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# TOOLSELF: UNIFYING TASK EXECUTION AND SELF-RECONFIGURATION VIA TOOL-DRIVEN INTRINSIC ADAPTATION

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## ABSTRACT

Agentic systems powered by Large Language Models (LLMs) have demonstrated remarkable potential in tackling complex, long-horizon tasks. However, their efficacy is fundamentally constrained by static configurations governing agent behaviors, which are fixed prior to execution and fail to adapt to evolving task dynamics. Existing approaches, relying on manual orchestration or heuristic-based patches, often struggle with poor generalization and fragmented optimization. To transcend these limitations, we propose TOOLSELF, a novel paradigm enabling **tool**-driven runtime **self**-reconfiguration. By abstracting configuration updates as a callable tool, TOOLSELF unifies task execution and self-adjustment into a single action space, achieving a phase transition from external rules to intrinsic parameters. Agents can thereby autonomously update their sub-goals and context based on task progression, and correspondingly adapt their strategy and toolbox, transforming from passive executors into dual managers of both task and itself. We further devise Configuration-Aware Two-stage Training (**CAT**), combining rejection sampling fine-tuning with trajectory-level reinforcement learning to internalize this meta-capability. Extensive experiments across diverse benchmarks demonstrate that TOOLSELF rivals specialized workflows while generalizing to novel tasks, achieving a 24.1% average performance gain and illuminating a path toward truly self-adaptive agents.<sup>1</sup>

## 1 Introduction

*Agentic systems* refer to large language model-based systems that go beyond passive text generation to autonomously plan, reason, and act in interactive environments through multi-step decision making [1]. By tightly coupling internal reasoning with external actions—such as tool invocation, environment interaction, and intermediate state updates—agentic systems enable models to tackle complex, long-horizon tasks that cannot be addressed through single-shot inference [2]. This paradigm has become increasingly important as real-world applications, including deep research [3], software engineering [4], and system control [5, 6], demand sustained goal pursuit, adaptive planning, and iterative integration of information over time.

Central to the behavior of an agentic system is its *configuration*, which defines the internal control variables governing how the agent reasons, acts, and interacts with its environment during execution. Configuration typically encompasses the agent’s execution strategy (e.g., persona or reasoning style) [7], the available toolbox of actions [8], and the task-relevant knowledge or context maintained across steps [9]. These elements implicitly shape the agent’s action space, information flow, and decision-making dynamics, and thus play a decisive role in long-horizon performance [10]. However, most existing agentic systems rely on a *static configuration* that is fixed prior to execution and remains

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<sup>1</sup>Code is being organized.

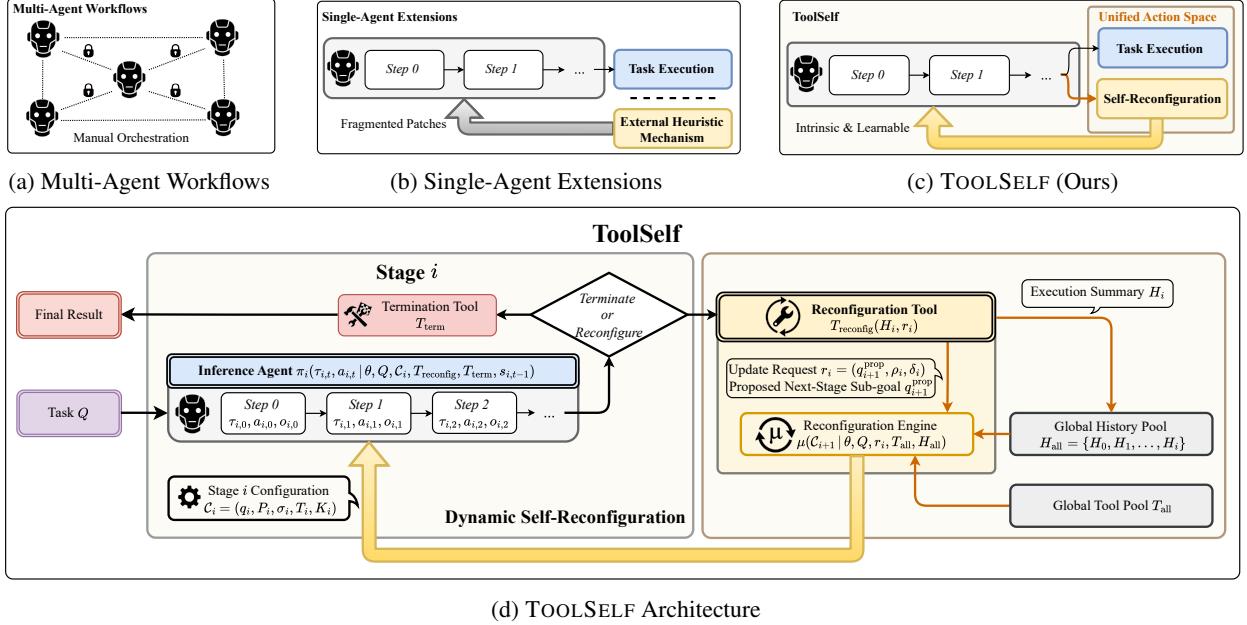


Figure 1: Illustration of TOOLSELF. (a) Multi-Agent Workflows rely on manual priors with poor generalization; (b) Single-Agent Extensions apply fragmented patches via external heuristic mechanisms; (c) TOOLSELF unifies task execution and self-reconfiguration into a single action space, achieving intrinsic and learnable adaptation. (d) The system operates through an *inference-reconfiguration* loop. In each stage  $i$ , the inference agent  $\pi_i$  executes tasks under dynamic configuration  $C_i = (q_i, \sigma_i, T_i, K_i)$ , comprising sub-goals, strategy, toolbox, and context. When the agent determines that reconfiguration is needed, it invokes the reconfiguration tool  $T_{\text{reconfig}}$ , which triggers the reconfiguration engine  $\mu$  to generate an updated configuration  $C_{i+1}$  for the next stage. By unifying task execution and self-configuration into a single action space, TOOLSELF achieves autonomous triggering (deciding *when*), intent-driven adaptation (specifying *how*), and joint optimization (learning end-to-end), thereby transforming agents from passive executors into dual managers of both task and self-configuration.

unchanged throughout the task. While adequate for short or deterministic questions, this rigidity becomes a fundamental bottleneck in long-horizon settings, where sub-goals evolve, information requirements shift, and tool needs change over time [11]. Consequently, configuration is not merely an implementation detail, but a first-class component of agentic systems that fundamentally determines their autonomy, efficiency, and capacity for sustained reasoning.

Prior work (Appendix 4) has explored two main directions to tackle these challenges. *Multi-agent workflows* [12, 13] rely on manually specified priors to decompose tasks in advance and orchestrate sub-agents with specialized configurations for collaborative execution. While effective in narrowly defined domains, the heavy reliance on human-designed decomposition, prompts, and orchestration logic severely limits their scalability, transferability, and generalization to unseen tasks. In contrast, *single-agent extensions* introduce external mechanisms for periodic configuration adjustment [14, 15] or interaction history compression [16, 9]. However, these solutions operate as fragmented patches targeting isolated symptoms rather than addressing the underlying cause. More critically, their triggering logic is typically governed by rigid heuristic thresholds—such as step counts or context length—which decouple configuration updates from task semantics and execution dynamics, thereby precluding end-to-end, data-driven optimization.

The limitations of these approaches highlight two critical challenges for enabling truly adaptive agents. The first is *autonomy*: instead of relying on externally imposed heuristics or predefined orchestration, agents should possess *runtime sovereignty*, enabling them to internally determine *when* and *how* to reconfigure their sub-goals, strategies, tools, and context in response to evolving task dynamics. The second is *unification*: self-configuration should be realized through a *unified and minimal interface* that tightly couples configuration updates with task execution, replacing fragmented, ad hoc mechanisms with an end-to-end, data-driven learning process. Together, these requirements position self-configuration as a principled solution to the rigidity and fragmentation of existing agentic systems, enabling adaptive behavior without sacrificing generality or trainability.

To this end, we propose **TOOLSELF** (**T**ool-driven **S**elf-reconfiguration), a novel paradigm that unifies task execution and self-configuration into a single action space by abstracting configuration updates as a callable tool, thereby effecting a phase transition from externally imposed rules to intrinsically learned control parameters. As illustrated in Figure 1, **TOOLSELF** departs from conventional static architectures by equipping the inference agent with a reconfiguration tool, enabling it to autonomously and dynamically update its sub-goals [14] and context in response to task progression and environmental feedback, while adaptively configuring appropriate execution strategies and toolsets for each task stage. Sub-goal updates provide macro-level guidance that mitigates blind exploration in exponentially growing search spaces [17], while proactive context management ensures refined and efficient information processing [16, 9]. Together, these mechanisms elevate agents from passive executors to dual managers of both task execution and self-configuration.

To enable the data-driven acquisition of self-reconfiguration capabilities, we further devise Configuration-Aware Two-stage Training (CAT). Both the inference agent and the reconfiguration engine share a single base model, yielding a compact and end-to-end trainable architecture. CAT optimizes both modules through two stages: Stage I employs rejection sampling fine-tuning (RFT) [18] to initialize both modules using teacher-generated successful trajectories, as effective self-reconfiguration is difficult to explore from scratch. Stage II applies KTO-based reinforcement learning [19] to further optimize reconfiguration decisions. Since self-reconfiguration is a meta-capability across execution stages whose quality only manifests through downstream task performance, we adopt trajectory-level credit assignment—propagating task success/failure to all reconfiguration decisions within the trajectory—for which KTO’s binary feedback is naturally well aligned.

Extensive experiments across diverse benchmarks demonstrate that **TOOLSELF** rivals specialized workflows while generalizing to novel tasks (Sec. 3.2), with the proposed training pipeline yielding a 24.1% average performance gain (Sec. 3.3). Ablation and case studies (Sec. 3.4, A.2) further validate each design choice and illuminate a promising path toward self-adaptive agentic systems. The main contributions are summarized as follows:

- We propose **TOOLSELF**, a paradigm unifying task execution and self-configuration into a single action space by abstracting configuration updates as a tool, achieving a phase transition from external rules to intrinsic parameters.
- We devise Configuration-Aware Two-stage Training (CAT) with RFT for cold-start priors and KTO-based reinforcement learning. As self-reconfiguration is a cross-stage meta-capability, trajectory-level credit assignment is adopted, naturally aligned with KTO’s binary feedback.
- Extensive experiments reveal that **TOOLSELF** achieves up to 24.1% improvement over strong single-agent baselines, demonstrating superior generalization across diverse domains while matching the efficacy of expert-designed workflows.

## 2 Method

**TOOLSELF** enables a single agent to achieve runtime self-configuration **by abstracting configuration updates as a callable tool**, thereby unifying task execution and self-configuration into a single action space. Formally, this paradigm distinguishes itself from existing approaches through three core properties: (1) **Autonomous Triggering**, where the agent intrinsically decides *when* to reconfigure rather than relying on external heuristics or fixed intervals; (2) **Intent-Driven Adaptation**, where the agent explicitly specifies *how* to update via reconfiguration requests rather than delegating to decoupled modules; and (3) **Joint Optimization**, where the configuration policy is end-to-end trainable alongside task execution. The system operates through an *inference-reconfiguration* loop: the inference agent  $\pi_i$  executes tasks and invokes the reconfiguration tool as needed, triggering the reconfiguration engine  $\mu$  to generate new configurations.

### 2.1 Preliminaries: Pre-Fixed Configuration Paradigm

Formally, the behavior policy of a ReAct-style [2] single-agent can be described as a conditional distribution:

$$\pi(\tau_t, a_t | \theta, Q, \mathcal{C}_{\text{static}}, s_{t-1}) \quad (1)$$

where  $\theta$  represents the LLM parameters,  $Q$  is the target task,  $\mathcal{C}_{\text{static}} \triangleq (\sigma, T, K)$  is the static configuration consisting of three elements: execution strategy  $\sigma$ , toolbox  $T$ , and background knowledge  $K$ . The agent’s context comprises the interaction history  $s_{t-1} = (\tau_0, a_0, o_0, \dots, \tau_{t-1}, a_{t-1}, o_{t-1})$ , where  $\tau_k, a_k, o_k$  represent the thought, action, and observation at step  $k$ , respectively.

The fundamental limitation of this paradigm stems from the pre-fixed nature of configurations: all elements of  $\mathcal{C}_{\text{static}}$  remain frozen from start to finish, with no mechanism for the agent to update them during execution. Such rigidity may

suffice for short, well-defined tasks, but becomes increasingly problematic as task horizons extend—objectives shift mid-execution, previously adequate tools become insufficient, and accumulated history obscures relevant information. Lacking any self-configuration capability within its action space, the agent operates as a passive executor, blindly following its initial setup regardless of how circumstances evolve. The practical consequences are twofold: an exponentially growing search space with no macro-level guidance, and progressively degraded reasoning due to context pollution.

