CHILL-HARNESS: COUNTERFACTUAL HARNESS LEARNING FOR EFFICIENT REASONING IN LONG-HORIZON AGENTS

Anonymous authors
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ABSTRACT

Agent harnesses have become the operational infrastructure of modern large language model agents, coordinating context, tools, verification, and execution control to translate latent model capability into reliable long-horizon behavior. However, reliable long-horizon behavior requires harness control to adapt to task demands, execution environments, and evolving execution states, whereas current harnesses predominantly rely on hand-crafted or globally fixed policies; this mismatch manifests as unnecessary computational overhead and, in adverse cases, reduced task success. To address this limitation, we formulate the task of enabling adaptive orchestration in harness systems as a causal learning problem and propose **C**ounterfactual **H**arness **I**ntervention **L**earning for **L**ong-Horizon Agents (**CHILL-Harness**). CHILL-Harness intervenes at the orchestration layer to enable advantage-guided workflow adaptation, with the goal of improving reasoning and execution efficiency without broadly sacrificing task performance. Specifically, we develop causal intervention effect learning as the effect-estimation component of CHILL-Harness to estimate intervention-relative workflow advantage from confidence-weighted matched execution evidence and identify advantageous workflow adaptations. We further introduce advantage-realizing causal orchestration as its realization component to adaptively allocate counterfactual reasoning and realize only workflow adjustments supported by sufficient expected advantage. Finally, we incorporate a success-preserving objective and advantage-margin authorization constraints into CHILL-Harness to promote reliable adaptation. Experiments on heterogeneous long-horizon tasks spanning information seeking, software engineering, and terminal interaction show that CHILL-Harness substantially reduces token consumption and execution time while maintaining competitive task success across the evaluated benchmarks.

1 INTRODUCTION

Large language model agents are increasingly deployed on long-horizon tasks Zhou et al. (2024); Xie et al. (2024) that require sustained context management Wang et al. (2025b), external tool interaction Yao et al. (2025), intermediate verification Pan et al. (2025), failure recovery Wang & Liu (2025), and execution control Guo et al. (2026). Agent harnesses have therefore become critical runtime infrastructure for translating latent model capability into reliable behavior Meng et al. (2026); Kapoor et al. (2026). However, effective harness control should adapt to task demands Hu et al. (2025d), execution environments Ba et al. (2026), and evolving execution states Zhang et al. (2026), whereas existing harnesses remain largely governed by hand-crafted rules, fixed thresholds, or globally configured workflows Li et al. (2026); Marchand et al. (2026). Over long execution horizons, this mismatch can compound redundant reasoning, delayed correction, and unnecessary workflow disruption, increasing execution cost and potentially degrading task success He et al. (2026); Sun et al. (2026).

Existing harness-level approaches to adaptive harness orchestration can be broadly grouped into two categories: (1) task-oriented engineered harnesses such as Terminus-KIRA integrate hand-engineered reasoning and tool-use procedures across long-horizon tasks KRAFTON AI & Ludo Robotics (2026), OpenHands and CodeSweep–SWE-agent provide iterative repository inspection,

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editing, and verification workflows for software repair Wang et al. (2025a); Yang et al. (2024); Kimi Team (2025), and LemonHarness develops a high-performing execution stack for complex terminal tasks Ren et al. (2026); despite their strong task-level performance, these systems rely primarily on domain-specific or globally configured control logic and provide limited adaptation to the value of an intervention at the current execution state; and (2) orchestration and harness optimization methods improve system-level coordination—AWorld dynamically organizes multi-agent collaboration Yu et al. (2025a), OWL Workforce coordinates a planner, coordinator, and specialized workers through hierarchical orchestration Hu et al. (2025b), and Meta-Harness performs outer-loop search over harness implementations using execution traces and evaluation feedback Lee et al. (2026); however, these methods primarily optimize collaboration structures or aggregate harness configurations rather than determine whether a concrete orchestration intervention causally improves the ongoing workflow. Consequently, existing methods still lack a unified framework that assesses whether a concrete orchestration adjustment improves the current workflow and translates this assessment into adaptive, success-preserving harness decisions for efficient reasoning.

In this work, we leverage a causal perspective to address this limitation. Causal reasoning is well suited to decisions whose observed outcomes conflate the effect of an action with the context in which it is taken Kuroki & Pearl (2014), since causal interventions can isolate the contribution of the action under a fixed context Rubin (1980); Pearl (2009). It has therefore been increasingly used to distinguish genuine contributions from spurious associations in large-language-model reasoning and autonomous driving Chi et al. (2024); Pourkeshavarz et al. (2024); Tang et al. (2026). Harness orchestration exhibits the same structure: the current workflow provides a factual reference, while admissible alternatives define counterfactual interventions under the same execution context. We therefore formulate the task of enabling adaptive orchestration in harness systems as a causal learning problem. Specifically, we introduce the *causal harness orchestration problem*:

> *How can a harness leverage causal interventions to realize efficient and admissible workflow orchestration while preserving task success?*

To address this problem, we propose **C**ounterfactual **H**arness **I**ntervention **L**earning for **L**ong-Horizon Agents (**CHILL-Harness**), a causal framework for adaptive harness orchestration and efficient long-horizon reasoning. CHILL-Harness intervenes at the orchestration layer to enable advantage-guided workflow adaptation. Specifically, we develop Causal Intervention Effect Learning (CIEL) as its effect-estimation component, which unifies heterogeneous orchestration behaviors and estimates their context-conditioned intervention-relative advantages from confidence-weighted matched execution evidence. We further introduce Advantage-Realizing Causal Orchestration (ARCO) as its realization component, which routes counterfactual deliberation before candidate generation and authorizes workflow adaptations only when they exhibit sufficient causal–operational advantage. Finally, we incorporate a success-preserving objective and advantage-margin authorization constraints to promote reliable orchestration under effect-estimation uncertainty. Experiments on long-horizon tasks spanning information seeking, software engineering, and terminal interaction show substantial reductions in token consumption and execution time while maintaining competitive task success across the evaluated benchmarks. Our contributions are summarized as follows:

- We propose CHILL-Harness, which formulates adaptive orchestration in harness systems as a causal learning problem over factual and admissible alternative workflows, enabling efficient reasoning through intervention.
- We introduce Causal Intervention Effect Learning, which unifies heterogeneous orchestration behaviors and learns their context-conditioned intervention-relative advantages from confidence-weighted execution evidence, enabling selective harness-level intervention.
- We develop Advantage-Realizing Causal Orchestration, which realizes workflow adaptations supported by sufficient estimated advantage, thereby achieving efficient and reliable harness orchestration under success-preserving constraints.

2 Preliminaries and Related Work

This section introduces the agent-harness setting and causal formulation, followed by a review of adaptive harness orchestration and causal intervention methods.

2.1 PRELIMINARIES: CAUSAL ADAPTATION IN HARNESSES

An agent harness is the runtime infrastructure that governs how a base language-model agent maintains context, invokes tools, verifies progress, and interacts with its task environment (Meng et al., 2026; Guo et al., 2026). We use an *execution step* to mean a harness decision point within a single task trajectory: the current state and environment feedback are available, and the harness must select the next workflow before execution continues. It is therefore neither a complete task execution nor necessarily the completion of a semantic subtask. For example, in software repair, a step may occur after a file inspection returns its observation and before the harness decides whether to inspect further, revise code, verify the current patch, or terminate. At execution step t, the current context is represented as $\chi_t = (s_t, c_t^{\text{env}}, g_t)$, where s_t, c_t^{env}, and g_t denote the execution state, environment context, and current task objective, respectively. The context is a structured state description and is not assumed to be continuous-valued. Given χ_t, the base agent proposes a factual workflow ω_t^0, consisting of the reasoning, tool-use, and execution operations.

Let $\mathcal{A}_t$ denote the admissible workflow set under the current task, environment, safety, and resource constraints, with $\omega_t^0 \in \mathcal{A}_t$, and define the alternative set $\mathcal{A}_t^{\text{cf}} = \mathcal{A}_t \setminus \{\omega_t^0\}$. The workflow selected for execution simply satisfies $W_t \in \mathcal{A}_t$. We retain the distinction between ω_t^0 and $\mathcal{A}_t^{\text{cf}}$ only when defining intervention-relative comparisons. For every candidate workflow, downstream performance is evaluated under the same continuation policy, remaining evaluation horizon, resource-accounting rule, and task evaluator. We refer to these shared conditions as the *common continuation and evaluation protocol*. Executing $W_t = \omega$ then produces a scalar downstream utility U_t; U_t is not assumed to be continuous and may combine discrete task outcomes with measured execution costs. Adaptive harness orchestration determines whether to retain ω_t^0 or execute an admissible alternative under χ_t.

This decision naturally induces a potential-outcome formulation (Rubin, 1974; Pearl, 2009). For each $\omega \in \mathcal{A}_t$, let $U_t(\omega)$ denote the performance under $\text{do}(W_t = \omega)$ with χ_t fixed and the common continuation and evaluation protocol held unchanged. We adopt the standard potential-outcome consistency condition: if the executed workflow is $W_t = \omega$, then the observed outcome equals its corresponding potential outcome, $U_t = U_t(\omega)$. The workflow effect relative to the factual workflow is $\Gamma_t(\omega) = \mathbb{E}\left[U_t(\omega) - U_t(\omega_t^0) \mid \chi_t\right], \Gamma_t(\omega_t^0) = 0$.

2.2 RELATED WORK: ADAPTIVE HARNESS ORCHESTRATION AND CAUSAL INTERVENTION

Existing work on adaptive harness orchestration includes engineered execution systems, automated harness optimization, and component-level adaptation. OpenHands, SWE-agent, and OWL improve execution through specialized interfaces or coordination (Wang et al., 2025a; Yang et al., 2024; Hu et al., 2025b); Automated Design of Agentic Systems, Multi-Agent Architecture Search, and Meta-Harness optimize agent structures, resources, or complete harnesses (Hu et al., 2025c; Zhang et al., 2025; Lee et al., 2026), while Agent Workflow Memory, HiAgent, and OSCAR adapt workflow reuse, context management, and recovery (Wang et al., 2025b; Hu et al., 2025a; Wang & Liu, 2025). Causal methods have also been explored for language-model reasoning and agent decision making. Causal Sufficiency and Necessity refines reasoning chains through counterfactual analysis (Yu et al., 2025b), Counterfactual Planning revises task-level actions using structural causal models (Fu et al., 2026), and Robust Agents Learn Causal World Models exploits causal environment structure for robust control (Richens & Everitt, 2024).

These methods target reasoning steps, agent actions, or environment models, but do not assess heterogeneous harness-level decisions or efficiently realize only workflow-improving adaptations. CHILL-Harness fills this gap by estimating context-conditioned workflow effects and translating them into success-preserving workflow adaptations.

3 CHILL-HARNESS: COUNTERFACTUAL HARNESS INTERVENTION LEARNING

CHILL-Harness decomposes causal harness orchestration into two coupled problems.

