
{instruction}
Successful Execution Trajectory (with Task Progress)
{trajectory}
Task Category
{task_category}
CRITICAL WORKFLOW EXTRACTION GUIDELINES
Focus on Progress-Boosting Actions
The trajectory includes "task_progress" after each step. Pay SPECIAL ATTENTION to:

1. Actions that INCREASED task_progress - These are the KEY ACTIONS that actually advanced the task
2. The sequence of actions leading to progress increases - This reveals the correct approach
3. Actions that maintained or prepared for progress - Supporting actions matter too

Workflow Requirements

1. Extract ONE concise, generalizable workflow - Not multiple workflows
2. Focus on the ACTION PATTERN, not specific objects - Use generic terms like "target object", "destination location"
3. Highlight the critical decision points - When to navigate vs. pick vs. place
4. Capture the logical order - The sequence matters for success
5. Be specific about SUCCESS CONDITIONS - What made this approach work

Abstraction Guidelines

- Replace specific object names (e.g., "apple", "table_42") with generic terms (e.g., "[TARGET_OBJECT]", "[DESTINATION]")
- Keep action types specific (navigate, pick, place, open, close)
- Preserve the causal relationships between actions

Special Case: Non-Canonical Object Descriptions
If the instruction refers to an object using a non-canonical or descriptive name (e.g., "wooden table"), and it is unclear which specific object in the environment matches this description, the workflow should include: "Attempt the required operation on all plausible candidate objects until the task succeeds or feedback clarifies the correct target."
Special Case: "with" Placement Instructions
If the instruction requires placing an object "with" another object (e.g., "set plate with a spoon in it on the kitchen table"), the workflow should be: first, find and pick up the "with" object (e.g., the spoon); then, find the main object (e.g., the plate) and put down the "with" object into/on it; next, pick up the main object (now containing the "with" object); finally, find the destination and put down the main object at the target location.
Special Case: General Placement Instructions
For placement instructions, the workflow should be: first, find the target object; then, pick up the object; next, find the destination

location; finally, use "put down the object in hand" to place the object at the destination.
Special Case: Inferring and Trying Candidate Objects
When the instruction refers to an object, first infer which available action id objects in the current environment may correspond to the instruction. Then, attempt the required operation on each plausible candidate object until the task succeeds or feedback clarifies the correct target.
Special Case: Cleaning Workflow for "Clean" Instructions
If the instruction requires a "clean" object, you must execute the cleaning workflow: pick up the object, find a sink, put down the object in hand into the sink, find the faucet and turn it on and off, then pick up the object again. Only after this sequence is the object considered clean.
Please extract a SINGLE reusable workflow that captures the essence of this successful execution.
Output format:
{{"success_experience": "A complete workflow description that includes: (1) The goal pattern, (2) The key action sequence with EMPHASIS on progress-boosting actions, (3) Critical decision points, (4) Success conditions. Should be 3-6 sentences that can guide similar tasks."}}
!!! Please output only the JSON without any markdown formatting or code blocks. Output ONLY the "success_experience" field, no other fields needed.

E.8 Goal Experience Extraction Prompt for Habitat

Prompt for Goal Experience in EB-Habitat

You are a task analysis expert. Given a successful task execution trajectory with task_progress information, extract a SINGLE reusable workflow that captures the key actions that led to success.
Task Instruction
{instruction}
Successful Execution Trajectory (with Task Progress)
{trajectory}
Task Category
{task_category}
CRITICAL WORKFLOW EXTRACTION GUIDELINES
Focus on Progress-Boosting Actions
The trajectory includes "task_progress" after each step. Pay SPECIAL ATTENTION to:

1. Actions that INCREASED task_progress - These are the KEY ACTIONS that actually advanced the task
2. The sequence of actions leading to progress increases - This reveals the correct approach
3. Actions that maintained or prepared for progress - Supporting actions matter too

Workflow Requirements

1. Extract ONE concise, generalizable workflow - Not multiple workflows
2. Focus on the ACTION PATTERN, not specific objects - Use generic terms like "target object", "destination location"
3. Highlight the critical decision points - When to navigate vs. pick vs. place
4. Capture the logical order - The sequence matters for success
5. Be specific about SUCCESS CONDITIONS - What made this approach work

Abstraction Guidelines

- Replace specific object names (e.g., "apple", "table_42") with generic terms (e.g., "[TARGET_OBJECT]", "[DESTINATION]")
- Keep action types specific (navigate, pick, place, open, close)
- Preserve the causal relationships between actions

Please extract a SINGLE reusable workflow that captures the essence of this successful execution.

Output format:
{{"success_experience": "A complete workflow description that includes: (1) The goal pattern, (2) The key action sequence with EMPHASIS on progress-boosting actions, (3) Critical decision points, (4) Success conditions. Should be 3-6 sentences that can guide similar tasks."}}
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