## 2.2 The TOOLSELF Paradigm

To overcome above limitations, TOOLSELF reconceptualizes configurations as dynamic, tool-updatable variables rather than pre-fixed constants, thereby effecting a phase transition from externally imposed rules to intrinsically learned control parameters. The paradigm comprises two tightly-coupled components: the inference agent  $\pi_i$  and the reconfiguration tool  $T_{\text{reconfig}}$  powered by a reconfiguration engine  $\mu$ , which collaborate to enable adaptive self-configuration, as illustrated in Figure 1.

We first formalize the dynamic configuration at each stage. We define a stage as the execution interval between two consecutive reconfigurations, and its configuration is formalized as:

$$\mathcal{C}_i \triangleq (q_i, \sigma_i, T_i, K_i) \quad (2)$$

Unlike the pre-fixed  $\mathcal{C}_{\text{static}} = (\sigma, T, K)$  that lies outside the agent’s action space, this formulation introduces sub-goals  $q_i$  and allows all elements to evolve with stage index  $i$ . Specifically,  $q_i$  specifies the current-stage objective to enable macro-level planning,  $\sigma_i$  represents the execution strategy,  $T_i$  is the local toolbox selected from the predefined global tool pool  $T_{\text{all}}$ , and  $K_i$  is the local knowledge containing task-relevant information and prior progress. The system also maintains a global history sequence  $H_{\text{all}}^{(i)}$  to record execution summaries up to stage  $i$ .

Building upon this configuration, we formalize the two core components as follows.

**Inference Agent** operates under the behavior policy:

$$\pi_i(\tau_{i,t}, a_{i,t} | \theta, Q, \mathcal{C}_i, T_{\text{reconfig}}, T_{\text{term}}, s_{i,t-1}) \quad (3)$$

At stage  $i$ , the agent operates under configuration  $\mathcal{C}_i$  and can invoke  $T_{\text{reconfig}}$  to trigger configuration adaptation or the termination tool  $T_{\text{term}}$  to terminate execution. Unlike the continuously growing  $s_{t-1}$  under pre-fixed configurations where self-configuration is absent, the stage-local history  $s_{i,t-1} = (\tau_{i,0}, a_{i,0}, o_{i,0}, \dots, \tau_{i,t-1}, a_{i,t-1}, o_{i,t-1})$  records only interactions within stage  $i$  and is cleared upon each update, thereby preventing cross-stage context accumulation.

**Reconfiguration tool**  $T_{\text{reconfig}}$  enables the inference agent to dynamically update its configuration via the reconfiguration engine  $\mu$ . Upon receiving the execution summary  $H_i$  for stage  $i$  and the reconfiguration request  $r_i$ , it archives  $H_i$  into the global history sequence  $H_{\text{all}}^{(i)} = (H_0, H_1, \dots, H_i)$  and invokes the reconfiguration engine:

$$\mu\left(\mathcal{C}_{i+1} \mid \theta, Q, r_i, T_{\text{all}}, H_{\text{all}}^{(i)}\right) \quad (4)$$

to generate a new configuration  $\mathcal{C}_{i+1}$  based on  $r_i$ , main task  $Q$ ,  $T_{\text{all}}$ , and  $H_{\text{all}}^{(i)}$ . The reconfiguration request is structured as:

$$r_i \triangleq (q_{i+1}^{\text{prop}}, \rho_i, \delta_i) \quad (5)$$

where  $q_{i+1}^{\text{prop}}$  denotes the proposed next-stage sub-goal,  $\rho_i$  specifies the reconfiguration rationale, and  $\delta_i$  encapsulates detailed requirements for adapting  $\sigma_{i+1}$ ,  $T_{i+1}$ , and  $K_{i+1}$  accordingly. Through  $H_i$  and  $q_{i+1}^{\text{prop}}$ , the inference agent  $\pi_i$  transcends mere task execution to assume dual roles as both executor and manager, autonomously handling context management and goal planning as intrinsic capabilities within the unified action space, thereby overcoming the inherent constraints of the pre-fixed-configuration paradigm.

Notably,  $\pi_i$  and  $\mu$  are not separate agents but two functional modes of the same LLM parameterized by  $\theta$ . Based on the dynamic collaboration of the above two components, the complete execution process of TOOLSELF can be described as the following *inference-reconfiguration* loop, as shown in Figure 1:

**1. Initialization:** Given the main task  $Q$ , the system invokes the reconfiguration engine  $\mu(\mathcal{C}_0 | \theta, Q, T_{\text{all}})$  with  $r_{-1} = \emptyset$  and  $H_{\text{all}}^{(-1)} = \emptyset$  to generate the initial configuration  $\mathcal{C}_0$ , and starts the initial inference agent under policy  $\pi_0(\tau_{0,t}, a_{0,t} | \theta, Q, \mathcal{C}_0, T_{\text{reconfig}}, T_{\text{term}}, s_{0,t-1})$  with  $s_{0,0} = \emptyset$ .

**2. Task Execution:** In stage  $i$ , the inference agent  $\pi_i$  executes the sub-goal  $q_i$  under configuration  $\mathcal{C}_i$ . When  $\pi_i$  determines that the current configuration cannot meet task requirements (e.g., sub-goal  $q_i$  completion, toolbox  $T_i$  insufficiency, knowledge  $K_i$  deficiency, strategy  $\sigma_i$  failure, or context nearing overflow), it first summarizes the

task execution process of this stage as  $H_i$ , then generates a reconfiguration request  $r_i = (q_{i+1}^{\text{prop}}, \rho_i, \delta_i)$  and invokes  $T_{\text{reconfig}}(H_i, r_i)$ .

**3. Reconfiguration:** The reconfiguration tool archives  $H_i$  into the global history sequence (i.e.,  $H_{\text{all}}^{(i)} \leftarrow H_{\text{all}}^{(i-1)} \oplus (H_i)$ ) and triggers the reconfiguration engine  $\mu$ . At this point, the lifecycle of the inference agent  $\pi_i$  terminates, and the interaction history  $s_i$  is discarded. The reconfiguration engine  $\mu$  generates a new configuration  $C_{i+1}$  based on  $r_i, Q, T_{\text{all}}$ , and  $H_{\text{all}}^{(i)}$ , and starts a new inference agent under policy  $\pi_{i+1}$ . The new agent continues execution with configuration  $C_{i+1}$ , where it will learn about previous progress and key information from  $K_{i+1}$ , clarify new goals according to  $q_{i+1}$ , while  $s_{i+1}$  will be reset to empty.

This loop continues iteratively until the inference agent determines that the main task  $Q$  is fully resolved and invokes  $T_{\text{term}}$  to terminate execution.

### 2.3 Configuration-Aware Two-stage Training

While TOOLSELF can function without task-specific training, dedicated optimization can further boost performance. We first formalize the reasoning process of TOOLSELF. A complete reasoning trajectory is defined as  $\mathcal{T} = ((\mathcal{C}_0, \xi_0), (\mathcal{C}_1, \xi_1), \dots, (\mathcal{C}_N, \xi_N))$ , where  $\xi_i = (\tau_{i,0}, a_{i,0}, o_{i,0}, \dots, \tau_{i,M_i}, a_{i,M_i}, o_{i,M_i})$  represents the execution trajectory at stage  $i$ . The generation probability of a stage trajectory is:

$$p(\xi_i | \theta, Q, \mathcal{C}_i) = \prod_{t=0}^{M_i} \pi_i(\tau_{i,t}, a_{i,t} | s_{i,t-1}) \cdot p(o_{i,t} | a_{i,t}) \quad (6)$$

The joint probability distribution of the complete trajectory decomposes as:

$$\begin{aligned} p(\mathcal{T} | \theta, Q, T_{\text{all}}) &= \mu(\mathcal{C}_0 | \theta, Q, T_{\text{all}}) \\ &\times \prod_{i=0}^N p(\xi_i | \theta, Q, \mathcal{C}_i) \\ &\times \prod_{i=0}^{N-1} \mu(\mathcal{C}_{i+1} | r_i, H_{\text{all}}^{(i)}) \end{aligned} \quad (7)$$

where  $r_i$  and  $H_i$  are deterministically generated from the final step of  $\xi_i$ . This probability decomposition lays the foundation for our subsequent training framework.

To internalize the meta-capability of self-reconfiguration, we propose **Configuration-Aware Two-stage Training (CAT)** to jointly train both the inference agent  $\pi_i$  and the reconfiguration engine  $\mu$ . CAT consists of Rejection Sampling Fine-tuning (RFT) [18] for cold-start initialization and Kahneman-Tversky Optimization (KTO) [19] for reinforcement learning refinement. Both  $\pi_i$  and  $\mu$  are fine-tuned via Low-Rank Adaptation (LoRA) [20] with independent adapters. Let  $\theta_0$  denote the frozen base model parameters, and let  $\Delta\theta_\pi$  and  $\Delta\theta_\mu$  denote the LoRA parameters for the inference agent and reconfiguration engine, respectively. The effective parameters of the two modules are thus  $\theta_\pi = \theta_0 + \Delta\theta_\pi$  and  $\theta_\mu = \theta_0 + \Delta\theta_\mu$ . Crucially,  $\pi_i$  and  $\mu$  share a single base model; LoRA adapters merely specialize it, yielding a compact and end-to-end trainable architecture.

**Stage I: Cold-Start Initialization.** To provide strong priors for configuration decisions, we bootstrap from teacher demonstrations [18]. We generate trajectories using a teacher model on the task dataset and filter successful trajectories via rejection sampling. For task  $Q^{(j)}$ , let  $\mathcal{T}_{\text{teacher}}^{(j)}$  denote the successful trajectory obtained through rejection sampling, and define a binary success label  $y(\mathcal{T}_{\text{teacher}}^{(j)}) \in \{0, 1\}$ , where 1 indicates successful task completion and 0 indicates failure. The filtered dataset is defined as:

$$\mathcal{D}_{\text{SFT}} = \left\{ (\mathcal{T}_{\text{teacher}}^{(j)}, Q^{(j)}) \right\}_{j=1}^M \quad (8)$$

where each  $\mathcal{T}_{\text{teacher}}^{(j)} \sim p(\mathcal{T} | \theta_{\text{teacher}}, Q^{(j)})$  with  $y(\mathcal{T}_{\text{teacher}}^{(j)}) = 1$ . Let  $N^{(j)}$  denote the number of stages in trajectory  $\mathcal{T}_{\text{teacher}}^{(j)}$ . The filtered trajectories are used to independently fine-tune the two LoRA adapters:

$$\Delta\theta_\pi \leftarrow \arg \min_{\Delta\theta_\pi} \sum_{j,i} -\log p(\xi_i^{(j)} | \theta_\pi, Q^{(j)}, \mathcal{C}_i^{(j)}) \quad (9)$$

$$\Delta\theta_\mu \leftarrow \arg \min_{\Delta\theta_\mu} \sum_{j,i} -\log \mu(\mathcal{C}_i^{(j)} | \theta_\mu, H_{\text{all}}^{(i-1,j)}) \quad (10)$$

We denote the resulting LoRA parameters as  $\Delta\theta_\pi^{\text{RFT}}$  and  $\Delta\theta_\mu^{\text{RFT}}$ , and correspondingly define  $\theta_\pi^{\text{RFT}} = \theta_0 + \Delta\theta_\pi^{\text{RFT}}$  and  $\theta_\mu^{\text{RFT}} = \theta_0 + \Delta\theta_\mu^{\text{RFT}}$ .

**Stage II: Reinforcement Learning Refinement.** To move beyond imitation, we continue optimizing the same pair of LoRA adapters using KTO, which directly optimizes models based on binary feedback. The KTO loss function is defined as:

$$\ell_{\text{KTO}}(x, y; \theta, \theta_{\text{ref}}) = \begin{cases} \lambda_D \cdot v(r(x) - z_0) & \text{if } y = 1 \\ \lambda_U \cdot v(z_0 - r(x)) & \text{if } y = 0 \end{cases} \quad (11)$$

where  $r(x) = \log \frac{p_\theta(x)}{p_{\theta_{\text{ref}}}(x)}$  is the log probability ratio,  $v(\cdot)$  is the value function,  $z_0$  is the KL target, and  $\lambda_D, \lambda_U$  are weighting coefficients.