Definition 1 (Harness Intervention Effect Problem)**.** *The Harness Intervention Effect Problem evaluates whether an admissible workflow alternative improves execution relative to the factual workflow under the same execution context.*

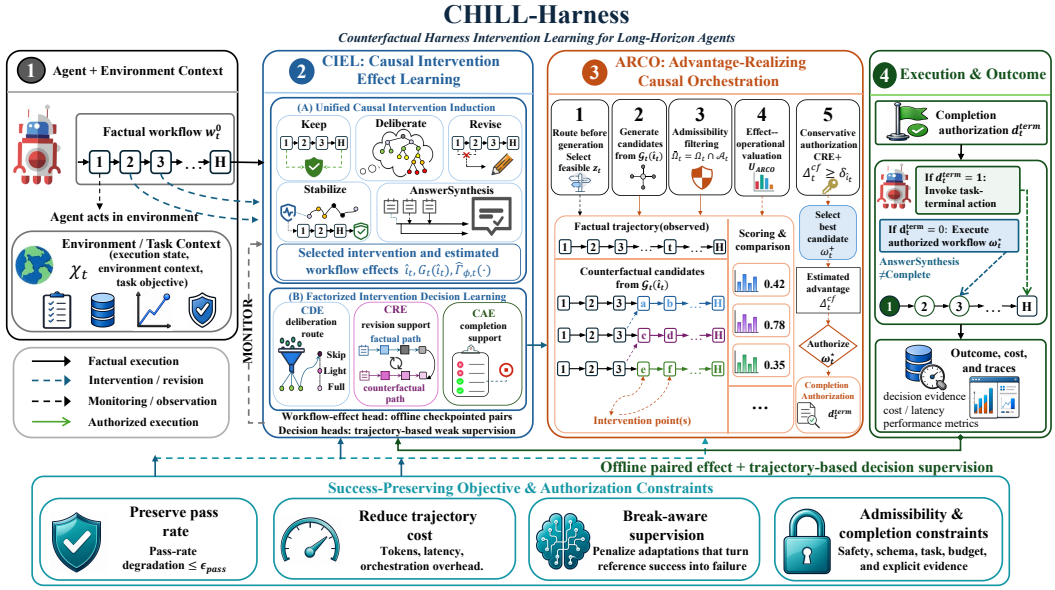


Figure 1: Overview of CHILL-Harness. Given context χ_t and factual workflow ω_t^0, CIEL estimates workflow effects and predicts intervention, deliberation, revision, and completion signals. ARCO realizes them through route-before-generation, admissibility filtering, causal–operational valuation, and conservative authorization. Offline checkpointed paired executions supervise workflow-effect estimation, while trajectory outcomes provide weak supervision for the factorized decision heads.

Definition 2 (Harness Intervention Realization Problem)**.** *The Harness Intervention Realization Problem determines whether the estimated benefit of an admissible alternative is sufficient to justify replacing the factual workflow.*

Following the preliminaries, χ_t, ω_t^0, $\mathcal{A}_t$, and $\Gamma_t(\omega)$ denote the execution context, factual workflow, admissible workflow set, and expected gain of ω over ω_t^0, respectively. As illustrated in Figure 1, CHILL-Harness addresses the two problems through **Causal Intervention Effect Learning (CIEL)** and **Advantage-Realizing Causal Orchestration (ARCO)**, under explicit success-preserving workflow authorization constraints.

3.1 CIEL: Causal Intervention Effect Learning

CIEL learns workflow-grounded intervention preferences for the Harness Intervention Effect Problem and converts them into factorized deliberation, revision, and completion signals.

Learned and provided quantities. CIEL learns the workflow-effect estimator and four prediction heads, $\Theta_{\text{CIEL}} = \{\phi, \theta_u, \theta_p, \theta_c, \theta_e\}$, corresponding to intervention-family, deliberation-route, revision, and completion decisions. The factual workflow, admissible set, environment observations, tools, and verifier are supplied by the underlying harness, whereas paired-effect targets, reliability weights, and weak decision targets are constructed offline from checkpointed executions. The paired differences are used as matched intervention-relative effect proxies rather than exact identified causal effects; full parameter roles, supervision sources, and the matched-replay conditions are given in Appendix A.4.

Unified Causal Intervention Induction. CIEL abstracts recurring harness adaptations, including additional reasoning, workflow correction, execution recovery, and answer construction, into a unified intervention space (Wang et al., 2025b; Yang et al., 2024; Wang & Liu, 2025). Let

$$\mathcal{R} = \{\text{INSPECT}, \text{VERIFY}, \text{VISUAL}\}, \quad \mathcal{Q} = \{\text{DEDUP}, \text{NOOPRECOVERY}\}$$

denote the revision and stabilization modes. The intervention space and its workflow realization are

$$\mathcal{I}_t^{\mathrm{wf}} = \{\textsc{Keep}, \textsc{Deliberate}, \textsc{AnswerSynthesis}\} \cup \{\textsc{Revise}(r) \mid r \in \mathcal{R}\} \cup \{\textsc{Stabilize}(q) \mid q \in \mathcal{Q}\},$$
$$\mathcal{G}_t(\iota) \equiv \mathcal{G}\left(\iota; \chi_t, \omega_t^0\right) \subseteq \mathcal{A}_t, \qquad \mathcal{G}_t(\textsc{Keep}) = \{\omega_t^0\}.$$

Here, $\mathcal{I}_t^{\mathrm{wf}}$ specifies adaptation intent and $\mathcal{G}_t(\iota)$ maps it to admissible workflows. KEEP preserves the factual workflow; DELIBERATE requests additional reasoning; REVISE acquires, verifies, or visually inspects evidence; STABILIZE suppresses repetition or recovers ineffective execution; and ANSWERSYNTHESIS redirects execution toward nonterminal answer construction. Each intervention inherits its causal contribution from its realized workflow (details in Appendix A.2).

CIEL estimates the context-conditioned workflow effect as $\widehat{\Gamma}_\phi(\omega; \chi_t, \omega_t^0) \approx \Gamma_t(\omega)$, with the factual workflow serving as the zero-effect reference. The estimates induce intervention-family preferences that are amortized into online prediction. We define $\widehat{V}_t^{\mathrm{int}}(\iota)$ as the estimated value of intervention family ι, obtained from the strongest workflow effect currently realizable by that family:

$$\widehat{V}_t^{\mathrm{int}}(\iota) = \max_{\omega \in \mathcal{G}_t(\iota)} \widehat{\Gamma}_\phi\left(\omega; \chi_t, \omega_t^0\right), \tag{1a}$$

$$\iota_t^* = \arg\max_{\iota \in \mathcal{I}_t^{\mathrm{wf}}} \widehat{V}_t^{\mathrm{int}}(\iota), \tag{1b}$$

$$\widehat{\iota}_t = \arg\max_{\iota \in \mathcal{I}_t^{\mathrm{wf}}} p_{\theta_u}\left(\iota \mid \chi_t, \omega_t^0\right). \tag{1c}$$

Equations 1a–1c separate workflow-effect aggregation, offline intervention induction, and amortized online prediction. Because $\mathcal{G}_t(\textsc{Keep}) = \{\omega_t^0\}$, conservative tie-breaking selects KEEP whenever no alternative family has a positive estimated effect. The workflow-effect estimator learns from checkpointed paired records, while the intervention predictor amortizes the induced offline preference:

$$\mathcal{L}_{\mathrm{eff}} = \mathbb{E}_{\mathcal{D}_{\mathrm{pair}}}\left[w_{t,\omega}\left(\widehat{\Gamma}_\phi\left(\omega; \chi_t, \omega_t^0\right) - \widetilde{\Gamma}_t^{\mathrm{pair}}(\omega)\right)^2\right], \quad \mathcal{L}_{\mathrm{int}} = -\log p_{\theta_u}\left(\iota_t^* \mid \chi_t, \omega_t^0\right).$$

Here, $\mathcal{D}_{\mathrm{pair}}$ contains factual–candidate executions restored from the same checkpoint and evaluated under the common continuation and evaluation protocol. The quantity $\widetilde{\Gamma}_t^{\mathrm{pair}}(\omega)$ is the resulting matched empirical utility difference and serves as a training proxy for the intervention-relative workflow effect. The reliability weight $w_{t,\omega} \geq 0$ is computed offline from pre-specified replay-validity diagnostics, replay count, and comparison stability; it is neither an externally supplied test-time parameter nor a quantity predicted by CHILL-Harness. The induced intervention selector is affected by both workflow-effect estimation error and amortization error. Appendix A.3 formalizes this relation and proves the corresponding intervention-selection regret bound.

Factorized Intervention Decision Learning. CIEL factorizes online control into three distinct decisions governing additional deliberation, workflow revision, and task completion. In the following equations, p_{θ_p}, p_{θ_c}, and p_{θ_e} denote the learned predictive distributions for CDE, CRE, and CAE, respectively; p_{θ_u} in Equation 1c is the learned distribution over intervention families. The four predictors act at different decision points: intervention intent, pre-generation compute allocation, post-generation workflow replacement, and termination.

Counterfactual Deliberation Effect (CDE). CDE addresses harness over-deliberation, where costly planning is repeatedly invoked even when the factual workflow is already sufficient. It predicts the required deliberation route:

$$p_{\theta_p}\left(z_t \mid \chi_t, \omega_t^0, \widehat{\iota}_t\right), \qquad z_t \in \mathcal{Z} = \{\textsc{Skip}, \textsc{Light}, \textsc{Full}\}. \tag{2}$$

SKIP bypasses candidate generation, LIGHT enables restricted diagnostics, and FULL enables broader evaluation. Thus, the intervention family specifies *what* adaptation is useful, whereas CDE determines *how much* computation realizes it.

Counterfactual Revision Effect (CRE). CRE addresses both workflow inertia and harmful replacement: the factual workflow may require correction, while an unsupported alternative may further degrade execution. Given an alternative workflow ω, CRE predicts whether it provides sufficient support for replacing the factual workflow:

$$p_{\theta_c}\left(y_t^{\mathrm{chg}} \mid \chi_t, \omega_t^0, \omega, \widehat{\iota}_t\right), \qquad y_t^{\mathrm{chg}} \in \{\textsc{Keep}, \textsc{Change}\}. \tag{3}$$

KEEP retains ω_t^0, whereas CHANGE supports replacement by the evaluated alternative.

Completion Attribution Effect (CAE). CAE predicts completion support to prevent both continued execution after task success and termination triggered solely by futility:

$$p_{\theta_e}\left(b_t \mid \chi_t, o_t, h_t\right), \qquad b_t \in \{0,1\}. \tag{4}$$

Here, o_t and h_t denote the latest observation and recent execution summary; $b_t = 1$ supports completion, which still requires explicit task evidence.

Logged trajectories provide weak targets for the preferred deliberation route, factual-versus-candidate revision, and evidence-attributed completion. Efficiency-related decisions receive positive supervision only when matched task success is preserved. CIEL jointly optimizes workflow-effect estimation, intervention-family prediction, and the three factorized decisions:

$$\mathcal{L}_{\mathrm{CIEL}} = \mathcal{L}_{\mathrm{eff}} + \mathcal{L}_{\mathrm{int}} + \mathcal{L}_{\mathrm{CDE}} + \mathcal{L}_{\mathrm{CRE}} + \mathcal{L}_{\mathrm{CAE}}.$$

The construction of z_t^*, $y_t^{\mathrm{chg},*}$, b_t^*, the head-specific losses, and their supervision sources are detailed in Appendix A.4. Here, $\mathcal{L}_{\mathrm{eff}}$ supervises workflow-effect estimation, $\mathcal{L}_{\mathrm{int}}$ intervention-family prediction, and $\mathcal{L}_{\mathrm{CDE}}, \mathcal{L}_{\mathrm{CRE}}, \mathcal{L}_{\mathrm{CAE}}$ deliberation, revision, and completion decisions, respectively; their targets and complete definitions are provided in Appendix A.4.

Remark. CIEL separates *what* adaptation is beneficial from *how* it should be realized: workflow-effect learning induces intervention preferences, while CDE, CRE, and CAE factorize deliberation, revision, and completion decisions.

3.2 ARCO: ADVANTAGE-REALIZING CAUSAL ORCHESTRATION

ARCO addresses the Harness Intervention Realization Problem through route selection, candidate valuation, conservative revision, and evidence-grounded completion. Let $\widehat{\Gamma}_{\phi,t}(\omega) := \widehat{\Gamma}_{\phi}(\omega; \chi_t, \omega_t^0)$. Then

$$\mathrm{ARCO}\left(\chi_t, \omega_t^0, o_t, h_t, \widehat{\iota}_t, \widehat{\Gamma}_{\phi,t}(\cdot)\right) \longmapsto \left(\omega_t^\star, d_t^{\mathrm{term}}\right).$$

ARCO first uses CDE to select a feasible deliberation route $z_t \in \{\mathrm{SKIP}, \mathrm{LIGHT}, \mathrm{FULL}\}$. SKIP retains the factual workflow without candidate generation, whereas the other routes expose a bounded candidate set from $\mathcal{G}_t(\widehat{\iota}_t)$; inadmissible candidates are removed before valuation. Route feasibility and candidate construction are specified in Appendix B.1.

Each admissible candidate is valued by combining operational utility and estimated workflow effect:

$$\widehat{U}_{\mathrm{ARCO}}\left(\omega \mid \chi_t, z_t, \widehat{\Gamma}_{\phi,t}\right) = \widehat{U}_{\mathrm{op}}\left(\omega \mid \chi_t, z_t\right) + \eta_\Gamma \widehat{\Gamma}_{\phi,t}(\omega). \tag{5}$$

Here, $\widehat{U}_{\mathrm{op}}$ aggregates progress, cost, risk, information gain, robustness, and safety, while $\eta_\Gamma \geq 0$ weights estimated intervention evidence; Appendix B.2 gives the full construction.

ARCO selects the highest-valued admissible candidate $\omega_t^+ \in \overline{\Omega}_t$ and compares it with the factual workflow using the causal–operational advantage Δ_t^{cf}. The exact maximization and advantage construction are given in Appendix B.2.

Instantiating the CRE predictor in Equation 3 with the selected candidate ω_t^+, ARCO obtains

$$y_t^{\mathrm{chg}} = \arg\max_{y \in \{\mathrm{KEEP}, \mathrm{CHANGE}\}} p_{\theta_c}\left(y \mid \chi_t, \omega_t^0, \omega_t^+, \widehat{\iota}_t\right).$$

The candidate is executed only when both CRE and its estimated advantage support revision:

$$\omega_t^\star = \begin{cases} \omega_t^+, & y_t^{\mathrm{chg}} = \mathrm{CHANGE} \ \wedge \ \Delta_t^{\mathrm{cf}} \geq \delta_{\widehat{\iota}_t}, \\ \omega_t^0, & \text{otherwise.} \end{cases} \tag{6}$$

In Equation 6, $\delta_{\widehat{\iota}_t} \geq 0$ is an intervention-dependent authorization margin. ARCO executes ω_t^+ only when both the CRE decision and its estimated advantage support replacement; otherwise, it retains ω_t^0 (see Appendix B.3 for details).

Finally, ARCO instantiates the CAE predictor in Equation 4 and combines its output with explicit task evidence:

$$\widehat{b}_t = \arg\max_{b \in \{0,1\}} p_{\theta_e}\left(b \mid \chi_t, o_t, h_t\right), \quad e_t^{\mathrm{comp}} = \mathbb{I}\left[\mathcal{V}_t\left(\chi_t, o_t, h_t\right) = 1\right], \quad d_t^{\mathrm{term}} = \widehat{b}_t e_t^{\mathrm{comp}}.$$

Here, $\mathcal{V}_t$ is the task verifier and $\mathbb{I}[\cdot]$ is the binary indicator.

Remark. ARCO realizes learned effects conservatively: routing limits candidate-generation cost, causal–operational valuation ranks admissible alternatives, and advantage-margin authorization retains the factual workflow when evidence is insufficient.

3.3 Success-Preserving Objective and Authorization Constraints

Let τ be a complete execution trajectory, $\pi_{\mathrm{CHILL},\Theta}$ the policy induced by CIEL and ARCO, and π_{ref} the matched reference harness. CHILL-Harness treats success preservation as a constrained optimization target:

$$\min_{\Theta} \ \mathbb{E}_{\tau\sim\pi_{\mathrm{CHILL},\Theta}}[\mathcal{J}_{\mathrm{eff}}(\tau)] \quad \text{s.t.} \quad \mathrm{PassRate}(\pi_{\mathrm{CHILL},\Theta}) \geq \mathrm{PassRate}(\pi_{\mathrm{ref}}) - \epsilon_{\mathrm{pass}}.$$

Because environment execution is not differentiable, this target is implemented through outcome-conditioned weak supervision and conservative local authorization rather than as a formal guarantee on unseen trajectories. At inference time, only admissible route-exposed workflows can be executed, and termination requires both learned completion support and explicit task evidence. Appendix C.1–C.3 gives the trajectory cost, failure penalties, decision-target construction, and local authorization constraints; the full inference procedure appears in Appendix C.4. Algorithm 1 in Appendix C.4 gives the full inference procedure, including route selection, candidate construction, authorization, termination, and execution logging.

4 Experiments

We evaluate whether CHILL-Harness learns useful intervention-relative workflow preferences, realizes them efficiently and admissibly, and maintains task effectiveness while reducing execution cost. We examine these properties through three empirical questions:

- **RQ1: Effectiveness.** Does solving the Harness Intervention Effect Problem in Definition 1 identify adaptations that preserve or improve task success?
- **RQ2: Efficiency.** Does solving the Harness Intervention Realization Problem in Definition 2 reduce reasoning and execution cost without premature failure or termination?
- **RQ3: Cross-domain consistency.** Are the effectiveness–efficiency patterns consistently observed across heterogeneous execution environments?

We conduct baseline comparisons to assess whether CHILL-Harness maintains competitive effectiveness while improving efficiency across benchmarks, and perform an Always-Full ablation to isolate the contribution of route-before-generation counterfactual deliberation.

4.1 Experimental Setup

Benchmarks. We evaluate CHILL-Harness on **GAIA** for information seeking and tool-assisted reasoning (Mialon et al., 2024), **SWE-bench Verified** for repository-level software repair (Jimenez et al., 2024; OpenAI, 2025), and **Terminal-Bench 2.0** for long-horizon terminal interaction (Merrill et al., 2026). These benchmarks cover deliberation, revision, stabilization, verification, and completion under distinct execution environments.

Baselines. Each CHILL-Harness evaluation is paired with a reference run using the same model, tools, environment, task, and resource limits. For external comparison, we report Terminus-KIRA on all benchmarks (KRAFTON AI & Ludo Robotics, 2026); AWorld and OWL Workforce on GAIA (Yu et al., 2025a; Hu et al., 2025b); OpenHands and CodeSweep–SWE-agent on SWE-bench Verified (Wang et al., 2025a; Yang et al., 2024; Kimi Team, 2025); and Meta-Harness and LemonHarness on Terminal-Bench 2.0 (Lee et al., 2026; Ren et al., 2026). Public systems may cover different numbers of valid evaluation instances; their aggregate resource results are therefore used for descriptive external comparison.

Model Configuration. GAIA uses deepseek-v4-flash, whereas SWE-bench Verified and Terminal-Bench 2.0 use deepseek-v4-pro DeepSeek-AI (2026). CIEL is trained offline on disjoint paired traces and frozen for evaluation; checkpointed replay is disabled at test time. All model calls use temperature 1.0 and at most 150 interaction turns.

Benchmark	Method	Success	Tokens	Token Gain vs. Min.-Token	Tokens/Solved	Rel. Runtime	Time Gain vs. Min.-Runtime
GAIA	Terminus-KIRA	70.2%	134M	–	2.03M	1.00×	–
	AWorld	69.7%	161M	–	2.45M	1.25×	–
	OWL Workforce	69.1%	174M	–	2.68M	1.30×	–
	CHILL-Harness	**71.3%**	**96M**	**28.4%↓**	**1.43M**	0.534×	**46.6%↓**
SWE-bench Verified	Terminus-KIRA	65.0%	157M	–	2.42M	1.00×	–
	OpenHands	65.4%	165M	–	2.52M	1.10×	–
	CodeSweep–SWE-agent	53.4%	153M	–	2.87M	0.92×	–
	CHILL-Harness	**65.6%**	**133M**	**13.1%↓**	**2.25M**	0.682×	**25.9%↓**
Terminal-Bench 2.0	Terminus-KIRA	49.4%	291M	–	7.11M	1.00×	–
	Meta-Harness	52.6%	340M	–	5.00M	1.25×	–
	LemonHarness	57.4%	380M	–	5.05M	1.40×	–
	CHILL-Harness	**56.1%**	**224M**	**23.1%↓**	**4.87M**	0.974×	**2.6%↓**

Table 1: Effectiveness and efficiency across three long-horizon benchmarks. Token Gain and Time Gain use the eligible non-CHILL baseline with the lowest token consumption and runtime, respectively. Relative runtime is normalized to Terminus-KIRA within each benchmark. Token totals are rounded to the nearest million, whereas Tokens/Solved is reported to two decimal places. CHILL-Harness token totals include all additional model calls for counterfactual deliberation and candidate valuation. Public systems may cover different numbers of valid evaluation instances, so aggregate resource differences are descriptive rather than task-matched comparisons.

Evaluation Metrics. We report task success, total model tokens, tokens per solved task, end-to-end relative runtime, and resource gain against the corresponding reference baseline. Token accounting includes all model-based harness components, and runtime includes inference, orchestration, tools, environment interaction, and verification. Formal metric definitions and normalization rules are provided in Appendix D.1.

4.2 Main Results

Table 1 reports the primary effectiveness and resource measurements against public baselines; the joint success–token view is shown in Appendix D.2, Figure 2. Matched-reference comparisons assess the intended success-preserving behavior, whereas public-system comparisons assess external competitiveness.

RQ1: Effectiveness. Under matched model, tool, environment, task, and resource settings, CHILL-Harness is evaluated against a matched reference to assess whether its cost reductions are accompanied by substantial loss of task effectiveness. Against the displayed public systems, it achieves the highest success rate on GAIA (71.3%) and SWE-bench Verified (65.6%). On Terminal-Bench 2.0, its 56.1% success exceeds Terminus-KIRA and Meta-Harness and remains close to LemonHarness (57.4%). These results indicate competitive task performance rather than uniform improvement over every public baseline.