Self-reconfiguration is a cross-stage meta-capability whose quality only manifests through downstream execution, making step-level credit assignment (i.e., attributing task success/failure to individual decisions) impractical. We therefore adopt trajectory-level inheritance: for each sampled trajectory  $\mathcal{T}_k^{(j)}$ , its label  $y_k^{(j)}$  propagates to all components, i.e.,  $y_{\xi_{i,k}^{(j)}} = y_{\mathcal{C}_{i,k}^{(j)}} = y_k^{(j)}$  for all stages  $i$ . KTO’s binary (success/failure) feedback aligns naturally with this scheme. The optimization proceeds as follows: for each of the  $M'$  tasks in the training set, we sample  $K$  trajectories using the cold-start model and annotate them with binary labels  $y_k^{(j)} \in \{0, 1\}$ . Using  $\Delta\theta_\pi^{\text{RFT}}$  and  $\Delta\theta_\mu^{\text{RFT}}$  as the reference model, we independently optimize the two modules to obtain the final parameters  $\Delta\theta_\pi^*$  and  $\Delta\theta_\mu^*$ :

$$\Delta\theta_\pi^* \leftarrow \arg \min_{\Delta\theta_\pi} \sum_{j,k,i} \ell_{\text{KTO}}(\xi_{i,k}^{(j)}, y_k^{(j)}; \theta_\pi, \theta_\pi^{\text{RFT}}) \quad (12)$$

$$\Delta\theta_\mu^* \leftarrow \arg \min_{\Delta\theta_\mu} \sum_{j,k,i} \ell_{\text{KTO}}(\mathcal{C}_{i,k}^{(j)}, y_k^{(j)}; \theta_\mu, \theta_\mu^{\text{RFT}}) \quad (13)$$

Through this decoupled optimization, the inference agent learns to efficiently execute tasks under given configurations, while the reconfiguration engine learns to generate configurations conducive to task success.

## 2.4 Design Advantages

**Autonomy.** The inference agent retains full authority over macro-level task management. By formulating reconfiguration requests  $r_i$ —including proposed sub-goals  $q_{i+1}^{\text{prop}}$ —the agent itself drives task decomposition and progress tracking; the reconfiguration engine  $\mu$  merely acts as a “compiler” translating these requests into concrete configurations. This contrasts with OWL [12] and OAgents [15], which delegate planning to a separate high-level module, incurring additional coordination overhead.

**Unification.** Context management is embedded within the standard tool-call interface. When invoking  $T_{\text{reconfig}}$ , the inference agent produces the stage summary  $H_i$  itself, so task execution and self-management share a single learnable pathway amenable to end-to-end optimization. This contrasts with ReSum [16], which depends on an external model for periodic context compression.

Together, these properties transform the agent into a *joint manager of task progress and self-state*, matching multi-agent workflow effectiveness while preserving single-agent simplicity.

## 3 Experiments

### 3.1 Experimental Setup

**Benchmarks** (Sec. A.3). We evaluate TOOLSELF on four benchmarks spanning diverse agentic capabilities: FRAMES [21] and xbench [22] for deep research, GAIA [23] for general AI assistant tasks, and SWE-bench Lite [24] for software engineering. For FRAMES (824 questions), we randomly partition 200 samples for testing and 624 for training. For GAIA, following WebSailor [18], we curate a subset of 103 samples that require only search and web browsing, denoted as GAIA(WS). Additionally, we incorporate 300 tasks from MathVista [25] to enhance multimodal capabilities.

**Baselines** (Sec. A.4). We compare against three categories of baselines: (1) *Single-agent* paradigms including Vanilla Agent equivalent to  $\pi_i$  without  $T_{\text{reconfig}}$ , WebSailor [18] specialized for information retrieval, and SWE-Agent [4] designed for software engineering; (2) *Single-agent extensions* that introduce external mechanisms for partial improvement, including ReSum [16] with periodic summarization and OAgents [15] with periodic plan updates via

Table 1: Main results on four benchmarks. Performance comparison of TOOLSELF against single-agent and multi-agent baselines across deep research (FRAMES, xbench), general AI assistant (GAIA), and software engineering (SWE-bench Lite) tasks. Vanilla Agent denotes a standard ReAct-style agent equivalent to  $\pi_i$  without  $T_{\text{reconfig}}$ . GAIA(WS) refers to the WebSailor subset of GAIA containing tasks solvable via search and browsing only. SWE-Lite abbreviates SWE-bench Lite. Avg. denotes the average performance across all available benchmarks.

Method	Qwen3-14B							Qwen3-8B						
	FRAMES	xbench	GAIA(WS)	GAIA	SWE-Lite	Avg.	FRAMES	xbench	GAIA(WS)	GAIA	SWE-Lite	Avg.		
<i>Single-Agent Baselines</i>														
Vanilla Agent	38.0	13.0	33.0	<u>32.1</u>	13.3	25.9	21.0	6.0	19.4	19.7	10.1	15.2		
WebSailor	42.0	<u>15.0</u>	35.0	—	—	30.7	28.0	4.0	18.5	—	—	16.8		
SWE Agent	—	—	—	—	14.2	14.2	—	—	—	—	10.9	10.9		
<i>Single-Agent Extensions</i>														
ReSum	46.5	11.0	35.9	—	—	<u>31.1</u>	<u>39.5</u>	7.0	27.2	—	—	24.6		
OAgents	<u>48.0</u>	12.0	30.1	—	—	30.0	33.0	9.0	22.3	—	—	21.4		
<i>Multi-Agent Workflows</i>														
OWL	37.0	12.0	<u>36.9</u>	29.2	—	28.8	23.0	7.0	23.3	<u>21.8</u>	—	18.8		
Co-Sight	46.0	<b>16.0</b>	31.1	—	—	31.0	32.0	<b>13.0</b>	<u>28.1</u>	—	—	24.4		
SWE-Search	—	—	—	—	<u>14.6</u>	14.6	—	—	—	—	<u>11.6</u>	11.6		
<i>Ours</i>														
TOOLSELF	<b>56.0</b>	<b>16.0</b>	<b>40.8</b>	<b>38.8</b>	<b>16.1</b>	<b>33.5</b>	<b>44.0</b>	<b>10.0</b>	<b>30.1</b>	<b>27.9</b>	<b>12.4</b>	<b>24.9</b>		

an LLM planner; (3) *Multi-agent workflows* including OWL [12] with hierarchical architecture, Co-Sight [26] with conflict-aware meta-verification, and SWE-Search [27] leveraging Monte Carlo tree search.

**Implementation** (Sec. A.5). Both the inference agent  $\pi_i$  and reconfiguration engine  $\mu$  employ Qwen3-8B/14B as base models, with Qwen3-235B-A22B-Thinking and DeepSeek-V3.2 serving as teacher models. Training follows a two-stage strategy: Stage I performs cold-start initialization via RFT using successful trajectories collected from 300 tasks, while Stage II applies KTO on trajectories sampled from 624 tasks for reinforcement learning refinement.

### 3.2 Main Results

**TOOLSELF consistently outperforms all baselines across benchmarks and model scales, validating the effectiveness of the unified action space paradigm.** As shown in Table 1, TOOLSELF achieves 33.5% and 24.9% average accuracy on Qwen3-14B and Qwen3-8B respectively, surpassing all single-agent extensions and multi-agent workflows. On FRAMES requiring multi-step retrieval, the advantages become most pronounced. Qwen3-14B-powered TOOLSELF reaches 56.0%, exceeding Vanilla Agent by 18.0, ReSum by 9.5, and OWL by 19.0 percentage points. On GAIA, TOOLSELF achieves 38.8%, outperforming OWL’s 29.2% by 9.6 percentage points. For software engineering, TOOLSELF reaches 16.1% on SWE-bench Lite, surpassing SWE-Agent’s 14.2% and SWE-Search’s 14.6%. These consistent gains across diverse task categories validate that internalizing self-configuration as an intrinsic tool action enables more effective adaptation than external orchestration or heuristic-based patches.

**Internalizing self-regulation as an intrinsic capability surpasses fragmented external mechanisms, enabling precise, intent-driven configuration management.** Single-agent baselines like Vanilla Agent, WebSailor, and SWE-Agent lack dynamic configurability, leading to disorientation in long-horizon tasks due to fixed strategies. Single-agent extensions rely on external interventions, where ReSum treats summarization as an auxiliary patch decoupled from primary reasoning and OAgents depends on periodic external planning, hindering seamless self-regulation. In contrast, TOOLSELF treats configuration updates as intrinsic tool actions driven by the agent’s own intent. This autonomy yields significant gains on long-horizon tasks. On FRAMES, TOOLSELF achieves 56.0%, outperforming ReSum’s 46.5% and OAgents’ 48.0% by 9.5 and 8.0 percentage points respectively. This confirms that embedding management decisions within the unified action space allows for more precise resource allocation than heuristic-based patches.

**TOOLSELF matches expert-level workflow efficacy while maintaining flexible cross-domain generalization, achieving dual advantages in performance and adaptability.** Specialized workflows rely on rigid architectural priors tailored to specific domains: OWL employs hierarchical planning for comprehensive tasks, Co-Sight utilizes meta-verification for information retrieval, and SWE-Search applies tree search for code repair. However, this specialization limits their versatility. In contrast, TOOLSELF internalizes these capabilities as dynamically configurable parameters. On Qwen3-14B, it adapts to diverse domain requirements, surpassing OWL on the planning-intensive FRAMES by 19.0 percentage points (56.0% vs 37.0%), matching Co-Sight on the retrieval-heavy xbench (16.0%), and outperforming

Table 2: Effect of Configuration-Aware Two-stage Training (CAT). Progressive performance gains through RFT cold-start initialization and KTO reinforcement learning refinement on Qwen3-8B. Vanilla Agent denotes a standard ReAct-style agent equivalent to  $\pi_i$  without  $T_{\text{reconfig}}$ . GAIA(WS) refers to the WebSailor subset of GAIA containing tasks solvable via search and browsing only. WebSailor-7B denotes the specialized model from (**author?**) [18]. TOOLSELF+RFT applies rejection sampling fine-tuning for cold-start initialization; TOOLSELF+RFT+KTO further incorporates KTO reinforcement learning. Avg. denotes the average performance across all available benchmarks.

Method	Qwen3-8B				
	FRAMES	xbench	GAIA(WS)	GAIA	Avg.
<i>Single-Agent Baselines</i>					
Vanilla Agent	21.0	6.0	19.4	19.7	16.5
WebSailor	28.0	4.0	18.5	–	16.8
WebSailor (WebSailor-7B)	31.0	5.0	17.5	–	17.8
<i>Single-Agent Extensions</i>					
ReSum	39.5	7.0	27.2	–	24.6
OAgents	33.0	9.0	22.3	–	21.4
<i>Multi-Agent Workflows</i>					
OWL	23.0	7.0	23.3	21.8	18.8
Co-Sight	32.0	13.0	28.1	–	24.4
<i>Ours</i>					
TOOLSELF	44.0	10.0	30.1	27.9	28.0
TOOLSELF + RFT	53.0	21.0	33.0	29.1	34.0
TOOLSELF + RFT + KTO	<b>58.0</b>	<b>25.0</b>	<b>41.7</b>	<b>37.6</b>	<b>40.6</b>

SWE-Search on the code-specific SWE-bench Lite by 1.5 percentage points (16.1% vs 14.6%). This proves that internalizing self-configuration enables a single generalist agent to dynamically emulate and exceed the efficacy of distinct expert workflows without structural ossification. We provide detailed case studies in Appendix A.2 illustrating these dynamics in practice.

### 3.3 Configuration-Aware Two-stage Training

**The joint RFT and KTO training pipeline achieves cumulative performance gains, elevating average accuracy from 28.0% to 40.6% with 12.6 percentage points absolute improvement.** As shown in Table 2, the un-tuned TOOLSELF on Qwen3-8B achieves 28.0% average accuracy. Stage I (RFT) cold-starts the model with teacher trajectories, improving accuracy to 34.0% (+6.0%) by establishing basic reconfiguration patterns. Stage II (KTO) further elevates it to 40.6% (+6.6%) by optimizing cross-stage meta-capabilities through trajectory-level reinforcement. This cumulative gain substantially surpasses all externally-orchestrated baselines, outperforming Vanilla Agent’s 16.5% by 24.1 and ReSum’s 24.6% by 16.0 percentage points, validating that end-to-end training of the unified architecture is superior to heuristic tuning.

**Trajectory-level reinforcement effectively captures the long-term benefits of self-reconfiguration, enabling the acquisition of cross-stage meta-capabilities.** Since self-reconfiguration effects manifest over subsequent stages, TOOLSELF leverages KTO with trajectory-level credit assignment to associate configuration decisions with final task success. This optimization strategy enables the model to look beyond immediate rewards and learn globally optimal configuration policies. Empirical results demonstrate strong generalization capabilities, with TOOLSELF achieving a 27.0 percentage points lead on FRAMES and a 20.0 percentage points lead on xbench over baselines like WebSailor-7B that also employ RFT and RL training, validating the effectiveness of optimizing the entire configuration lifecycle.

### 3.4 Ablation Study

**Empowering the agent to decide both the timing (When) and requirements (How) of reconfiguration is essential for effective self-regulation.** As shown in Table 3, we first ablate autonomous triggering (When) by enforcing fixed

Table 3: Ablation study on the unified action space design using Qwen3–8B. Impact of “**When**” (agent-determined triggering timing) and “**How**” (adherence to agent-specified requirements) on GAIA performance (%). “w/o ‘When’” replaces adaptive triggering with fixed 5-step intervals; “w/o ‘How’” decouples configuration from the agent’s intent by discarding the entire reconfiguration request  $r_i = (q_{i+1}^{\text{prop}}, \rho_i, \delta_i)$  (i.e., ignoring all agent-specified requirements) during updates.