RQ2: Efficiency. CHILL-Harness achieves the highest number of solved tasks per one million tokens in each benchmark group. Its reported token totals are lower than the lowest-token public baselines by (28.4%), (13.1%), and (23.1%) on GAIA, SWE-bench Verified, and Terminal-Bench 2.0, respectively. The corresponding reported runtime differences are (46.6%), (25.9%), and (2.6%).

RQ3: Cross-domain consistency. CHILL-Harness improves both success and token efficiency over all displayed baselines on GAIA and SWE-bench Verified. On Terminal-Bench 2.0, it achieves the highest token efficiency, while LemonHarness retains a small success advantage, placing both systems on the effectiveness–efficiency frontier. The effectiveness–efficiency pattern is thus observed across information seeking, software repair, and terminal interaction. This evaluation establishes cross-domain breadth rather than cross-benchmark or cross-model transfer generalization.

Remark. Matched-reference comparisons assess the intended success-preserving behavior, while public-system comparisons show that CHILL-Harness consistently improves token efficiency and

Benchmark	Variant	Success	Tokens	Tokens/Solved	Full Calls / Revision Rate	Always-Full Overhead
GAIA	**CHILL-Harness**	**71.3%**	**96.00M**	**1.43M**	–	–
	Always-Full	27.7%	114.33M	4.40M	2,615 / 76.1%	18.33M tokens 37.73 h
SWE-bench Verified	**CHILL-Harness**	**65.6%**	**133.00M**	**2.25M**	–	–
	Always-Full	53.3%	160.40M	3.34M	3,708 / 3.5%	27.40M tokens 70.95 h
Terminal-Bench 2.0	**CHILL-Harness**	**56.1%**	**224.19M**	**4.87M**	–	–
	Always-Full	56.3%	259.77M	5.65M	4,234 / 3.9%	35.58M tokens 91.98 h

Table 2: Ablation Experiment Results. Full Calls / Revision Rate reports the number of full CDE events and the fraction of those events that authorize workflow revision. Always-Full Overhead reports the additional planner token consumption and cumulative planner latency incurred by Always-Full relative to CHILL-Harness on the same benchmark.

remains competitive in task effectiveness across the three evaluated long-horizon domains. These results support the design goal but do not constitute a formal success-preservation guarantee.

4.3 Ablation Experiment

We evaluate the contribution of CDE and its route-before-generation realization in ARCO. The Always-Full variant disables adaptive deliberation by setting $z_t = \textbf{FULL}$ whenever feasible, while retaining CIEL intervention prediction, CRE, and CAE, as well as ARCO candidate generation, admissibility filtering, valuation, and authorization. The comparison therefore isolates the effect of selecting deliberation depth before candidate generation.

Table 2 shows that forced full deliberation causes over-intervention on GAIA, increases cost while reducing success on SWE-bench Verified, and incurs substantial planner overhead with little benefit on Terminal-Bench 2.0. This suggests that additional deliberation is not uniformly beneficial: unnecessary candidate generation can introduce extra workflow alternatives and increase the chance of replacing an already adequate factual workflow. The result also indicates that CDE contributes not only by reducing planning cost, but by controlling when broader counterfactual search should be exposed to downstream revision and authorization. These results validate the contribution of CDE and its route-before-generation realization in ARCO.

Remark. CDE acts before candidate generation: CRE can reject unsupported workflow revisions only after the corresponding candidate-generation cost has been incurred, whereas route-before-generation suppresses low-value deliberation and avoids the associated planner overhead.

5 Conclusion

We introduced CHILL-Harness, a causal framework that learns whether and how the harness should intervene in the choice between factual and admissible alternative workflows. CIEL learns intervention-relative workflow advantage from matched execution evidence, and ARCO uses these estimates to allocate counterfactual reasoning and authorize workflow changes conservatively. Across information seeking, software repair, and terminal interaction, CHILL-Harness substantially improves token efficiency while maintaining competitive task effectiveness; the Always-Full ablation further supports the value of selective route-before-generation deliberation. These experiments demonstrate breadth across three heterogeneous domains rather than cross-benchmark or cross-model transfer generalization, and the success-preserving objective should be interpreted as a design target rather than a formal guarantee under prediction error. We hope this work encourages the development of learned, intervention-aware orchestration for more efficient and reliable long-horizon agents.

AI USE STATEMENT

Generative AI tools were used for limited research and authoring assistance. Cursor was used to assist with code implementation and modification, while ChatGPT was used for manuscript editing, including language refinement and presentation improvement. The research methodology, causal formulation, experimental design, result analysis, and interpretation of the findings were conducted by the authors. All AI-assisted outputs and edits were reviewed and revised by the authors, who take full responsibility for the final manuscript, code, experiments, and reported results.

ETHICS STATEMENT

This work studies adaptive orchestration for language-model-based agents using existing public benchmarks and model services. It does not involve the collection of new data from human participants or personally identifiable information. We use the corresponding benchmarks, environments, and model services subject to their applicable licenses and terms of use. As with other language-model-based agent systems, CHILL-Harness may inherit limitations, biases, or unsafe behaviors from the underlying language models, tools, and execution environments. The proposed authorization and admissibility mechanisms are intended to constrain workflow adaptation during evaluation, but they should not be interpreted as providing formal safety guarantees for deployment in unconstrained real-world environments.

REPRODUCIBILITY STATEMENT

We provide detailed descriptions of CHILL-Harness, including the causal harness orchestration formulation, intervention space, Causal Intervention Effect Learning (CIEL), factorized deliberation, revision, and completion decisions, and Advantage-Realizing Causal Orchestration (ARCO) in Section 3. The experimental settings, including benchmark environments, base models, comparison systems, evaluation metrics, and evaluation protocols, are described in Section 4. Appendix A.1–A.4 provides the formal problem definition, workflow-grounded intervention construction, intervention-selection analysis, matched paired-replay effect estimation, and CIEL training details. Appendix B.1–B.3 specifies route feasibility, candidate construction, causal–operational valuation, and conservative workflow authorization. Appendix C.1–C.4 further describes the success-preserving trajectory objective, weak-supervision construction, local authorization constraints, offline paired-effect collection, and complete inference procedure. Appendix D.1 provides the formal definitions of the reported effectiveness and efficiency metrics. Together, these descriptions specify the training, inference, evaluation, and resource-accounting procedures used in our experiments.

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A Problem Formalization and CIEL Foundations

This appendix provides the formal definitions, theoretical grounding, and training implementation of Causal Intervention Effect Learning (CIEL). Appendix A.1 formalizes the two harness intervention problems. Appendix A.2 specifies the structural connection between semantic interventions and executable workflows. Appendix A.3 derives an error-dependent bound for amortized intervention selection. Appendix A.4 specifies matched paired-replay effect estimation and details the separated supervision of workflow effects and factorized decisions.

A.1 Formalization of the Harness Intervention Problems

At execution step t, understood as a harness decision point within a single task trajectory, let

$$\chi_t = (s_t, c_t^{\mathrm{env}}, g_t)$$

denote the fixed execution context, where s_t is the execution state, c_t^{env} is the environment context, and g_t is the current task objective. The context is structured and is not assumed to be a continuous-valued state.

Let ω_t^0 denote the factual workflow proposed without additional harness adaptation, and let $\mathcal{A}_t$ denote the workflows admissible under the current task, environment, safety, and resource requirements, with

$$\omega_t^0 \in \mathcal{A}_t.$$

The executed workflow is represented by W_t, and its task- and resource-aware execution performance is represented by U_t.

For any $\omega \in \mathcal{A}_t$,

$$\mathrm{do}(W_t = \omega)$$

denotes executing workflow ω while holding χ_t fixed. All potential outcomes are evaluated under the same continuation policy π^{cont}, evaluation horizon, resource-accounting rule, and task evaluator; these shared conditions constitute the common continuation and evaluation protocol. The scalar $U_t(\omega)$ captures downstream task performance and is not assumed to be continuous, whereas local cost, risk, and execution-quality signals are represented separately by $\widehat{U}_{\mathrm{op}}$. We use the standard consistency condition: when $W_t = \omega$ is actually executed, the observed outcome satisfies $U_t = U_t(\omega)$.

Definition A.1: Harness Intervention Effect Problem. For an admissible workflow

$$\omega \in \mathcal{A}_t \setminus \{\omega_t^0\},$$

its intervention effect relative to the factual workflow is

$$\Gamma_t(\omega) = \mathbb{E}\left[U_t \mid \mathrm{do}(W_t = \omega), \chi_t\right] - \mathbb{E}\left[U_t \mid \mathrm{do}(W_t = \omega_t^0), \chi_t\right]. \tag{A1}$$

A positive value indicates expected improvement relative to the factual workflow, whereas a negative value indicates expected degradation. The factual workflow is the zero-effect reference:

$$\Gamma_t(\omega_t^0) = 0.$$

The estimand therefore assigns causal value to concrete executable workflows rather than directly to abstract intervention labels.

Definition A.2: Harness Intervention Realization Problem. Let

$$\widehat{\Gamma}_{\phi,t}(\omega) := \widehat{\Gamma}_\phi\left(\omega; \chi_t, \omega_t^0\right)$$

denote the estimated workflow effect, and let $\overline{\Omega}_t \subseteq \mathcal{A}_t$ be the route-exposed admissible workflow set with $\omega_t^0 \in \overline{\Omega}_t$. The highest-valued exposed candidate is

$$\omega_t^+ = \arg\max_{\omega \in \overline{\Omega}_t} \widehat{U}_{\mathrm{ARCO}}\left(\omega \mid \chi_t, z_t, \widehat{\Gamma}_{\phi,t}\right). \tag{A2}$$

The authorized workflow then satisfies

$$\omega_t^\star \in \left\{\omega_t^0, \omega_t^+\right\}. \tag{A3}$$

Candidate selection and execution authorization are distinct: selection identifies the strongest currently exposed candidate, whereas replacement additionally requires admissibility, learned revision support, and a sufficient estimated advantage. The resulting orchestration chain is workflow-effect estimation $\longrightarrow$ route-exposed valuation $\longrightarrow$ execution authorization.

A.2 WORKFLOW-GROUNDED INTERVENTION INDUCTION

Let

$$I_t \in \mathcal{I}_t^{\mathrm{wf}}$$

denote the semantic harness intervention selected at step t. The intervention families have the following meanings.

- KEEP preserves the factual workflow ω_t^0.
- DELIBERATE allocates additional reasoning without prescribing a particular workflow revision.
- REVISE(INSPECT) acquires execution evidence missing from the current context.
- REVISE(VERIFY) validates an intermediate state, tool result, or candidate answer.
- REVISE(VISUAL) invokes visual processing when image or multimodal evidence is required.
- STABILIZE(DEDUP) suppresses repeated or semantically redundant operations.
- STABILIZE(NOOPRECOVERY) redirects an execution that has produced an empty, ineffective, or stalled action.
- ANSWERSYNTHESIS redirects broad exploration toward evidence organization and answer construction without itself terminating execution.

These intervention families describe adaptation intents rather than unique workflows. The realization map

$$\mathcal{G}_t(\iota) = \mathcal{G}\left(\iota; \chi_t, \omega_t^0\right) \subseteq \mathcal{A}_t$$

instantiates intervention ι according to the current context, factual workflow, available tools, and task constraints. Unavailable intervention families are removed from the set considered at step t, so $\mathcal{G}_t(\iota) \neq \emptyset$ for every family entering a maximization.

Implementation correspondence. The intervention predictor produces a discrete intervention-family label. A workflow-construction component then converts the label into one or more structured workflow candidates. For KEEP, the constructed set contains only ω_t^0. For DELIBERATE, the harness allocates an additional reasoning step without forcing a tool or workflow change. For the three REVISE modes, candidate templates constrain the next workflow toward evidence inspection, result verification, or visual analysis. For the two STABILIZE modes, recent execution traces are checked for duplicate actions, repeated tool arguments, empty results, or stalled progress. ANSWERSYNTHESIS generates a nonterminal workflow that organizes available evidence into a candidate answer. Each generated workflow is parsed into the same internal representation used by the base harness before ARCO filtering and valuation.

Assumption A.1: Workflow Mediation. For fixed χ_t, each $\omega \in \mathcal{G}_t(\iota)$ is an executable realization of intervention ι, intervention I_t affects U_t only through the realized workflow W_t, and the potential-outcome consistency condition defined in Appendix A.1 holds. This is a structural modeling restriction rather than an identification result: semantic labels index workflow families but are not assigned context-independent causal values.

Under this assumption,

$$\mathbb{E}\left[U_t \mid \mathrm{do}(I_t = \iota, W_t = \omega), \chi_t\right] = \mathbb{E}\left[U_t \mid \mathrm{do}(W_t = \omega), \chi_t\right]. \tag{A4}$$

Hence, the effect associated with intervention ι is evaluated through its concrete realization ω, relative to ω_t^0. The same intervention family may therefore induce different effects across contexts and workflow realizations.

A.3 ERROR-BOUNDED AMORTIZED INTERVENTION SELECTION

For fixed (χ_t, ω_t^0), define the true and estimated values of intervention family ι as

$$V_t^{\mathrm{int}}(\iota) = \max_{\omega \in \mathcal{G}_t(\iota)} \Gamma_t(\omega), \tag{A5}$$

$$\widehat{V}_t^{\mathrm{int}}(\iota) = \max_{\omega \in \mathcal{G}_t(\iota)} \widehat{\Gamma}_\phi\left(\omega; \chi_t, \omega_t^0\right). \tag{A6}$$

Let

$$\mathcal{C}_t = \bigcup_{\iota \in \mathcal{I}_t^{\mathrm{wf}}} \mathcal{G}_t(\iota)$$

denote all workflows considered at step t, including the factual workflow, and define

$$\varepsilon_t = \sup_{\omega \in \mathcal{C}_t} \left| \widehat{\Gamma}_\phi\left(\omega; \chi_t, \omega_t^0\right) - \Gamma_t(\omega) \right|.$$

Let

$$\iota_t^\dagger = \arg\max_{\iota \in \mathcal{I}_t^{\mathrm{wf}}} V_t^{\mathrm{int}}(\iota)$$

be a true best intervention family,

$$\iota_t^* = \arg\max_{\iota \in \mathcal{I}_t^{\mathrm{wf}}} \widehat{V}_t^{\mathrm{int}}(\iota)$$

be the offline estimated target, and define the amortization gap

$$\rho_t = \widehat{V}_t^{\mathrm{int}}(\iota_t^*) - \widehat{V}_t^{\mathrm{int}}(\widehat{\iota}_t) \geq 0.$$

Proposition A.1: Effect-and-Amortization Error Bound. For any estimated workflow-effect function and online intervention predictor,

$$V_t^{\mathrm{int}}(\iota_t^\dagger) - V_t^{\mathrm{int}}(\widehat{\iota}_t) \leq 2\varepsilon_t + \rho_t. \tag{A7}$$

Proof. For every intervention family ι, the maximum operator and the definition of ε_t imply

$$\left| \widehat{V}_t^{\mathrm{int}}(\iota) - V_t^{\mathrm{int}}(\iota) \right| \leq \varepsilon_t.$$

Therefore,

$$\begin{aligned} V_t^{\mathrm{int}}(\iota_t^\dagger) &\leq \widehat{V}_t^{\mathrm{int}}(\iota_t^\dagger) + \varepsilon_t \\ &\leq \widehat{V}_t^{\mathrm{int}}(\iota_t^*) + \varepsilon_t \\ &= \widehat{V}_t^{\mathrm{int}}(\widehat{\iota}_t) + \rho_t + \varepsilon_t \\ &\leq V_t^{\mathrm{int}}(\widehat{\iota}_t) + 2\varepsilon_t + \rho_t. \end{aligned}$$

Rearranging proves Equation A7. □

Corollary A.1: Exact Intervention Recovery. Suppose that $\iota_t^\dagger$ is unique and define its true margin as

$$\Delta_t^{\mathrm{int}} = V_t^{\mathrm{int}}(\iota_t^\dagger) - \max_{\iota \neq \iota_t^\dagger} V_t^{\mathrm{int}}(\iota).$$

If

$$\Delta_t^{\mathrm{int}} > 2\varepsilon_t + \rho_t,$$

then

$$\widehat{\iota}_t = \iota_t^\dagger.$$

The result does not assume that estimated and true rankings are identical. Instead, it quantifies how workflow-effect estimation error and amortized prediction error jointly determine intervention-selection quality. When the online predictor reproduces the offline target, $\rho_t = 0$, and the selection regret is bounded by $2\varepsilon_t$.

A.4 CIEL Training and Separated Supervision

CIEL separates workflow-effect supervision from factorized decision supervision. The workflow-effect estimator is trained only from offline checkpointed paired executions that compare factual and alternative workflows from the same restored execution context. Retrospective trajectory evidence provides weak supervision for deliberation, revision, and completion decisions, but is not interpreted as direct supervision of the underlying conditional causal effect.

Checkpointed paired intervention records. For a selected training state, the harness checkpoints the execution context χ_t, including the agent context, recent execution memory, environment state, tool state, intermediate artifacts, and current task progress. The checkpoint is restored to execute the factual workflow ω_t^0 and an admissible alternative workflow ω as two isolated branches. Both branches use the same continuation policy π^{cont}, evaluation horizon, model and tool configuration, task evaluator, and resource-accounting rule. Branch-specific planning, model inference, tool interaction, and execution costs are included in the resulting utility.

Post-checkpoint randomness is either matched across branches when the environment permits common randomization, or independently sampled from the same continuation distribution. Candidate construction, the replay budget, and replay-inclusion criteria are determined before the corresponding paired outcomes are observed, so replay inclusion does not depend on the sign or magnitude of the realized utility difference.

The analysis set $\mathcal{C}_t$ in Appendix A.3 includes the factual workflow. For paired replay, define the counterfactual subset

$$\mathcal{C}_t^{\text{cf}} = \mathcal{C}_t \setminus \{\omega_t^0\}. \tag{A8}$$

No replay count is required for ω_t^0, whose relative effect is fixed to zero. If $\mathcal{C}_t^{\text{cf}} = \emptyset$, no paired-effect record is constructed at that state and KEEP remains the only available reference family.

For each $\omega \in \mathcal{C}_t^{\text{cf}}$, let $K_{t,\omega} \geq 1$ denote the number of valid paired replays, and let

$$U_t^{(k)}(\omega) \quad \text{and} \quad U_t^{(k)}(\omega_t^0)$$

denote the alternative and factual utilities in replay k. The empirical paired workflow difference is

$$\widetilde{\Gamma}_t^{\text{pair}}(\omega) = \frac{1}{K_{t,\omega}} \sum_{k=1}^{K_{t,\omega}} \left[U_t^{(k)}(\omega) - U_t^{(k)}(\omega_t^0) \right]. \tag{A9}$$

The factual reference is fixed by construction:

$$\widetilde{\Gamma}_t^{\text{pair}}(\omega_t^0) = \widehat{\Gamma}_\phi\left(\omega_t^0; \chi_t, \omega_t^0\right) = 0.$$

Matched-replay estimand. Because a finite checkpoint does not in general guarantee that every variable relevant to future execution has been perfectly reproduced, we distinguish the ideal intervention effect $\Gamma_t(\omega)$ from the effect represented by the checkpointed replay procedure. For an admissible alternative ω, define

$$\Gamma_t^{\text{pair}}(\omega) = \mathbb{E}\left[U_t^{\text{rep}}(\omega) - U_t^{\text{rep}}(\omega_t^0) \mid \chi_t, \mathcal{P}_t \right], \tag{A10}$$

where $U_t^{\text{rep}}(\cdot)$ denotes the downstream utility induced by the checkpoint-and-replay procedure and $\mathcal{P}_t$ denotes its fixed continuation, candidate-construction, evaluation, and inclusion protocol. Thus, $\Gamma_t^{\text{pair}}(\omega)$ is the *matched intervention-relative replay estimand* used to construct training supervision. It is not assumed a priori to equal the ideal conditional intervention effect $\Gamma_t(\omega)$.

We define the replay approximation gap as

$$\beta_t = \sup_{\omega \in \mathcal{C}_t^{\text{cf}}} \left| \Gamma_t^{\text{pair}}(\omega) - \Gamma_t(\omega) \right|. \tag{A11}$$

The quantity β_t captures residual discrepancy arising from checkpoint insufficiency, stochastic continuation, selective candidate construction, or other differences between the replay distribution and the ideal intervention distribution.

Assumption A.2: Outcome-Independent Matched Replay. For every retained paired record, the factual and alternative branches start from the same restored checkpoint, follow the same continuation and evaluation protocol, and do not interfere after branching. Conditional on the restored checkpoint and the fixed replay protocol $\mathcal{P}_t$, post-checkpoint randomness is independent of workflow assignment. Candidate construction, replay counts, and replay-inclusion criteria are determined without using the corresponding realized paired utility differences.

This assumption concerns the validity of the matched replay comparison. It does not by itself require the restored checkpoint to contain every latent variable needed to identify the ideal causal effect $\Gamma_t(\omega)$.

Proposition A.2: Unbiasedness and Concentration for the Matched-Replay Estimand. Under Assumption A.2,

$$\mathbb{E}\left[\widetilde{\Gamma}_t^{\mathrm{pair}}(\omega) \mid \chi_t, \mathcal{P}_t\right] = \Gamma_t^{\mathrm{pair}}(\omega) \tag{A12}$$

for every $\omega \in \mathcal{C}_t^{\mathrm{cf}}$.