Level	Qwen3–8B			
	Full	w/o “When”	w/o “How”	w/o Both
<i>GAIA Performance (%)</i>				
All	<b>27.9</b>	25.5	21.8	21.2
Level 1	<b>35.8</b>	34.0	22.6	28.3
Level 2	<b>29.1</b>	26.7	26.7	23.3
Level 3	<b>7.69</b>	3.85	3.85	0.00

Table 4: Ablation study on configuration components using Qwen3–8B. Impact of removing individual reconfiguration elements on GAIA performance (%). “w/o” denotes “without”. Context management and sub-goal planning are critical for long-horizon reasoning.

Level	Qwen3–8B				
	Full	w/o Sub-goal	w/o Strategy	w/o Toolbox	w/o Context
<i>GAIA Performance (%)</i>					
All	27.9	23.6	27.3	26.1	20.0
Level 1	35.8	34.0	37.7	32.1	37.7
Level 2	29.1	24.4	27.9	30.2	15.1
Level 3	7.69	0.00	3.85	0.00	0.00

5-step intervals (similar to OAgents), causing accuracy to drop from 27.9% to 25.5%. We then ablate the agent’s control over configuration content (How) by discarding its entire reconfiguration request  $r_i$  during updates, which leads to a substantial decline to 21.8%. This demonstrates that merely allowing updates is insufficient, as they must be aligned with the agent’s intent. When both timing and content are decoupled from the agent’s action space, the performance drops further to 21.2%, creating a 6.7 percentage points gap with the full model. This confirms that the core advantage stems from internalizing both decisions within the unified action space, enabling the agent to actively manage its own adaptation.

**The unified action space paradigm enables thorough exploration while maintaining bounded context, significantly outperforming passive execution baselines.** As shown in Table 5, TOOLSELF on Qwen3–8B achieves 27.9% overall accuracy on GAIA, outperforming Vanilla Agent’s 18.8% by 9.1 percentage points. Vanilla Agent terminates after only 7.96 steps on average, whereas TOOLSELF sustains 32.8 steps of thorough exploration by autonomously invoking reconfiguration. Notably, despite a 4 times increase in execution steps, maximum input tokens rise only marginally from 9,527 to 10,276, demonstrating that agent-driven context compression effectively bounds history accumulation. In comparison, Co-Sight consumes 229K/261K/315K tokens per task on GAIA Level 1/2/3 respectively, while TOOLSELF uses 49K/49K/71K tokens—achieving 4.4 to 5.3 times higher token efficiency with superior accuracy. To isolate the unified action space contribution from computational scaling, we evaluate Vanilla Agent with 5-run majority voting under comparable token budget: it yields only 21.2% accuracy versus TOOLSELF’s 27.9%, confirming that gains originate from internalizing self-configuration rather than increased compute.

**Context management and sub-goal planning serve as core pillars for long-horizon tasks, with each configuration component exhibiting differentiated contributions.** As shown in Table 4, we systematically ablate each component on GAIA using Qwen3–8B. Removing context management causes the largest overall drop of 7.9 percentage points, from 27.9% to 20.0%, with Level 2 declining by 14.0% and Level 3 failing entirely, confirming its essential role in long-horizon reasoning. Removing sub-goal planning reduces overall accuracy by 4.3 percentage points, from 27.9% to 23.6%, with Level 3 dropping from 7.69% to 0%, underscoring macro-level planning for complex multi-stage tasks. Removing strategy halves Level 3 accuracy from 7.69% to 3.85%, while removing toolbox causes complete Level 3 failure, validating their complementary roles in high-difficulty scenarios.

**Joint training improves both task performance and configuration decision efficiency.** As shown in Table 6, TOOLSELF+RFT+KTO on Qwen3-8B achieves 37.6% overall accuracy on GAIA with Level 3 accuracy doubling from 7.69% to 15.4%. Beyond performance gains, training substantially improves efficiency. Average steps decrease from 32.8 to 28.8, reducing by 12.2%, and reconfiguration iterations drop from 7.71 to 6.89, reducing by 10.6%, indicating that the model learns to make more effective configuration decisions with fewer exploration attempts.

**TOOLSELF exhibits task-aware behavioral patterns through adaptive self-reconfiguration, with reconfiguration frequency scaling with task difficulty.** As shown in Table 6, Level 1 tasks average 6.39 reconfiguration iterations, Level 2 increases to 8.20, and Level 3 reaches 11.5, demonstrating adaptive computational resource allocation. This task awareness also manifests in tool selection as shown in Table 7. `visit` and `search` reach 82.5% for web browsing, `code_interpreter` reaches 96.5% for coding, `bash` reaches 94.9% for multi-modality, and `file_analyzer` reaches 95.1% for diverse filetypes. Ablation in Table 4 validates this design. Removing dynamic toolbox causes 1.8% accuracy drop and complete Level 3 failure, confirming that precise tool constraints narrow the search space and reduce reasoning interference.

## 4 Related Work

As established in Sec. 1, the *configuration* of an agentic system—comprising execution strategy, toolbox, and task-relevant knowledge—governs its reasoning and action dynamics. Existing approaches to long-horizon tasks can be categorized by how they manage configuration: through *static pre-specification*, *external orchestration*, or *heuristic-triggered adjustment*. However, none of these achieves the autonomy and unification required for principled self-configuration.

**Single-agents with static configurations.** Single-agents, epitomized by ReAct [2], adopt minimally-prescriptive autonomous execution through iterative thought-action-observation cycles. Domain-specific variants include SWE-Agent [4] and OpenHands [28] for software engineering, and WebSailor [18], Search-o1 [29], and WebThinker-RL [30] for deep research. While offering flexibility across domains, these agents operate under *static configurations* fixed prior to execution. As analyzed in Sec. 1, this rigidity becomes a fundamental bottleneck in long-horizon settings: sub-goals cannot be decomposed adaptively, tool selection cannot respond to evolving needs, and context accumulates without principled management—ultimately manifesting as search space explosion and context poisoning.

**Multi-agent workflows with externally orchestrated configurations.** Multi-agent workflows [12, 13] decompose tasks through human prior knowledge and assign specialized configurations to sub-agents via predefined orchestration. OWL [12] implements a hierarchical architecture where a Planner decomposes tasks, a Coordinator dispatches them to specialized Workers (e.g., Web Agent, Coding Agent), and re-plans upon failure. Magentic-One [13] employs a similar orchestrator-workers pattern. Co-Sight [26] enhances multi-agent reliability through conflict-aware meta-verification and structured fact management. WebWeaver [31] utilizes a Planner Agent followed by a Writer Agent for deep research. For software engineering, SWE-Search [27] leverages Monte Carlo tree search to systematically explore solution spaces. While effective in narrowly defined domains, these workflows rely on *manually pre-specified configurations* for each sub-agent, with orchestration logic hard-coded by human designers. This fundamentally limits their scalability and generalization: the configuration space is constrained by what designers anticipate, leaving them brittle when confronted with unfamiliar tasks or dynamically changing requirements [32].

**Single-agent extensions with heuristic-triggered adjustment.** Recent efforts introduce external mechanisms for partial configuration adjustment on single-agents. ReSum [16] and MEM1 [9] address context management through periodic summarization and learned compression strategies, respectively; OAgents [15] employs an external LLM planner to periodically update the agent’s plan during execution; AdaPlanner [14] adapts plans based on environmental feedback. However, these approaches share two critical limitations: (1) they target *isolated symptoms* rather than providing unified configuration management, and (2) their triggering logic is governed by *rigid heuristic thresholds*—such as step counts or context length—which decouple configuration updates from task semantics and execution dynamics, thereby precluding end-to-end, data-driven optimization.

In contrast, TOOLSELF achieves *autonomous self-configuration* by abstracting configuration updates as a callable tool within the agent’s native action space. This design satisfies both requirements identified in Sec. 1: *autonomy*, by granting the agent runtime sovereignty to determine when and how to reconfigure based on task dynamics; and *unification*, by enabling end-to-end learning of self-configuration as an intrinsic capability rather than an external patch. Consequently, TOOLSELF elevates agents from passive executors to dual managers of both task execution and self-configuration, achieving workflow-level performance while preserving generalist flexibility.

## 5 Conclusion

We propose TOOLSELF, unifying task execution and self-reconfiguration into a single action space to shift from external rules to intrinsic parameters. Empowered by Configuration-Aware Two-stage Training (CAT), it transforms agents into dual managers of task and self. Achieving a 24.1% gain, TOOLSELF proves self-adaptive agents can rival specialized workflows while preserving generalist flexibility.

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## A Appendix

### A.1 Additional Experimental Results

Table 5: Unified action space paradigm vs. passive execution paradigm on GAIA using Qwen3-8B. Comparison of TOOLSELF and Vanilla Agent across accuracy (%), average execution steps, maximum input tokens, and total token consumption. Vanilla Agent denotes a standard ReAct-style agent equivalent to  $\pi_i$  without  $T_{\text{reconfig}}$ .

Method	Level	Qwen3-8B			
		Acc.	Avg. Steps	Max Input Tokens	Total Tokens
<i>Passive Execution (No Self-Reconfiguration)</i>					
Vanilla Agent	All	18.8	7.96	9527.5	9527.5
	Level 1	20.8	7.85	8866.1	8866.1
	Level 2	22.1	8.10	10288.2	10288.2
	Level 3	3.85	7.56	8999.6	8999.6
<i>Unified Action Space (Ours)</i>					
TOOLSELF	All	<b>27.9</b>	32.8	10276.2	52535.5
	Level 1	<b>35.8</b>	33.2	9787.9	49204.5
	Level 2	<b>29.1</b>	31.0	9690.3	49468.6
	Level 3	<b>7.69</b>	38.0	13498.8	71148.1

Table 6: Detailed analysis of different training stages on GAIA using Qwen3-8B. Accuracy (%), average execution steps, and reconfiguration iterations across difficulty levels. TOOLSELF+RFT applies rejection sampling fine-tuning for cold-start initialization; TOOLSELF+RFT+KTO further incorporates KTO reinforcement learning. Joint training improves both task performance and configuration efficiency.

Level	Qwen3-8B								
	TOOLSELF			TOOLSELF+RFT			TOOLSELF+RFT+KTO		
	Acc.	Steps	Iters	Acc.	Steps	Iters	Acc.	Steps	Iters
<i>GAIA Performance</i>									
All	27.9	32.8	7.71	29.1	33.2	8.09	<b>37.6</b>	28.8	6.89
Level 1	35.8	33.2	6.39	45.3	23.2	5.63	<b>49.1</b>	25.3	5.18
Level 2	29.1	31.0	8.20	25.6	38.8	9.40	<b>37.2</b>	25.3	7.42
Level 3	7.69	38.0	11.5	7.69	36.5	10.4	<b>15.4</b>	48.5	11.3

Table 7: Task-adaptive tool selection patterns on GAIA using Qwen3-8B. Tool selection probabilities (%) across different task types demonstrate TOOLSELF’s ability to dynamically configure task-appropriate toolboxes through self-reconfiguration. `code_interp.` abbreviates `code_interpreter`.

Task Type	Qwen3-8B					
	visit	search	code_interp.	bash	str_replace	file_analyzer
<i>Tool Selection Probability (%)</i>						
Web browsing	<b>82.5</b>	<b>82.5</b>	46.3	13.8	20.6	67.5
Coding	38.4	38.4	<b>96.5</b>	10.5	75.6	59.3
Multi-modality	8.47	8.47	30.5	<b>94.9</b>	66.1	83.1
Diverse filetype	21.6	21.6	38.2	63.7	77.5	<b>95.1</b>

### A.2 Case Studies

To illustrate how TOOLSELF operates through the inference-reconfiguration loop, we present two representative case studies from the GAIA benchmark. These cases demonstrate the core capabilities of tool-driven runtime self-reconfiguration: dynamic sub-goal evolution, adaptive toolbox switching, context knowledge accumulation, and autonomous task completion decision.

Table 8: Configuration evolution across stages in both case studies. “reconfig” indicates invoking  $T_{\text{reconfig}}$ ; “term” indicates invoking  $T_{\text{term}}$ .