Suppose additionally that

$$U_t^{\mathrm{rep}}(\omega) \in [u_{\min}, u_{\max}], \qquad R = u_{\max} - u_{\min}.$$

For nonempty $\mathcal{C}_t^{\mathrm{cf}}$, define

$$M_t = \left|\mathcal{C}_t^{\mathrm{cf}}\right|, \qquad K_t^{\mathrm{pair}} = \min_{\omega \in \mathcal{C}_t^{\mathrm{cf}}} K_{t,\omega}.$$

If paired replays are independent conditional on $(\chi_t, \mathcal{P}_t)$, then, with probability at least $1 - \zeta$,

$$\sup_{\omega \in \mathcal{C}_t^{\mathrm{cf}}} \left|\widetilde{\Gamma}_t^{\mathrm{pair}}(\omega) - \Gamma_t^{\mathrm{pair}}(\omega)\right| \le R\sqrt{\frac{2\log(2M_t/\zeta)}{K_t^{\mathrm{pair}}}}. \tag{A13}$$

Proof. Conditional on the restored checkpoint and fixed replay protocol, each paired difference is sampled from the matched replay distribution associated with the factual–alternative comparison. Linearity of expectation yields Equation A12. Each paired utility difference lies in $[-R, R]$. Hoeffding's inequality bounds the candidate-wise deviation of the empirical mean from its matched-replay expectation, and a union bound over the M_t counterfactual candidates gives Equation A13. □

Relation to the ideal intervention effect. Equation A12 establishes unbiasedness with respect to the matched-replay estimand, not unconditional identification of $\Gamma_t(\omega)$. If the restored checkpoint is additionally sufficient for the post-intervention outcome distribution and the replay continuation coincides with the continuation defining the potential outcomes in Appendix A.1, then

$$\Gamma_t^{\mathrm{pair}}(\omega) = \Gamma_t(\omega), \qquad \beta_t = 0.$$

Under this stronger condition, the paired replay estimator is also unbiased for the ideal intervention-relative effect. In the general case, CIEL uses $\widetilde{\Gamma}_t^{\mathrm{pair}}(\omega)$ as a matched intervention-relative effect proxy and does not require $\beta_t = 0$.

Connection to intervention-selection error. Define the effect-model fitting error relative to the paired targets as

$$\alpha_t = \sup_{\omega \in \mathcal{C}_t^{\mathrm{cf}}} \left|\widehat{\Gamma}_\phi\left(\omega; \chi_t, \omega_t^0\right) - \widetilde{\Gamma}_t^{\mathrm{pair}}(\omega)\right|.$$

Because the factual effect and its estimate are both fixed to zero, the workflow-effect error ε_t defined in Appendix A.3 satisfies, whenever $\mathcal{C}_t^{\mathrm{cf}} \neq \emptyset$,

$$\begin{aligned}\varepsilon_t &= \sup_{\omega \in \mathcal{C}_t} \left|\widehat{\Gamma}_\phi\left(\omega; \chi_t, \omega_t^0\right) - \Gamma_t(\omega)\right| \\ &\le \alpha_t + \sup_{\omega \in \mathcal{C}_t^{\mathrm{cf}}} \left|\widetilde{\Gamma}_t^{\mathrm{pair}}(\omega) - \Gamma_t^{\mathrm{pair}}(\omega)\right| + \beta_t.\end{aligned} \tag{A14}$$

Combining Equation A13 with Equation A14 gives, with probability at least $1 - \zeta$,

$$\varepsilon_t \le \alpha_t + R\sqrt{\frac{2\log(2M_t/\zeta)}{K_t^{\mathrm{pair}}}} + \beta_t. \tag{A15}$$

Applying Proposition A.1 then yields

$$\begin{aligned}V_t^{\mathrm{int}}(\iota_t^\dagger) - V_t^{\mathrm{int}}(\widehat{\iota}_t) \le 2\alpha_t + 2R\sqrt{\frac{2\log(2M_t/\zeta)}{K_t^{\mathrm{pair}}}} \\ + 2\beta_t + \rho_t.\end{aligned} \tag{A16}$$

The bound separates four sources of intervention-selection error: workflow-effect fitting error, finite paired-replay error, mismatch between the replay and ideal intervention distributions, and amortized intervention prediction error. When the stronger replay-sufficiency condition holds, $\beta_t = 0$, recovering the corresponding bound for an exact matched intervention comparison.

Paired workflow-effect training set. The workflow-effect training set is

$$\mathcal{D}_{\text{pair}} = \left\{ \left(\chi_t, \omega_t^0, \omega, \widetilde{\Gamma}_t^{\text{pair}}(\omega), w_{t,\omega} \right) : \omega \in \mathcal{C}_t^{\text{cf}} \right\},$$

where $w_{t,\omega} \geq 0$ is an offline-computed reliability weight determined from pre-specified replay-validity diagnostics, replay count, and comparison stability. The weight is constructed without using the sign of the observed paired effect and is used only during training; it is neither an externally supplied inference-time parameter nor a quantity predicted by CHILL-Harness.

Pairs are excluded when the checkpoint cannot be restored, when the two branches do not share the required continuation and evaluation protocol, or when their downstream outcomes cannot be isolated. Only valid checkpointed paired executions are treated as direct workflow-effect training records. Unpaired trajectories, incomplete comparisons, and model-scored candidates do not directly supervise $\widehat{\Gamma}_\phi$.

The workflow-effect estimator is trained by

$$\mathcal{L}_{\text{eff}} = \mathbb{E}_{\left(\chi_t, \omega_t^0, \omega, \widetilde{\Gamma}_t^{\text{pair}}(\omega), w_{t,\omega}\right) \sim \mathcal{D}_{\text{pair}}} \left[w_{t,\omega} \left(\widehat{\Gamma}_\phi \left(\omega; \chi_t, \omega_t^0 \right) - \widetilde{\Gamma}_t^{\text{pair}}(\omega) \right)^2 \right]. \tag{A17}$$

Accordingly, $\widehat{\Gamma}_\phi$ is trained to predict the intervention-relative signal represented by the paired replay distribution. Its interpretation as the ideal conditional intervention effect depends on the replay approximation gap characterized above.

Intervention target and objective. Candidate workflows are grouped by semantic intervention family. The offline intervention target is induced from the learned workflow-effect scores:

$$\iota_t^* = \arg \max_{\iota \in \mathcal{I}_t^{\text{wf}}} \max_{\omega \in \mathcal{G}_t(\iota)} \widehat{\Gamma}_\phi \left(\omega; \chi_t, \omega_t^0 \right). \tag{A18}$$

When no alternative family has a positive estimated effect, conservative tie-breaking assigns

$$\iota_t^* = \textsc{Keep}.$$

The amortized intervention predictor is trained by

$$\mathcal{L}_{\text{int}} = -\log p_{\theta_u} \left(\iota_t^* \mid \chi_t, \omega_t^0 \right). \tag{A19}$$

Thus, the intervention head amortizes preferences induced by the learned paired-effect estimator rather than independently constructing causal-effect labels.

Trajectory evidence for factorized decisions. For each intervention step, the implementation extracts

$$\mathcal{E}_t^{\text{dec}} = \left(Y_\tau, Y_{\text{ref}}, E_t^{\text{err}}, C_t^{\text{main}}, C_t^{\text{plan}}, r_t, c_t, \Delta_t^{\text{cf}}, \mathcal{H}_t^{\text{exec}} \right),$$

where Y_τ and Y_{ref} are the current and reference task outcomes; E_t^{err} records execution failure; C_t^{main} and C_t^{plan} record main-agent and planner costs; r_t and c_t summarize route and candidate statistics; and $\mathcal{H}_t^{\text{exec}}$ contains progress, repetition, failure, and completion evidence. A decision-target operator produces

$$\Psi_{\text{dec}} \left(\mathcal{E}_t^{\text{dec}} \right) = \left(z_t^*, y_t^{\text{chg},*}, b_t^* \right).$$

These quantities are outcome-conditioned weak decision labels. They are supervision for control decisions and are not interpreted as observations of either $\Gamma_t(\omega)$ or $\Gamma_t^{\text{pair}}(\omega)$.

Counterfactual Deliberation Effect target. The target

$$z_t^* \in \{\textsc{Skip}, \textsc{Light}, \textsc{Full}\}$$

specifies the preferred amount of additional deliberation. SKIP is assigned when the factual workflow is sufficient or additional planning yields no useful decision evidence. LIGHT is assigned when restricted diagnostics or a small candidate set is sufficient. FULL is assigned when broader generation or evaluation is required to improve intervention selection, recover ineffective execution, or avoid a high-risk factual action. Among routes that preserve decision quality and task success, the target favors the least costly route.

Counterfactual Revision Effect target. The target

$$y_t^{\mathrm{chg},*} \in \{\textsc{Keep}, \textsc{Change}\}$$

specifies whether the selected candidate ω_t^+ should replace the factual workflow. CHANGE requires evidence that the candidate improves the factual execution while preserving task success and satisfying the applicable authorization conditions. When valid paired execution evidence is available, the matched workflow difference provides the primary comparison signal. Unpaired retrospective evidence may provide auxiliary decision supervision but does not enter $\mathcal{D}_{\mathrm{pair}}$. Unsafe, invalid, task-incompatible, over-budget, duplicate, ineffective, or success-breaking candidates receive KEEP supervision.

Completion Attribution Effect target. The target

$$b_t^* \in \{0, 1\}$$

indicates whether task completion is supported by evidence already available at step t. The label $b_t^* = 1$ requires retrospective evidence that the task requirements were satisfied, such as a valid final answer, passing tests, a required artifact, or an environment-provided success state. Budget exhaustion, inactivity, repeated failure, predicted futility, or the absence of another action does not by itself produce a positive completion target.

Head-specific objectives. The factorized decision heads are trained by

$$\mathcal{L}_{\mathrm{CDE}} = -\log p_{\theta_p}\left(z_t^* \mid \chi_t, \omega_t^0, \widehat{\iota}_t\right), \tag{A20}$$

$$\mathcal{L}_{\mathrm{CRE}} = -\log p_{\theta_c}\left(y_t^{\mathrm{chg},*} \mid \chi_t, \omega_t^0, \omega_t^+, \widehat{\iota}_t\right), \tag{A21}$$

$$\mathcal{L}_{\mathrm{CAE}} = -\log p_{\theta_e}\left(b_t^* \mid \chi_t, o_t, h_t\right). \tag{A22}$$

The complete CIEL objective is

$$\mathcal{L}_{\mathrm{CIEL}} = \mathcal{L}_{\mathrm{eff}} + \mathcal{L}_{\mathrm{int}} + \mathcal{L}_{\mathrm{CDE}} + \mathcal{L}_{\mathrm{CRE}} + \mathcal{L}_{\mathrm{CAE}}. \tag{A23}$$

The terms use distinct sources of supervision: $\mathcal{L}_{\mathrm{eff}}$ fits workflow effects to valid checkpointed paired-replay targets; $\mathcal{L}_{\mathrm{int}}$ amortizes intervention preferences induced by the learned effect estimator; and $\mathcal{L}_{\mathrm{CDE}}$, $\mathcal{L}_{\mathrm{CRE}}$, and $\mathcal{L}_{\mathrm{CAE}}$ learn route, revision, and completion decisions from outcome-conditioned trajectory evidence. This separation prevents heuristic, retrospective, or model-scored decision signals from being presented as directly identified causal-effect observations.

B ARCO REALIZATION AND AUTHORIZATION DETAILS

This appendix explains how Advantage-Realizing Causal Orchestration (ARCO) implements CIEL decisions through route selection, candidate generation, causal–operational valuation, workflow authorization, and completion verification.