Stage	Sub-goal Focus	Toolbox Changes	Knowledge Update	Decision
<i>Case 1: NASA Astronaut Task (Level 3)</i>				
1	Identify astronauts in APOD	visit, code_interp., str_replace, search	empty	reconfig
2	Determine Conrad’s group	visit, code_interp., <b>execute_bash</b> , search	Identified Conrad & Bean	reconfig
3	List Group 2 members	maintained	ALL	reconfig
4	Collect space time data	maintained	ALL	reconfig
5	Verify and output answer	visit, code_interp., search	ALL	<b>term</b>
<i>Case 2: ASEAN Distance Calculation (Level 2)</i>				
1	Identify ASEAN members (partial)	visit, code_interp., execute_bash, search	empty	reconfig
2	Retry with explicit URL/parsing	maintained	Capitals not found	reconfig
3	<b>Pivot:</b> visit each country	maintained	ALL	reconfig
4	Get capital coordinates	maintained	ALL	reconfig
5	Haversine calculation	<b>code_interp., execute_bash</b>	ALL	<b>term</b>

**Why TOOLSELF Matters: Key Advantages Demonstrated.** Unlike pre-fixed configuration paradigms where agents operate with static goals and toolsets, TOOLSELF enables agents to *autonomously* manage their own configurations at runtime. The following case studies highlight four critical advantages:

1. **Dynamic Sub-goal Planning.** Complex tasks are progressively planned into manageable sub-goals. In Case 1, the agent autonomously evolves through five distinct phases: image identification → group determination → member enumeration → data collection → verification. Each transition is initiated by the agent itself via  $T_{\text{reconfig}}$ , not by external orchestration.
2. **Adaptive Toolbox Management.** The agent dynamically adjusts its available tools based on current needs. Case 2 Stage 5 demonstrates significant toolbox pruning: once data collection is complete, the agent removes visit and search tools, retaining only code\_interpreter and execute\_bash for Haversine distance calculation. This focused toolset reduces action space complexity and improves execution efficiency.
3. **Autonomous Strategy Adaptation.** When initial strategies fail, agents can pivot without external intervention. In Case 2, when the ASEAN Wikipedia page lacks capital information (Stage 1-2), the agent autonomously decides to visit individual country pages (Stage 3)—a major strategic pivot recorded in the reconfiguration request and propagated through inter-agent knowledge.
4. **Self-Determined Task Completion.** Agents decide when to terminate based on their own assessment. Both cases end with the agent invoking  $T_{\text{term}}$  after verifying answer correctness, rather than relying on external completion signals or fixed iteration limits.

These capabilities emerge from TOOLSELF’s unified action space design, where task execution tools and management tools ( $T_{\text{reconfig}}, T_{\text{term}}$ ) coexist, enabling seamless transitions between “doing” and “managing”.

### A.2.1 Case 1: NASA Astronaut Task (GAIA Level 3)

**Task Description.** *In NASA’s Astronomy Picture of the Day on 2006 January 21, two astronauts are visible, with one appearing much smaller than the other. As of August 2023, out of the astronauts in the NASA Astronaut Group that the smaller astronaut was a member of, which one spent the least time in space, and how many minutes did he spend in space, rounded to the nearest minute? Exclude any astronauts who did not spend any time in space. Give the last name of the astronaut, separated from the number of minutes by a semicolon.*

**Task Information.** Difficulty: Level 3 (Highest); Total Stages: 5; Final Answer: White;5876 ✓

#### Stage 1: Identify Astronauts in APOD Image

*Agent Configuration  $\mathcal{C}_1$ :*

- **Sub-goal** ( $q_1$ ): Visit the NASA APOD page for 2006-01-21 to identify the two astronauts.
- **Execution Strategy** ( $\sigma_1$ ): As a Data Analyst: (1) Use ‘visit’ to access NASA APOD page for 2006-01-21; (2) Analyze image description to identify astronauts; (3) Determine which one appears smaller.
- **Toolbox** ( $T_1$ ): [visit, code\_interpreter, str\_replace\_editor, search]

- **Context ( $K_1$ ):** empty

*Execution Result:* Identified Charles ‘Pete’ Conrad (smaller, reflected in Bean’s helmet) and Alan Bean.

*Reconfiguration Request  $r_1$*  (invoking  $T_{\text{reconfig}}$ ):

- **execution\_summary ( $H_1$ ):** Identified the two astronauts as Charles ‘Pete’ Conrad (smaller) and Alan Bean. Next, need to determine which NASA Astronaut Group Conrad belonged to.
- **update\_content: sub\_goal**
- **update\_reason ( $\rho_1$ ):** The current sub\_goal is complete. The next step is to identify the NASA Astronaut Group that Charles Conrad was part of.
- **new\_sub\_goal ( $q_2^{\text{prop}}$ ):** Determine the NASA Astronaut Group that Charles ‘Pete’ Conrad was part of.

## Stage 2: Determine Astronaut Group Membership

*Agent Configuration  $C_2$ :*

- **Sub-goal ( $q_2$ ):** Determine the NASA Astronaut Group that Charles ‘Pete’ Conrad was part of.
- **Execution Strategy ( $\sigma_2$ ):** As a Data Analyst: (1) Use ‘visit’ to search NASA’s astronaut group listings; (2) If ambiguous, use ‘code\_interpreter’ to cross-reference; (3) If confirmed, proceed to next sub\_goal.
- **Toolbox ( $T_2$ ):** [visit, code\_interpreter, execute\_bash, search]
- **Context ( $K_2$ ):** Confirmed astronauts are Conrad and Bean.

*Execution Result:* Conrad was part of NASA Astronaut Group 2 (selected 1962).

*Reconfiguration Request  $r_2$*  (invoking  $T_{\text{reconfig}}$ ):

- **execution\_summary ( $H_2$ ):** Charles ‘Pete’ Conrad was part of NASA Astronaut Group 2, confirmed through search results stating he was selected in 1962.
- **update\_content: sub\_goal**
- **update\_reason ( $\rho_2$ ):** The sub\_goal has been completed by identifying the correct NASA Astronaut Group for Pete Conrad.
- **new\_sub\_goal ( $q_3^{\text{prop}}$ ):** Identify all members of NASA Astronaut Group 2 and their total time spent in space.

## Stage 3: List All Group 2 Members

*Agent Configuration  $C_3$ :*

- **Sub-goal ( $q_3$ ):** Identify all members of NASA Astronaut Group 2.
- **Execution Strategy ( $\sigma_3$ ):** As a Data Analyst: (1) Use ‘visit’ to search for NASA Astronaut Group 2 member listings; (2) Extract astronaut list from webpage; (3) If unstructured, use ‘code\_interpreter’ to parse data; (4) Cross-verify from multiple sources if needed.
- **Toolbox ( $T_3$ ):** [visit, code\_interpreter, execute\_bash, search]
- **Context ( $K_3$ ):** “ALL” (all contents from Global History Pool)

*Execution Result:* Identified 9 members (Armstrong, Borman, Conrad, Lovell, McDivitt, See, Stafford, White, Young).

*Reconfiguration Request  $r_3$*  (invoking  $T_{\text{reconfig}}$ ):

- **execution\_summary ( $H_3$ ):** Identified NASA Astronaut Group 2 members. Next step is to gather cumulative time in space for each member as of August 2023.
- **update\_content: sub\_goal**
- **update\_reason ( $\rho_3$ ):** Member list completed, need to enter data collection stage for cumulative space time.
- **new\_sub\_goal ( $q_4^{\text{prop}}$ ):** Determine cumulative time in space for each NASA Astronaut Group 2 member as of August 2023.
- **additional\_details ( $\delta_3$ ):** {“knowledge\_requirements”: “Need to cross-validate space time data from multiple sources”}

#### Stage 4: Collect Space Time Data

*Agent Configuration  $C_4$ :*

- **Sub-goal** ( $q_4$ ): Determine cumulative time in space for each Group 2 member as of August 2023.
- **Execution Strategy** ( $\sigma_4$ ): As a Data Analyst: (1) Use ‘visit’ to search NASA astronaut biographies and mission logs; (2) Extract time-in-space data from official sources; (3) If incomplete, use ‘execute\_bash’ for targeted searches; (4) Use ‘code\_interpreter’ to verify discrepancies.
- **Toolbox** ( $T_4$ ): [visit, execute\_bash, code\_interpreter, search]
- **Context** ( $K_4$ ): “ALL” (all contents from Global History Pool)

*Execution Result:* Ed White has least time (5876 min); Elliot See excluded (0 min).

*Reconfiguration Request  $r_4$  (invoking  $T_{\text{reconfig}}$ ):*

- **execution\_summary** ( $H_4$ ): Collected cumulative time in space for all Group 2 members. Ed White has the least time (5876 minutes), Elliot See is excluded (0 minutes).
- **update\_content: sub\_goal**
- **update\_reason** ( $\rho_4$ ): Data collection complete, astronaut with minimum time identified. Ready to verify and output final answer.
- **new\_sub\_goal** ( $q_5^{\text{prop}}$ ): Verify data accuracy for Ed White’s time (5876 minutes), format and output the final answer.

#### Stage 5: Verify and Output Final Answer

*Agent Configuration  $C_5$ :*

- **Sub-goal** ( $q_5$ ): Confirm data accuracy and format final answer.
- **Execution Strategy** ( $\sigma_5$ ): As a Data Analyst: (1) Validate existing data using ‘visit’ to cross-check NASA records; (2) If discrepancies found, use ‘code\_interpreter’ to recalculate; (3) Confirm Ed White’s time and Elliot See’s exclusion.
- **Toolbox** ( $T_5$ ): [visit, code\_interpreter, search]
- **Context** ( $K_5$ ): “ALL” (all contents from Global History Pool)

*Execution Result:* Agent invokes  $T_{\text{term}}$  (termination tool).

**Final Answer:** White; 5876

**Key Observations.** This case demonstrates: (1) *dynamic sub-goal evolution* from image identification → group determination → member enumeration → data collection → verification; (2) *adaptive toolbox switching* where str\_replace\_editor is replaced by execute\_bash when search requirements change; (3) *context accumulation* where astronaut identities and group membership propagate across stages via  $K_i$ .

#### A.2.2 Case 2: ASEAN Capital Distance Calculation (GAIA Level 2)

**Task Description.** In terms of geographical distance between capital cities, which 2 countries are the furthest from each other within the ASEAN bloc according to wikipedia? Answer using a comma separated list, ordering the countries by alphabetical order.

**Task Information.** Difficulty: Level 2; Total Stages: 5; Final Answer: Indonesia, Myanmar ✓

#### Stage 1: Identify ASEAN Members (Partial Success)

*Agent Configuration  $C_1$ :*

- **Sub-goal** ( $q_1$ ): Identify ASEAN member states and their capital cities from Wikipedia.
- **Execution Strategy** ( $\sigma_1$ ): As a Data Analyst: (1) Use ‘visit’ to access Wikipedia page for ASEAN member states; (2) If page lacks detail, use ‘execute\_bash’ to search for URLs or ‘code\_interpreter’ to parse data; (3) If incomplete, refine search with specific URLs.
- **Toolbox** ( $T_1$ ): [visit, code\_interpreter, execute\_bash, search]

- **Context** ( $K_1$ ): empty

*Execution Result:* Successfully identified 10 ASEAN member states, but capital cities not explicitly listed on the main ASEAN Wikipedia page.

*Reconfiguration Request*  $r_1$  (invoking  $T_{\text{reconfig}}$ ):

- **execution\_summary** ( $H_1$ ): Visited ASEAN Wikipedia page and identified all 10 member states. However, capital cities are not listed on this page; need to adjust strategy.
- **update\_content: sub\_goal**
- **update\_reason** ( $\rho_1$ ): Member states identified but capitals not found; need explicit URL and HTML parsing strategy.
- **new\_sub\_goal** ( $q_2^{\text{prop}}$ ): Retry with explicit ASEAN Wikipedia URL and HTML parsing strategy to extract capital cities.

## Stage 2: Retry with Explicit URL and Parsing

*Agent Configuration*  $\mathcal{C}_2$ :

- **Sub-goal** ( $q_2$ ): Retry with explicit ASEAN Wikipedia URL and HTML parsing strategy to extract capital cities.
- **Execution Strategy** ( $\sigma_2$ ): As a Data Analyst: (1) Use ‘visit’ to access <https://en.wikipedia.org/wiki/ASEAN>; (2) Use ‘code\_interpreter’ to parse HTML tables or search for ‘capital’ keywords; (3) If incomplete, use ‘execute\_bash’ with curl and BeautifulSoup.
- **Toolbox** ( $T_2$ ): [visit, code\_interpreter, execute\_bash, search]
- **Context** ( $K_2$ ): “Member states identified but capitals not found on main page; need explicit URL and parsing strategy.”

*Execution Result:* ASEAN page parsed but capitals still not explicitly listed in tables or text.

*Reconfiguration Request*  $r_2$  (invoking  $T_{\text{reconfig}}$ ):

- **execution\_summary** ( $H_2$ ): Parsed ASEAN Wikipedia page with explicit URL and HTML parsing, but capitals still not found in tables or text. The page lists member states but does not explicitly provide their capital cities.
- **update\_content: sub\_goal**
- **update\_reason** ( $\rho_2$ ): HTML parsing of ASEAN page unsuccessful for capitals; need to pivot strategy to visit individual country pages.
- **new\_sub\_goal** ( $q_3^{\text{prop}}$ ): For each ASEAN member state, visit their Wikipedia page to extract their respective capital cities.
- **additional\_details** ( $\delta_2$ ): {“‘toolbox\_requirements’: ‘Continue using execute\_bash or code\_interpreter for individual country page scraping.’”}

## Stage 3: Strategy Pivot—Visit Individual Country Pages

*Agent Configuration*  $\mathcal{C}_3$ :

- **Sub-goal** ( $q_3$ ): Identify capitals by visiting individual country Wikipedia pages. (**Major pivot!**)
- **Execution Strategy** ( $\sigma_3$ ): As a Data Analyst: (1) Use ‘visit’ to access Wikipedia pages for each ASEAN country; (2) Use ‘code\_interpreter’ to parse HTML and extract capital names; (3) If not listed, use ‘execute\_bash’ to search geographic data; (4) Mark as ‘unknown’ if no data found.
- **Toolbox** ( $T_3$ ): [visit, code\_interpreter, execute\_bash, search]
- **Context** ( $K_3$ ): “ALL” (all contents from Global History Pool)

*Execution Result:* Successfully extracted all 10 ASEAN capitals.