B.1 ROUTE FEASIBILITY AND CANDIDATE CONSTRUCTION

Let

$$\mathcal{Z} = \{\textsc{Skip}, \textsc{Light}, \textsc{Full}\}, \qquad \textsc{Skip} \prec \textsc{Light} \prec \textsc{Full}.$$

The ordering represents increasing deliberation depth, candidate-generation coverage, and execution cost. The provisional route is

$$\widetilde{z}_t = \arg\max_{z \in \mathcal{Z}} p_{\theta_p}\left(z \mid \chi_t, \omega_t^0, \widehat{\iota}_t\right). \tag{B1}$$

Let $C^{\mathrm{plan}}(z)$ be the predicted planning cost of route z, B_t^{plan} the remaining planning budget, N_t^{full} the number of previous full-deliberation calls, B^{full} their maximum allowed number, $t_{\mathrm{last}}^{\mathrm{full}}$ the most recent full-deliberation step, κ the full-route cooldown, $\mathcal{T}(z)$ the tools or capabilities required by route z, and $\mathcal{T}_t^{\mathrm{avail}}$ the currently available tools and capabilities. If no full route has previously been executed, set $t_{\mathrm{last}}^{\mathrm{full}} = -\infty$.

Define the common planning-and-tool feasibility indicator as

$$g_t(z) = \mathbb{I}\left[C^{\text{plan}}(z) \le B_t^{\text{plan}}\right] \mathbb{I}\left[\mathcal{T}(z) \subseteq \mathcal{T}_t^{\text{avail}}\right]. \tag{B2}$$

The route feasibility is

$$f_t(z) = \begin{cases} 1, & z = \textsc{Skip}, \\ g_t(z), & z = \textsc{Light}, \\ g_t(z)\,\mathbb{I}\left[\begin{array}{c} N_t^{\text{full}} < B^{\text{full}}, \\ t - t_{\text{last}}^{\text{full}} \ge \kappa \end{array}\right], & z = \textsc{Full}. \end{cases} \tag{B3}$$

The feasible route set is

$$\mathcal{F}_t = \{z \in \mathcal{Z} : f_t(z) = 1\}.$$

Because SKIP is always feasible, $\mathcal{F}_t \neq \emptyset$. The executed route is

$$z_t = \max_{\prec} \{z \in \mathcal{F}_t : z \preceq \widetilde{z}_t\}. \tag{B4}$$

Thus, an infeasible prediction is downgraded to the highest feasible route and is never upgraded beyond the learned prediction.

The raw route-specific candidate set is

$$\Omega_t^{\text{raw}} = \begin{cases} \{\omega_t^0\}, & z_t = \textsc{Skip}, \\ \{\omega_t^0\} \cup \mathcal{G}_t^{\text{light}}(\widehat{\iota}_t), & z_t = \textsc{Light}, \\ \{\omega_t^0\} \cup \mathcal{G}_t(\widehat{\iota}_t), & z_t = \textsc{Full}. \end{cases} \tag{B5}$$

Here, $\mathcal{G}_t^{\text{light}}(\widehat{\iota}_t) \subseteq \mathcal{G}_t(\widehat{\iota}_t)$ is a restricted, low-cost realization set. Candidate exposure is bounded by

$$K_{\textsc{Skip}} = 1, \qquad K_{\textsc{Light}} < K_{\textsc{Full}}.$$

These route budgets are distinct from the paired-replay quantity K_t^{pair} in Appendix A.4.

Let $\widehat{S}_t(\omega \mid \chi_t)$ be the workflow-safety score and ξ_t its minimum accepted threshold. Before expensive valuation, the retained candidate set is

$$\Omega_t = \{\omega_t^0\} \cup \text{TopK}_{K_{z_t}-1}\left\{\omega \in \Omega_t^{\text{raw}} \setminus \{\omega_t^0\} : \widehat{S}_t(\omega \mid \chi_t) \ge \xi_t\right\}, \tag{B6}$$

where $\text{TopK}_0(\cdot) = \emptyset$. When more candidates pass the safety threshold than the route budget allows, TopK retains them according to the low-cost workflow-construction score produced before full valuation. The admissible route-exposed set is

$$\overline{\Omega}_t = \Omega_t \cap \mathcal{A}_t. \tag{B7}$$

Because $\omega_t^0 \in \mathcal{A}_t$, the filtered set is nonempty.

Implementation correspondence. The CDE head outputs scores for the three route classes. A deterministic feasibility stage checks route-specific planning budgets, full-route limits and cooldown, required tools, and environment capabilities. Under SKIP, planner and candidate-generation calls are bypassed. Under LIGHT, the implementation uses restricted diagnostics and a small candidate budget. Under FULL, all configured route-compatible generation and evaluation operations are available. The implementation records the provisional route, executed route, downgrade reason, exposed candidates, prescreening decisions, and incurred planning cost.

B.2 CAUSAL–OPERATIONAL VALUATION

For each $\omega \in \overline{\Omega}_t$, let $\widehat{P}_t(\omega)$, $\widehat{C}_t(\omega)$, $\widehat{R}_t(\omega)$, $\widehat{I}_t(\omega)$, $\widehat{B}_t(\omega)$, and $\widehat{S}_t(\omega \mid \chi_t)$ denote estimated task progress, execution cost, operational risk, information gain, robustness, and workflow safety, respectively. All available signals are calibrated to a common bounded range before aggregation. A signal unavailable for a benchmark is omitted rather than assigned an arbitrary value.

Define the shared progress–risk–safety score and the full-route information–robustness bonus as

$$\widehat{Q}_t(\omega) = \alpha_{\text{prog}}\widehat{P}_t(\omega) - \alpha_{\text{risk}}\widehat{R}_t(\omega) + \alpha_{\text{safe}}\widehat{S}_t(\omega \mid \chi_t), \tag{B8}$$

$$\widehat{H}_t(\omega) = \alpha_{\text{info}}\widehat{I}_t(\omega) + \alpha_{\text{rob}}\widehat{B}_t(\omega). \tag{B9}$$

The route-conditioned operational utility is

$$\widehat{U}_{\text{op}}(\omega \mid \chi_t, z_t) = \begin{cases} 0, & z_t = \textsc{Skip}, \\ \widehat{Q}_t(\omega) - \alpha_{\text{cost}}^{\text{light}}\widehat{C}_t(\omega), & z_t = \textsc{Light}, \\ \widehat{Q}_t(\omega) - \alpha_{\text{cost}}^{\text{full}}\widehat{C}_t(\omega) + \widehat{H}_t(\omega), & z_t = \textsc{Full}. \end{cases} \tag{B10}$$

All coefficients are nonnegative. The light route omits information-gain and robustness estimation when restricted diagnostics are sufficient, whereas the full route uses the complete configured valuation.

The causal–operational utility is

$$\widehat{U}_{\text{ARCO}}\left(\omega \mid \chi_t, z_t, \widehat{\Gamma}_{\phi,t}\right) = \widehat{U}_{\text{op}}(\omega \mid \chi_t, z_t) + \eta_\Gamma \widehat{\Gamma}_{\phi,t}(\omega), \tag{B11}$$

where $\eta_\Gamma \geq 0$ controls the contribution of estimated workflow effect evidence. The strongest exposed candidate is

$$\omega_t^+ = \arg\max_{\omega \in \overline{\Omega}_t} \widehat{U}_{\text{ARCO}}\left(\omega \mid \chi_t, z_t, \widehat{\Gamma}_{\phi,t}\right). \tag{B12}$$

Its advantage over the factual workflow is

$$\begin{aligned} \Delta_t^{\text{cf}} = \widehat{U}_{\text{op}}\left(\omega_t^+ \mid \chi_t, z_t\right) - \widehat{U}_{\text{op}}\left(\omega_t^0 \mid \chi_t, z_t\right) \\ + \eta_\Gamma\left[\widehat{\Gamma}_{\phi,t}(\omega_t^+) - \widehat{\Gamma}_{\phi,t}(\omega_t^0)\right]. \end{aligned} \tag{B13}$$

The estimator enforces

$$\widehat{\Gamma}_{\phi,t}(\omega_t^0) = 0.$$

Implementation correspondence. Task-progress signals may be derived from newly acquired evidence, intermediate environment states, test results, or predicted goal advancement. Cost signals use expected or observed model tokens, planner calls, tool calls, and latency. Risk signals capture invalid actions, destructive operations, execution errors, or uncertain state changes. Information-gain signals estimate whether the candidate obtains evidence absent from the factual path. Robustness signals favor candidates that depend less on unverified assumptions or fragile execution sequences. The final score ranks only candidates in the route-exposed admissible set $\overline{\Omega}_t$.

B.3 Conservative Workflow Authorization

The CRE decision for the selected candidate is

$$y_t^{\text{chg}} = \arg\max_{y \in \{\textsc{Keep},\textsc{Change}\}} p_{\theta_c}\left(y \mid \chi_t, \omega_t^0, \omega_t^+, \widehat{\iota}_t\right). \tag{B14}$$

Keep retains the factual workflow, whereas Change provides learned support for replacement by ω_t^+. CRE and causal–operational valuation have complementary roles: CRE determines whether replacement is contextually supported, while Δ_t^{cf} determines whether the estimated improvement is large enough to justify revision.

The authorization rule is

$$\omega_t^\star = \begin{cases} \omega_t^+, & y_t^{\text{chg}} = \textsc{Change} \wedge \Delta_t^{\text{cf}} \geq \delta_{\widehat{\iota}_t}, \\ \omega_t^0, & \text{otherwise}, \end{cases} \tag{B15}$$

where $\delta_{\widehat{\iota}_t} \geq 0$ is the authorization margin for the predicted intervention family. Because ω_t^+ is selected from $\overline{\Omega}_t$, admissibility, safety, schema, task-compatibility, and budget checks have already been satisfied before this rule is applied.

For implementation diagnostics, define

$$a_t^{\text{sup}} = \mathbb{I}\left[y_t^{\text{chg}} = \textsc{Change}\right] \mathbb{I}\left[\Delta_t^{\text{cf}} \geq \delta_{\widehat{\iota}_t}\right], a_t^{\text{feas}} = \mathbb{I}\left[\omega_t^+ \in \overline{\Omega}_t\right], \tag{B16}$$

and

$$a_t^{\text{chg}} = a_t^{\text{sup}} a_t^{\text{feas}}.$$

The learned CRE output and final authorization result are logged separately, allowing prediction errors to be distinguished from constraint-triggered fallback. If either support or feasibility fails, ARCO retains ω_t^0.

Scope of workflow optimality. ARCO does not claim global optimization over the complete admissible workflow space $\mathcal{A}_t$. Instead,

$$\omega_t^+ = \arg\max_{\omega \in \overline{\Omega}_t} \widehat{U}_{\text{ARCO}}\left(\omega \mid \chi_t, z_t, \widehat{\Gamma}_{\phi,t}\right)$$

is optimal only within the route-exposed admissible set. CHILL-Harness executes this candidate when authorized and otherwise retains the factual workflow.

B.4 Evidence-Grounded Completion and Answer Synthesis

The CAE prediction is

$$\widehat{b}_t = \arg\max_{b \in \{0,1\}} p_{\theta_e}\left(b \mid \chi_t, o_t, h_t\right). \tag{B17}$$

The value $\widehat{b}_t = 1$ indicates learned completion support, whereas $\widehat{b}_t = 0$ indicates that completion is unsupported by the CAE head.

An explicit task verifier produces

$$e_t^{\text{comp}} = \mathbb{I}\left[\mathcal{V}_t\left(\chi_t, o_t, h_t\right) = 1\right], \tag{B18}$$

where $\mathcal{V}_t$ is the task-specific completion verifier. Termination is authorized by

$$d_t^{\text{term}} = \widehat{b}_t e_t^{\text{comp}}. \tag{B19}$$

Thus, termination requires both learned completion support and explicit task evidence.