*Reconfiguration Request*  $r_3$  (invoking  $T_{\text{reconfig}}$ ):

- `execution_summary` ( $H_3$ ): Visited Wikipedia pages for all ASEAN member states and successfully extracted their capital cities. The list of capitals is now complete.
- `update_content: sub_goal`
- `update_reason` ( $\rho_3$ ): Capital list completed, need to enter coordinate collection stage.
- `new_sub_goal` ( $q_4^{\text{prop}}$ ): Retrieve the geographical coordinates (latitude and longitude) of each ASEAN capital city.
- `additional_details` ( $\delta_3$ ): {“knowledge\_requirements”: “Need to obtain coordinates in decimal degrees format”}

#### Stage 4: Retrieve Geographic Coordinates

*Agent Configuration*  $C_4$ :

- **Sub-goal** ( $q_4$ ): Retrieve latitude/longitude for each capital from Wikipedia.
- **Execution Strategy** ( $\sigma_4$ ): As a Data Analyst: (1) Use ‘visit’ to access Wikipedia pages for each ASEAN capital; (2) Use ‘code\_interpreter’ to parse coordinates from page content; (3) If not listed, use ‘execute\_bash’ to search for geographic data; prioritize alternative sources if missing.
- **Toolbox** ( $T_4$ ): [visit, code\_interpreter, execute\_bash, search]
- **Context** ( $K_4$ ): “ALL” (all contents from Global History Pool)

*Execution Result:* All coordinates retrieved in decimal degrees format (Bandar Seri Begawan, Phnom Penh, Jakarta, Vientiane, Kuala Lumpur, Naypyidaw, Manila, Singapore, Bangkok, Hanoi).

*Reconfiguration Request*  $r_4$  (invoking  $T_{\text{reconfig}}$ ):

- `execution_summary` ( $H_4$ ): Coordinates for all ASEAN capital cities have been successfully retrieved in decimal degrees format.
- `update_content: sub_goal`
- `update_reason` ( $\rho_4$ ): Coordinate data complete, ready for distance calculation stage.
- `new_sub_goal` ( $q_5^{\text{prop}}$ ): Calculate geographical distances between all ASEAN capital city pairs using Haversine formula; identify maximum pair.
- `additional_details` ( $\delta_4$ ): {“execution\_strategy\_requirements”: “Use Haversine formula to calculate great-circle distance”}

#### Stage 5: Calculate Distances and Output Result

*Agent Configuration*  $C_5$ :

- **Sub-goal** ( $q_5$ ): Calculate pairwise distances using Haversine formula; identify maximum pair.
- **Execution Strategy** ( $\sigma_5$ ): As a Data Analyst: (1) Use ‘code\_interpreter’ to implement Haversine formula; (2) Validate coordinate data from previous history; (3) Identify maximum distance pair; (4) Sort country names alphabetically; if calculations fail, use ‘execute\_bash’ to cross-verify coordinates.
- **Toolbox** ( $T_5$ ): [code\_interpreter, execute\_bash] **(Major adjustment! Removed visit, search)**
- **Context** ( $K_5$ ): “ALL” (all contents from Global History Pool)

*Execution Result:* Agent invokes  $T_{\text{term}}$  (termination tool).

**Final Answer:** Indonesia, Myanmar

**Key Observations.** This case demonstrates: (1) *error recovery* where the agent autonomously pivots from “overall ASEAN page” to “individual country pages” after initial failure; (2) *strategy learning* where failure experience is recorded in  $K_2$  and informs subsequent stages; (3) *significant toolbox adjustment* where data collection tools (visit, search) are removed once the computation stage begins.

### A.3 Benchmarks

To comprehensively evaluate the performance improvements of TOOLSELF on long-horizon multi-step reasoning tasks, we conduct experiments on four benchmarks spanning diverse domains: FRAMES and xbench for deep research tasks,

GAIA for general AI assistant capabilities, and SWE-bench Lite for software engineering tasks. These benchmarks collectively assess the effectiveness of our approach across multiple dimensions.

**FRAMES** [21] (Factuality, Retrieval, And reasoning MEasurement Set) comprises 824 deep research questions that evaluate an agent’s multi-document retrieval and complex reasoning capabilities. Each question requires retrieving and integrating scattered information from 2–15 Wikipedia articles, encompassing five reasoning types: numerical computation, table parsing, multi-constraint satisfaction, temporal reasoning, and post-processing. We randomly sample 200 questions as the test set, with the remaining 624 questions used for model training.

**xbench** [22]. We adopt the DeepSearch-2510 version, containing 100 deep research questions focused on search and retrieval. Tasks require agents to locate, filter, and integrate key content from massive candidate information through multi-step reasoning, evaluating tool-use capabilities in realistic information retrieval environments.

**GAIA** [23] (General AI Assistants Benchmark) evaluates general AI assistant capabilities; we use its validation set with publicly available answers. This benchmark comprises real-world multi-step question-answering tasks across three difficulty levels (Level 1/2/3), spanning domains including science, history, and geography. Tasks require agents to decompose complex questions, utilize tools such as search engines, calculators, and code executors, and integrate multi-source information. Additionally, following WebSailor [18], we filter 103 samples from the validation set that can be solved using only search and web browsing, denoted as GAIA(WS), for separate evaluation.

**SWE-bench Lite** [24] contains 300 high-quality software engineering questions curated from real GitHub repositories, evaluating AI systems’ capabilities to understand, locate, and fix code defects. Each instance includes a problem description, relevant codebase, and test cases. Tasks require agents to understand cross-file code structures, locate bugs, design repair solutions, and pass all tests. The evaluation metric is **Resolve Rate**, with success defined as the generated patch passing all relevant test cases.

**Training Data Supplement.** In addition to the above evaluation benchmarks, we incorporate tasks from the MathVista [25] dataset for model training. MathVista is a mathematical visual reasoning benchmark comprising various mathematical question types that require agents to combine visual understanding with mathematical reasoning capabilities. Specifically, we use 100 MathVista tasks for RFT training and 200 tasks for KTO training, enhancing the model’s ability to handle multimodal tasks with attachments in GAIA.

#### A.4 Baselines

Brief descriptions of all baseline methods are as follows:

**Vanilla Reasoning Agent.** A single-agent following the standard ReAct paradigm, essentially equivalent to the inference agent  $\pi_i$  in TOOLSELF without the Reconfiguration Tool. This method employs a pre-fixed configuration  $C_{\text{static}} = (\sigma, T, K)$  throughout the entire task execution process, lacking macro-level planning and dynamic context management mechanisms. The interaction history  $s_{t-1}$  continuously accumulates until task completion, representing the passive execution paradigm where self-configuration is absent from the agent’s action space as described in Sec. 2.1.

**SWE Agent.** A single-agent optimized for software engineering tasks. It proposes the Agent-Computer Interface (ACI) as a specialized interaction interface replacing the general-purpose Linux shell. The system is equipped with a code-task-optimized toolset including file search and navigation commands (`find_file`, `search_file`, `search_dir`), a window-based file viewer, a line-based editor, and an automatic linting mechanism for syntax error detection.

**WebSailor.** A single-agent optimized for complex information retrieval tasks, particularly excelling at high-uncertainty tasks. It is equipped with two core tools: `search` supports parallel multi-query search returning top-10 results, and `visit` generates goal-directed webpage summaries based on specified objectives, extracting only relevant information rather than returning complete page content, effectively avoiding context overload caused by lengthy raw content. Beyond employing the same backbone as TOOLSELF, we also utilize WebSailor-7B, a specialized deep research model jointly trained through RFT and RL based on WebSailor.

**OWL.** A representative Agent Workflow paradigm employing a hierarchical multi-agent architecture that decouples strategic planning from domain execution. The collaboration workflow proceeds as follows: the Planner first decomposes tasks into sub-task sequences based on available Worker capabilities; the Coordinator assigns sub-tasks to specialized Workers (e.g., Web Agent, Document Agent, Coding Agent) and monitors execution status; each Worker, equipped with domain-specific toolsets, independently completes tasks and returns only final results without execution details to the Coordinator; the Coordinator integrates all results and returns them to the Planner. Upon Worker execution failure, the Planner dynamically re-plans based on failure feedback and generates new sub-tasks.

**ReSum.** A long-horizon search paradigm managing context through periodic summarization. When reaching context limits, it invokes a summarization tool to compress interaction history into a compact state containing verified evidence

and information gaps, then continues exploration from this compressed state. It is also equipped with Search and Visit tools responsible for parallel search and goal-directed web browsing, respectively.

**SWE-Search.** A software engineering agent framework that enhances code repair through Monte Carlo tree search (MCTS) and iterative refinement, systematically exploring solution spaces to resolve software issues.

**Co-Sight.** A multi-agent framework that enhances LLM-based agents via conflict-aware meta-verification and trustworthy reasoning with structured facts [26]. It employs multiple agents to cross-verify information and resolve conflicts through structured fact management, improving reliability in complex reasoning tasks.

**OAgents.** A single-agent framework [15] that employs an external LLM planner to update the agent’s plan every 5 steps during execution, enabling adaptive task decomposition and progress tracking throughout the execution lifecycle.

**Unified Evaluation Infrastructure.** To ensure fair comparison, within the constraints of each baseline’s framework, we strive to use the same tool implementations as TOOLSELF wherever possible. For baselines whose architectures are incompatible with certain tool substitutions, we retain their original tool invocation logic to preserve method integrity.

## A.5 Experimental Details

This section provides detailed descriptions of experimental configurations, hyperparameter settings, and implementation details for the TOOLSELF paradigm across all benchmarks.

### A.5.1 Inference Agent $\pi_i$ Configuration

We employ Qwen3-8B and Qwen3-14B as base models for the inference agent  $\pi_i$ , adopting the ReAct reasoning paradigm. Model inference parameters are set to `temperature=0.6` and `top_p=0.95` to balance output stability with exploration capability, as agentic systems require moderate stochasticity to avoid repetitive failure patterns and enable adaptive strategy exploration. The prompt template for the inference agent is shown in Sec. A.6.1. We adopt differentiated context management strategies tailored to the characteristics of different benchmarks: for deep research and general AI assistant tasks (FRAMES, xbench, GAIA), the maximum iteration count is set to 200, maximum reconfiguration count to 30 (exceeding 30 reconfigurations is treated as task failure), and maximum context window length to 32,000 tokens. When context length exceeds 80% of maximum capacity (i.e., 25,600 tokens), the system automatically triggers a context cleanup mechanism, removing all historical interaction content except the most recent 10 iterations, thereby preserving critical recent information while preventing context overflow. For SWE-bench Lite software engineering tasks, in addition to the above base configuration, we implement more refined context compression strategies following SWE Agent practices to address verbose outputs common in code tasks. These include: (1) A single-message truncation mechanism that iterates through all iterations and performs length checks on all messages except the most recent one. If a single message exceeds 8,000 characters, it undergoes head-preserving truncation with truncation markers (e.g., `... (truncated 1234 characters) ...`) to prevent large log files and codebase scan results from excessively consuming the token budget; (2) An observation history compression mechanism that identifies tool responses (Observations) across all iterations, retaining only the 10 most recent complete observations while replacing earlier observations with concise summaries (e.g., `Old environment output: (42 lines omitted)`), thereby significantly reducing context burden while maintaining reasoning coherence. These hyperparameter choices are based on extensive grid search experiments, empirically achieving a balance between reasoning performance and computational efficiency.

### A.5.2 Reconfiguration Engine $\mu$ Configuration

The reconfiguration engine  $\mu$  is also powered by Qwen3-8B and Qwen3-14B, with inference parameters maintained consistent with the inference agent (`temperature=0.6`, `top_p=0.95`). The prompt template for the reconfiguration engine is shown in Sec. A.6.3.

### A.5.3 Model Training Configuration

To enable the inference agent  $\pi_i$  and reconfiguration engine  $\mu$  to acquire runtime self-reconfiguration capabilities, we adopt a two-stage training strategy: Stage I performs cold-start initialization via Rejection Sampling Fine-tuning (RFT), and Stage II performs reinforcement learning refinement via Kahneman-Tversky Optimization (KTO).

**Training Data Construction.** We construct the training set from the FRAMES and MathVista datasets. Specifically, the FRAMES dataset contains 824 deep research questions; we randomly sample 200 questions as the test set, with the remaining 624 questions used for training. To enhance the model’s ability to handle multimodal tasks with attachments in GAIA, we introduce the MathVista dataset as training data supplement. For Stage I RFT training,

we use 200 FRAMES tasks and 100 MathVista tasks, totaling  $M = 300$  tasks; for Stage II KTO training, we use 424 FRAMES tasks and 200 MathVista tasks, totaling  $M' = 624$  tasks. Regarding teacher models, the inference agent employs Qwen3-235B-A22B-Thinking, while the reconfiguration engine employs DeepSeek-V3.2. For RFT training, each task generates 1 trajectory through rejection sampling, retaining trajectories that successfully complete tasks as supervision signals, with success determined by answer correctness verified through official evaluation scripts. We ultimately collect 162 successful trajectories, with an average of 8.72 reconfigurations per trajectory. During trajectory generation, the teacher model is configured with the same tool pool  $T_{\text{all}}$  and context management strategies as the inference agent.

**LoRA Configuration.** Both the inference agent and reconfiguration engine employ LoRA [20] for parameter-efficient fine-tuning. The LoRA rank is set to  $r = 16$  with scaling factor  $\alpha = 32$ . Base model parameters  $\theta_0$  remain frozen throughout training.

**Stage I: RFT Training Details.** We adopt the AdamW optimizer with learning rate set to 8e-6, weight decay of 0.08,  $\beta_1 = 0.9$ , and  $\beta_2 = 0.95$ . Per-device batch size is set to 1, gradient accumulation steps to 8, global batch size to 16, training for 2 epochs. Learning rate follows a cosine scheduler with warmup ratio of 0.15. Gradient clipping max norm is set to 0.5. Training employs mixed precision (bfloating16) with distributed training on 2 NVIDIA A100 GPUs via DeepSpeed ZeRO-2. The two LoRA adapters for the inference agent  $\pi_i$  and reconfiguration engine  $\mu$  are trained independently.

**Stage II: KTO Training Details.** Building upon the RFT model, we sample  $K = 4$  trajectories for each of the  $M' = 624$  tasks (424 FRAMES tasks and 200 MathVista tasks) for KTO optimization. During trajectory sampling, model parameters are initialized to  $\theta_{\pi}^{\text{RFT}}$  and  $\theta_{\mu}^{\text{RFT}}$ , with inference parameters set to `temperature=0.7` and `top_p=0.9` to increase exploration diversity. Trajectory annotation is based on official evaluation metrics: success yields  $y = 1$ , failure yields  $y = 0$ . We ultimately collect 2496 annotated trajectories with a positive-to-negative sample ratio of approximately 0.83:1.

KTO hyperparameters are set to  $\lambda_D = 1.0$ ,  $\lambda_U = 1.0$ , and KL divergence coefficient  $\beta = 0.1$ . The optimizer is AdamW with learning rate of 3e-6 (lower than RFT's 8e-6 to maintain stability),  $\beta_1 = 0.9$ ,  $\beta_2 = 0.95$ , weight decay of 0.01, and warmup ratio of 0.1. Per-device batch size is set to 1, gradient accumulation steps to 4, global batch size to 4, training for 1 epoch. Gradient clipping max norm is set to 1.0. Reference models  $\theta_{\pi}^{\text{RFT}}$  and  $\theta_{\mu}^{\text{RFT}}$  remain frozen during training. Training employs mixed precision (bfloating16) on 4 NVIDIA A100 GPUs. The two LoRA adapters for the inference agent  $\pi_i$  and reconfiguration engine  $\mu$  are trained independently.

**Training Implementation Details.** All training experiments are implemented based on PyTorch 2.9.0 and Transformers 4.57.3. LoRA implementation uses the PEFT 0.18.0 library, with the training framework using ms-swift 3.12.0. For the RFT stage, distributed training employs the DeepSpeed 0.18.3 ZeRO-2 strategy (2 GPUs). Checkpoint saving occurs every 40 steps, retaining the 3 most recent checkpoints. Training progress is monitored via training loss, validation loss, and token accuracy to assess convergence. Final model selection is based on the checkpoint with the lowest eval\_loss on the validation set. For the KTO stage, training proceeds in single-process mode on 4 GPUs. Checkpoint saving occurs every 300 steps, retaining the 3 most recent checkpoints, with `load_best_model_at_end` enabled. Training progress is monitored via training loss, validation loss, KTO reward margins, and positive/negative sample losses to assess learning progress. Final model is automatically selected based on the optimal checkpoint with the lowest eval\_loss on the validation set. Both stages employ mixed precision training (bfloating16) with gradient checkpointing to optimize memory usage.

#### A.5.4 Core Tool Definitions

**Reconfiguration Tool  $T_{\text{reconfig}}$  and Termination Tool  $T_{\text{term}}$ .** These two core tools are fundamental components of the TOOLSELF paradigm; their definition prompts are shown in Sec. A.6.4.

#### A.5.5 Global History Pool $H_{\text{all}}$

The global history pool stores execution summaries from all previous stages in string format; its data format is shown in Sec. A.6.5.

#### A.5.6 Global Tool Pool $T_{\text{all}}$

The global tool pool  $T_{\text{all}}$  comprises the following six tools:

**1. visit (Web Access Tool).** The tool definition prompt is shown in Sec. A.6.4. Implementation follows WebSailor [18], using the Jina Reader API service to access and parse webpage content, supporting single or batch URL access. This tool performs intelligent content extraction through an LLM, automatically locating and extracting relevant information and evidence from pages based on user-specified objectives, avoiding lengthy raw HTML returns. Content extraction employs the same backbone as the inference agent  $\pi_i$ .

**2. search.** The tool definition prompt is shown in Sec. A.6.4. Implementation follows WebSailor [18], supporting batch query submission, automatic language detection, and concurrent request handling, returning formatted search results including title, link, summary, publication date, and source domain. We adopt differentiated search backends tailored to benchmark characteristics: for the FRAMES dataset, whose data sources are specific Wikipedia pages, we pre-download all relevant pages locally and deploy an efficient retrieval service based on the BM25 algorithm; for other tasks, the search engine is powered by SearxNG.

**3. code\_interpreter (Python Code Interpreter).** The tool definition prompt is shown in Sec. A.6.4. It executes Python code in an isolated Jupyter Kernel environment, with each agent instance maintaining an independent kernel state to support cross-call variable persistence and state retention. Pre-installed libraries include NumPy, Pandas, Matplotlib, SciPy, and other mainstream scientific computing packages, supporting data analysis, statistical modeling, visualization, and mathematical computation tasks.

**4. execute\_bash.** The tool definition prompt is shown in Sec. A.6.4. Implementation follows SWE Agent [4], executing Bash commands in an isolated Shell session, supporting file system operations (create, read, modify, delete files or directories), script execution, system queries (e.g., git version control operations, environment variable checks). It incorporates timeout control mechanisms and automatic output truncation strategies.

**5. str\_replace\_editor.** The tool definition prompt is shown in Sec. A.6.4. Implementation follows SWE Agent [4], an advanced file editing tool designed specifically for software engineering tasks. It supports five core operations: view for viewing file contents or specified line ranges, create for creating new files, str\_replace for content replacement based on exact string matching, insert for inserting content at specified lines, and undo for reverting the last edit.

**6. file\_analyzer (File Analysis Tool).** The tool definition prompt is shown in Sec. A.6.4. An intelligent tool designed specifically for multimodal file analysis, supporting two major file categories: text documents and images. For text documents (PDF, Word, Excel, PowerPoint, TXT, Markdown, etc.), it employs a document parser for intelligent chunking, using the same backbone as the inference agent  $\pi_i$  to extract relevant information and evidence based on user-specified objectives. For image files (JPG, PNG, GIF, BMP, WebP, etc.), it employs the Qwen3-VL-30B-A3B-Instruct multimodal model for visual understanding and content extraction. This tool, through its goal-directed information extraction mechanism, returns only key content relevant to user objectives, effectively avoiding context overload from lengthy raw file content. It is particularly suitable for handling multimodal tasks with attachments in the GAIA benchmark.

**Environment Interaction Configuration.** We adopt differentiated environment interaction strategies tailored to the evaluation environment characteristics of different benchmarks. For SWE-bench Lite, the inference agent interacts with Docker-based sandbox environments through code\_interpreter, execute\_bash, and str\_replace\_editor, with each test instance running in an independent container to ensure environment consistency and reproducibility. For other tasks, the inference agent’s aforementioned tools interact directly with the local environment.

## A.5.7 Model Evaluation

All benchmark tests employ their official evaluation metrics and scripts for result computation, ensuring comparability with published baseline methods. Specifically, FRAMES, xbench, and GAIA employ LLM-as-Judge to evaluate whether results match ground-truth answers, using Qwen2.5-72B-Instruct as the evaluation model with parameters set to temperature=0.0 and top\_p=1.0. We additionally performed a consistency check via manual (human) verification on a randomly sampled subset of instances, and observed high agreement with the LLM-as-Judge outcomes. SWE-bench Lite employs resolve rate as the evaluation metric, defined as the proportion of generated patches passing all relevant test cases. All reported results are based on **pass@1** evaluation.

## A.5.8 Computational Resources

All experiments are executed on a high-performance computing node equipped with 16 NVIDIA A100 GPUs (40 GB memory each). The software stack employs PyTorch 2.4.0, linked with CUDA 12.1 and NCCL 2.20.5.

## A.6 Prompt Templates

### A.6.1 Inference Agent ( $\pi_i$ ) Prompt Template

The inference agent uses a three-part prompt structure: the SYSTEM section provides configuration (main task, sub-goal, strategy, toolbox, knowledge), the USER section contains tool definitions and ReAct format instructions, and the ASSISTANT section records execution history.

Inference Agent System Prompt
<pre>==== SYSTEM ==== ## Role and Core Objective You are a professional task execution agent. Your core objective is to efficiently complete the specified task using the given main task, sub-goal, and available toolset.  ## Input Information You will receive the following information, please analyze carefully:  1. **Main Task '<main_task>'**: This is the ultimate goal to be completed. &lt;main_task&gt; {MAIN_TASK_CONTENT} &lt;/main_task&gt;  2. **Current Sub_goal '<sub_goal>'**: This is the specific task you need to focus on completing now. &lt;sub_goal&gt; {SUB_GOAL_CONTENT} &lt;/sub_goal&gt;  3. **Execution Strategy '<strategy>'**: The execution methodology for the current sub_goal. &lt;strategy&gt; {EXECUTION_STRATEGY} &lt;/strategy&gt;  4. **Toolbox '<toolbox>'**: This is the list of tools available for the current sub_goal. &lt;toolbox&gt; {TOOLBOX_LIST} &lt;/toolbox&gt;  5. **Knowledge Information '<knowledge>'**: This is the background information and constraints related to the task. &lt;knowledge&gt; {KNOWLEDGE_CONTENT} &lt;/knowledge&gt;  ## Tool Usage Guidelines - **Precision**: Select the most appropriate tools based on the current sub-goal - **Efficiency**: Prioritize tools that can directly solve the problem - **Completeness**: Ensure the task execution process is complete and logically clear  ## Agent Management Tools **Reconfiguration Tool** - Use when agent needs configuration updates: - Current sub-task completed but main task not finished → update sub_goal - Current sub-task execution failed → try new sub-task approach - Current toolbox insufficient → update toolbox - Knowledge lacks necessary information → update knowledge - Execution strategy no longer fits → update execution_strategy  **Termination Tool** - Use only when: - Main task is completely finished (not just sub-goal) - All objectives have been achieved and no further work is needed  ## Execution Requirements 1. **CRITICAL - Focus ONLY on Sub_goal**: Your ONLY objective is to complete the current sub_goal. DO NOT attempt to complete the entire main task. 2. **Main Task Usage**: Use the main task information ONLY to understand the broader context and make informed decisions about the current sub_goal. 3. **Tool Selection**: Choose appropriate tools from the toolbox to complete the sub_goal. 4. **Result Reporting**: Use the termination tool only when the MAIN TASK is completely finished. Use the reconfiguration tool when needing to update agent configuration. 5. **Error Handling**: When encountering problems, use the reconfiguration tool to modify agent configuration rather than simply reporting errors.</knowledge></toolbox></strategy></sub_goal></main_task></pre>

## A.6.2 ReAct Execution Format

### ReAct Format Specification

```
The inference agent operates within a structured prompt format:

USER_PROMPT_PREFIX:
"A conversation between User and Assistant. The user asks a question, and the
assistant solves it by calling one or more of the following tools."

[Tool definitions inserted here]

USER_PROMPT_SUFFIX:
"The assistant starts with one or more cycles of (thinking about which tool to
use -> performing tool call -> waiting for tool response), and ends by calling
the 'finish' tool with a final summary and completion status. The thinking
processes, tool calls, and tool responses are enclosed within their tags."

## Execution Cycle Structure

<think> [reasoning about current situation and next action] </think>
<tool_call>
{"name": "tool_name", "arguments": {"arg1": "value1", "arg2": "value2"}}
</tool_call>
<tool_response>
[Environment's response]
</tool_response>
[Multiple cycles continue...]
<think> [final reasoning] </think>
<tool_call>
{"name": "finish", "arguments": {
    "task_completion_status": "complete",
    "final_result": "result summary",
    "execution_summary": {
        "detailed_execution": ["step1", "step2"],
        "tools_used": ["tool1", "tool2"]
    }
}}
</tool_call>
```

### A.6.3 Reconfiguration Engine ( $\mu$ ) Prompt Template

#### Reconfiguration Engine System Prompt

```

## Role and Core Objective
You are a professional "Agent Configuration Engineer". Your core objective is to
generate the next-step configuration for a ReAct-based inference agent executing
a complex main task. You must:
1. Mentally plan the overall task execution to understand the big picture
2. Identify the immediate next step based on current progress
3. Generate appropriate configuration (sub_goal, strategy, toolbox, knowledge)
## Input Information
You will receive the following parts:
1. **Main Task** '<main_task>': The final goal the Agent needs to accomplish.
<main_task>
{MAIN_TASK_CONTENT}
</main_task>
2. **Available Tools** '<available_tools>': Complete list of tools available
to the Agent during the entire task lifecycle.
<available_tools>
{ALL_AVAILABLE_TOOLS}
</available_tools>
3. **Execution History** '<execution_history>': Summarized record of all
previous steps. Can be empty ("NONE").
<execution_history>
{EXECUTION_HISTORY}
</execution_history>
4. **Update Requirement** '<update_requirement>': Update suggestions from
previous Agent. Can be empty ("NONE").
<update_requirement>
{UPDATE_REQUIREMENT}
</update_requirement>
## Configuration Generation Process
### Step 1: Determine Next Sub-Goal
Carefully consider the proposed sub-goal in '<update_requirement>' and adopt
it whenever possible. Only re-plan a new sub-goal if the proposal is entirely
irrelevant to the task.
### Step 2: Generate Other Configuration Components
Based on the determined sub-goal and other requirements specified in
'<update_requirement>', generate the following elements:
**2.1 Execution Strategy**
For **execution_strategy**, design a heuristic algorithm specifically for
the next sub_goal:
1. **Define Persona**: Assign an expert persona (e.g., "Senior Software
Engineer", "Data Analyst").
2. **Create a Step-by-Step Plan**: Simulate the thinking process to
accomplish the next sub_goal.
3. **Identify Decision Points**: Mark key decision points in the plan.
4. **Link to Tools**: Specify which concrete tool should be used in each step.
**2.2 Toolbox Selection**
Select tools for the **toolbox**:
- **CRITICAL**: The toolbox must include at least three tools specifically
needed for the NEXT sub_goal ONLY.
- **VERY IMPORTANT**: Focus EXCLUSIVELY on tools required to complete the
next sub_goal.
- **IMPORTANT**: The toolbox must be a **strict subset** of
'<available_tools>'.
**2.3 Inter-Agent Knowledge**
Determine the 'inter_agent_knowledge' field based on '<execution_history>':
1. **Initial Step**: If '<execution_history>' is 'NONE' or empty,
'inter_agent_knowledge' must be an empty string "".
2. **Use ALL**: If history is concise and relevant, use the string "ALL".
3. **Summarize**: If history is long or contains exploratory steps, extract
a concise summary.
## Output Format
Your final output **must** be a strict JSON object:
{
  "next_sub_goal": "Detailed description of the next step to execute",
  "execution_strategy": "As a [expert persona], I will follow these
  steps to accomplish the NEXT sub_goal: 1. [first step and tool]
  2. [second step and tool] 3. [key decision points]...",
  "toolbox": ["ToolName1", "ToolName2", "ToolName3"],
  "inter_agent_knowledge": "One of three forms: summary, 'ALL', or ''"
}

```

#### A.6.4 Tool Definitions

The reconfiguration tool arguments correspond to the formal definitions in Sec. 2 as follows: `new_sub_goal` corresponds to  $q_{i+1}^{\text{prop}}$ , `update_reason` to  $\rho_i$ , and `additional_details` to  $\delta_i$  in the reconfiguration request  $r_i = (q_{i+1}^{\text{prop}}, \rho_i, \delta_i)$ . Additionally, `execution_summary` corresponds to the execution summary  $H_i$ , while `update_content` serves as a metadata field for analysis purposes and is not passed to the reconfiguration engine  $\mu$ .

**Reconfiguration Tool Definition**

```
{
  "name": "reconfigure",
  "description": "Update current Agent's components including sub_goal, toolbox, knowledge, or execution strategy. Use when the current sub-task is completed but main task isn't, when current sub-task execution fails, when current toolset is insufficient, when knowledge lacks necessary information or contains irrelevant information, or when the execution strategy no longer fits the task requirements.",
  "arguments": {
    "type": "object",
    "properties": {
      "execution_summary": {
        "type": "string",
        "description": "Step-by-step detailed summary of current Agent's task execution process"
      },
      "update_content": {
        "type": "string",
        "enum": ["sub_goal", "toolbox", "knowledge",
                 "execution_strategy"],
        "description": "What needs to be updated"
      },
      "update_reason": {
        "type": "string",
        "description": "Why this update is needed"
      },
      "new_sub_goal": {
        "type": "string",
        "description": "The new sub_goal that the updated Agent needs to execute. If the current task is complete, set to 'Task completed, use finish tool next'"
      },
      "additional_details": {
        "type": "object",
        "properties": {
          "toolbox_requirements": {
            "type": "string",
            "description": "Requirements for the new toolbox based on current limitations"
          },
          "knowledge_requirements": {
            "type": "string",
            "description": "Requirements for the new knowledge based on missing information"
          },
          "execution_strategy_requirements": {
            "type": "string",
            "description": "Requirements for the new execution strategy based on current limitations"
          }
        },
        "description": "Additional details for specific update types"
      }
    },
    "required": ["execution_summary", "update_content", "update_reason",
                "new_sub_goal"]
  }
}
```

## Finish Tool Definition

```
{
  "name": "finish",
  "description": "Signal the completion of the main task and end the entire
    task execution. Use only when the current Agent has completely finished
    the main task.",
  "arguments": {
    "type": "object",
    "properties": {
      "task_completion_status": {
        "type": "string",
        "enum": ["complete", "partial", "incomplete"],
        "description": "Main task completion status"
      },
      "final_result": {
        "type": "string",
        "description": "Final result of the main task execution"
      },
      "execution_summary": {
        "type": "object",
        "properties": {
          "detailed_execution": {
            "type": "array",
            "items": {"type": "string"},
            "description": "Detailed step-by-step execution process including
              steps taken, key decisions made, challenges encountered and
              how resolved, blocking factors, progress updates, and critical
              insights."
          },
          "tools_used": {
            "type": "array",
            "items": {"type": "string"},
            "description": "List of tools used during the task"
          },
          "key_achievements": {
            "type": "array",
            "items": {"type": "string"},
            "description": "Major achievements and milestones reached"
          }
        },
        "required": ["detailed_execution", "tools_used"],
        "description": "Comprehensive summary of the task execution process"
      },
      "results_details": {
        "type": "object",
        "properties": {
          "deliverables": {
            "type": "array",
            "items": {"type": "string"},
            "description": "Concrete deliverables produced"
          },
          "evidence": {
            "type": "array",
            "items": {"type": "string"},
            "description": "Evidence supporting the results"
          },
          "confidence_level": {
            "type": "string",
            "enum": ["High", "Medium", "Low"],
            "description": "Confidence level in the results"
          }
        },
        "description": "Detailed information about the results achieved"
      },
      "issues_encountered": {
        "type": "object",
        "properties": {
          "blocking_issues": {
            "type": "array",
            "items": {"type": "string"},
            "description": "Issues that prevented full completion"
          },
          "workarounds_used": {
            "type": "array",
            "items": {"type": "string"},
            "description": "Workarounds employed to overcome issues"
          },
          "unresolved_issues": {
            "type": "array",
            "items": {"type": "string"},
            "description": "Issues that remain unresolved"
          }
        },
        "description": "Issues encountered during execution"
      }
    },
    "required": ["task_completion_status", "final_result",
      "execution_summary"]
  }
}
```

**Visit Tool Definition**

```
{
  "name": "visit",
  "description": "Visit webpage(s) and return the summary of the content.",
  "arguments": {
    "type": "object",
    "properties": {
      "url": {
        "type": ["string", "array"],
        "items": {"type": "string"},
        "minItems": 1,
        "description": "The URL(s) of the webpage(s) to visit."
      },
      "goal": {
        "type": "string",
        "description": "The goal of the visit for webpage(s)."
      }
    },
    "required": ["url", "goal"]
  }
}
```

**Search Tool Definition**

```
{
  "name": "searx_search",
  "description": "Performs batched web searches via a Searx instance.",
  "arguments": {
    "type": "object",
    "properties": {
      "query": {
        "type": "array",
        "items": {"type": "string"},
        "description": "Array of query strings."
      }
    },
    "required": ["query"]
  }
}
```

**File Analyzer Tool Definition**

```
{
  "name": "file_analyzer",
  "description": "Intelligently analyze and extract information from various file types including documents and images.",
  "arguments": {
    "type": "object",
    "properties": {
      "file_path": {
        "type": "string",
        "description": "The absolute or relative path to the file."
      },
      "goal": {
        "type": "string",
        "description": "A clear, specific question or goal describing what information you want to extract from the file."
      }
    },
    "required": ["file_path", "goal"]
  }
}
```

**Bash Tool Definition**

```
{
  "name": "bash",
  "description": "Execute bash commands with safety checks. Supports timeout,
    working directory specification, and output truncation. Use absolute
    paths when possible. Dangerous commands are blocked.",
  "arguments": {
    "type": "object",
    "properties": {
      "command": {
        "type": "string",
        "description": "The bash command to execute (use '&&' to chain
          commands)."
      },
      "timeout": {
        "type": "integer",
        "description": "Timeout in seconds (default 120)."
      },
      "cwd": {
        "type": "string",
        "description": "Optional working directory (absolute path
          recommended)."
      }
    },
    "required": ["command"]
  }
}
```

**Code Interpreter Tool Definition**

```
{
  "name": "code_interpreter",
  "description": "Python code sandbox, which can be used to execute Python
    code.",
  "arguments": {
    "type": "object",
    "properties": {
      "code": {
        "type": "string",
        "description": "The python code."
      }
    },
    "required": ["code"]
  }
}
```

## String Replace Editor Tool Definition

```
{
  "name": "str_replace_editor",
  "description": "Advanced file editor with intelligent features. Commands: view (display file/directory contents with optional line range), create (create a new file, cannot overwrite existing files), str_replace (replace text, old_str must match EXACTLY and be UNIQUE), insert (insert text at a specific line number), undo_edit (revert the last edit operation). Key Features: automatic tab expansion, shows edited code snippet with context after changes, smart window expansion to include complete functions/classes, integrated linter to detect syntax errors immediately, edit history with undo support, detailed error messages to help diagnose issues. IMPORTANT for str_replace: old_str must match the file content EXACTLY (character by character), old_str must be UNIQUE in the file (appears only once), always use 'view' first to get the exact text to replace, include enough context to make old_str unique, pay attention to whitespace and indentation.",
  "arguments": {
    "type": "object",
    "properties": {
      "command": {
        "type": "string",
        "enum": ["view", "create", "str_replace", "insert", "undo_edit"],
        "description": "Operation to perform."
      },
      "path": {
        "type": "string",
        "description": "Absolute file or directory path."
      },
      "file_text": {
        "type": "string",
        "description": "Required for 'create': new file content."
      },
      "old_str": {
        "type": "string",
        "description": "Required for 'str_replace': The exact text to replace. CRITICAL: Must match the file content EXACTLY (character-by-character, including all whitespace). Must appear only ONCE in the file. BEST PRACTICE: First use 'view' to see the exact content, then copy it here verbatim."
      },
      "new_str": {
        "type": "string",
        "description": "New text for 'str_replace' or 'insert'."
      },
      "insert_line": {
        "type": "integer",
        "description": "Required for 'insert': line number to insert at (0-indexed)."
      },
      "view_range": {
        "type": "array",
        "items": {"type": "integer"},
        "description": "Optional for 'view': [start, end], 1-indexed, -1 for end of file."
      }
    },
    "required": ["command", "path"]
  }
}
```

### A.6.5 Execution History Format

#### Execution History Structure

```
<execution_history>
Iteration 1:
Sub-goal: [Description of the sub-goal for stage 0]
Summary: [Execution summary including completed work, encountered issues,
key findings, and decisions made during stage 0]

Iteration 2:
Sub-goal: [Description of the sub-goal for stage 1]
Summary: [Execution summary for stage 1]

...
Iteration N:
Sub-goal: [Description of the sub-goal for stage N-1]
Summary: [Execution summary for stage N-1]
</execution_history>
```