The verifier may decompose completion evidence into strong, weak, and contradictory signals:

$$e_t^{\text{comp}} = \mathbb{I}\left[E_t^{\text{strong}} = 1 \ \vee \ \left(E_t^{\text{weak}} = 1 \ \wedge \ E_t^{\text{fail}} = 0\right)\right].$$

Strong evidence includes passing tests, successful builds, accepted solutions, or explicit environment success. Weak evidence includes a valid final answer or task-completion signal, whereas traceback, assertion, permission, and execution failures constitute contradictory evidence.

Implementation correspondence. The CAE head does not directly invoke the terminal action; its output is passed to the task-specific verifier. Depending on the benchmark, the verifier checks a required answer format, successful tests or evaluator results, the existence and validity of a required artifact, an environment-provided success state, or another explicit completion condition. Predicted futility, budget exhaustion, repeated failure, or lack of progress does not set $e_t^{\text{comp}} = 1$. Such signals may instead redirect execution toward AnswerSynthesis or another workflow adaptation. Therefore,

$$\textsc{AnswerSynthesis} \neq \textsc{Complete}.$$

The former is a nonterminal adaptation; the latter is an authorized terminal decision. The implementation records the CAE output, verifier result, supporting evidence, synthesis decision, and final terminal action.

C Success-Preserving Learning and Complete Inference

This appendix specifies the trajectory-level objective, the separated supervision scheme, local authorization constraints, offline paired-effect collection, and the complete CHILL-Harness inference procedure.

C.1 Success-Preserving Trajectory Objective

The learnable CIEL parameter set is

$$\Theta = \{\phi, \theta_u, \theta_p, \theta_c, \theta_e\}.$$

ARCO introduces no separate prediction parameters in the current formulation. It realizes CIEL outputs through candidate generation, valuation, filtering, and rule-based authorization with calibrated weights and thresholds. The underlying harness or environment supplies the factual workflow, admissibility constraints, tool availability, environment observations, and task verifier; paired-effect targets, reliability weights, and weak decision targets are constructed offline and are not learned inference-time inputs.

Let $\mathcal{K}$ denote the resource channels measured for a benchmark. The trajectory-level execution cost is

$$\mathcal{J}_{\text{eff}}(\tau) = \sum_{k \in \mathcal{K}} \lambda_k C_k(\tau), \tag{C1}$$

where $C_k(\tau)$ is the amount of resource k consumed by trajectory τ, and $\lambda_k \geq 0$ is its weight. For the reported experiments, the principal resource channels are

$$C_{\text{tok}}(\tau) = C^{\text{in}}_{\text{main}}(\tau) + C^{\text{out}}_{\text{main}}(\tau) + C^{\text{in}}_{\text{plan}}(\tau) + C^{\text{out}}_{\text{plan}}(\tau),$$

and

$$C_{\text{time}}(\tau) = T_{\text{main}}(\tau) + T_{\text{plan}}(\tau) + T_{\text{tool}}(\tau) + T_{\text{env}}(\tau) + T_{\text{verify}}(\tau). \tag{C2}$$

The reported total token count includes main-agent and counterfactual-planner calls made during benchmark inference. Offline paired-replay collection is a training-data construction procedure and is not included in test-time token or runtime measurements; its cost is tracked separately.

The global objective is

$$\begin{aligned} \min_{\Theta} \quad & \mathbb{E}_{\tau \sim \pi_{\text{CHILL},\Theta}} \left[\mathcal{J}_{\text{eff}}(\tau)\right] \\ \text{s.t.} \quad & \text{PassRate}\left(\pi_{\text{CHILL},\Theta}\right) \geq \text{PassRate}\left(\pi_{\text{ref}}\right) - \epsilon_{\text{pass}}. \end{aligned} \tag{C3}$$

Here, $\pi_{\text{CHILL},\Theta}$ is the execution policy induced by CIEL and ARCO; π_{ref} is the matched reference harness; $\text{PassRate}(\pi)$ is the fraction of evaluated tasks completed successfully by policy π; and $\epsilon_{\text{pass}} \geq 0$ is the allowed aggregate pass-rate degradation. This constrained objective states the desired optimization target; because training relies on finite logged and paired executions, it does not provide a formal pass-rate guarantee on unseen trajectories. Success is determined by the benchmark evaluator rather than by the harness completion prediction.

C.2 Trajectory Supervision and Decision-Target Construction

Let

$$Y_\tau \in \{0, 1\} \quad \text{and} \quad Y_{\text{ref}} \in \{0, 1\}$$

indicate whether the CHILL-Harness and matched reference trajectories succeed, respectively. The trajectory supervision score is

$$\mathcal{L}_{\text{traj}}(\tau) = \mathcal{J}_{\text{eff}}(\tau) + \lambda_{\text{fail}}\left(1 - Y_\tau\right) + \lambda_{\text{break}} \mathbb{I}\left[Y_{\text{ref}} = 1 \ \wedge \ Y_\tau = 0\right]. \tag{C4}$$

The first term measures execution cost, the second penalizes task failure, and the third penalizes adaptations that break a successful reference trajectory. The coefficients $\lambda_{\text{fail}}, \lambda_{\text{break}} \geq 0$ control the two failure penalties.

Separated supervision correspondence. The trajectory score is not differentiated through external tools or the environment. Instead, it determines valid samples, confidence weights, and weak decision targets:

$$\mathcal{L}_{\text{traj}} \longrightarrow \left(z_t^*, y_t^{\text{chg},*}, b_t^*\right).$$

Workflow-effect supervision is constructed separately:

$$\mathcal{D}_{\text{pair}} \longrightarrow \widetilde{\Gamma}_t^{\text{pair}}(\omega) \longrightarrow \widehat{\Gamma}_\phi \longrightarrow \iota_t^*.$$

Thus, retrospective trajectory evidence does not directly define or supervise the identified workflow-effect target. CDE targets select the least costly route preserving decision quality; CRE targets determine whether the selected candidate should replace the factual workflow; and CAE targets determine whether completion is already supported by evidence.

C.3 Local Authorization Constraints

Using the unified safety score from Appendix B, the admissible workflow set is

$$\begin{aligned}\mathcal{A}_t = \{\omega : \widehat{S}_t\left(\omega \mid \chi_t\right) \geq \xi_t \\ \wedge\ \mathrm{SchemaValid}(\omega) \\ \wedge\ \mathrm{TaskCompatible}\left(\omega; \chi_t\right) \\ \wedge\ \mathrm{WithinBudget}\left(\omega; \chi_t\right) \\ \wedge\ \neg\,\mathrm{Repeated}_t(\omega)\}.\end{aligned} \tag{C5}$$

Here, $\widehat{S}_t(\omega \mid \chi_t)$ is the workflow-safety score and ξ_t its minimum threshold; $\mathrm{SchemaValid}$ checks workflow and tool-call structure; $\mathrm{TaskCompatible}$ checks that proposed operations are permitted in the current task and environment; $\mathrm{WithinBudget}$ checks remaining model, planning, tool, revision, and execution budgets; and $\mathrm{Repeated}_t$ identifies duplicate or repeatedly ineffective workflows.

Each generated candidate is parsed and passed through these checks before valuation and authorization. Rejected candidates are removed from

$$\overline{\Omega}_t = \Omega_t \cap \mathcal{A}_t,$$

and their rejection reasons are stored in the execution trace. Revision satisfies

$$\omega_t^\star = \omega_t^+ \Longrightarrow \left[y_t^{\mathrm{chg}} = \textsc{Change} \ \wedge\ \Delta_t^{\mathrm{cf}} \geq \delta_{\widehat{\iota}_t}\right],$$

and completion satisfies

$$d_t^{\mathrm{term}} = 1 \Longrightarrow \left[\widehat{b}_t = 1 \ \wedge\ e_t^{\mathrm{comp}} = 1\right].$$

Together, these constraints ensure

$$\omega_t^\star \in \overline{\Omega}_t \subseteq \mathcal{A}_t$$

and prevent unsupported revision or premature termination.

C.4 Complete Inference, Offline Pairing, and Logging

Algorithm 1 Complete CHILL-Harness Inference

1: **Input**: $\chi_t, \omega_t^0, o_t, h_t$; **Output**: $\omega_t^\star, d_t^{\text{term}}$
2: Predict
$$\widehat{\iota}_t = \arg\max_{\iota \in \mathcal{I}_t^{\text{wf}}} p_{\theta_u}\left(\iota \mid \chi_t, \omega_t^0\right)$$
3: Predict the provisional route
$$\widetilde{z}_t = \arg\max_{z \in \mathcal{Z}} p_{\theta_p}\left(z \mid \chi_t, \omega_t^0, \widehat{\iota}_t\right)$$
and select the highest feasible route $z_t \preceq \widetilde{z}_t$
4: Generate the raw route-conditioned candidate set Ω_t^{raw} using Equation B5
5: Prescreen candidates using Equation B6 and obtain Ω_t
6: Filter admissible candidates:
$$\overline{\Omega}_t = \Omega_t \cap \mathcal{A}_t$$
7: For each $\omega \in \overline{\Omega}_t$, estimate
$$\widehat{\Gamma}_{\phi,t}(\omega) = \widehat{\Gamma}_\phi\left(\omega; \chi_t, \omega_t^0\right)$$
and compute $\widehat{U}_{\text{ARCO}}(\omega \mid \chi_t, z_t, \widehat{\Gamma}_{\phi,t})$
8: Select ω_t^+ and compute Δ_t^{cf} using Equations B12 and B13
9: Predict CRE support:
$$y_t^{\text{chg}} = \arg\max_{y \in \{\textsc{Keep},\textsc{Change}\}} p_{\theta_c}\left(y \mid \chi_t, \omega_t^0, \omega_t^+, \widehat{\iota}_t\right)$$
10: Authorize $\omega_t^\star$ using Equation B15
11: Compute
$$\widehat{b}_t = \arg\max_{b \in \{0,1\}} p_{\theta_e}\left(b \mid \chi_t, o_t, h_t\right)$$
and
$$d_t^{\text{term}} = \widehat{b}_t \mathbb{I}\left[\mathcal{V}_t\left(\chi_t, o_t, h_t\right) = 1\right]$$
12: **if** $d_t^{\text{term}} = 1$ **then**
13: Invoke the task-terminal action
14: **else**
15: Execute $\omega_t^\star$
16: **end if**
17: Log decisions, candidate evaluations, rejection reasons, execution costs, observations, errors, and task outcomes

The inference record contains at least

$$\left(\chi_t, \omega_t^0, \widehat{\iota}_t, \widetilde{z}_t, z_t, \Omega_t^{\text{raw}}, \Omega_t, \overline{\Omega}_t, \omega_t^+, \Delta_t^{\text{cf}}, y_t^{\text{chg}}, \omega_t^\star, \widehat{b}_t, e_t^{\text{comp}}, d_t^{\text{term}}\right), \tag{C6}$$

together with tool calls, observations, rejection reasons, costs, errors, and final task outcomes.

Offline paired-effect collection. Checkpointed paired replay is performed only during offline training-data construction. For each selected training checkpoint and counterfactual candidate, the implementation restores the same checkpoint, executes the factual and candidate branches under the common continuation and evaluation protocol, computes Equation A9, and adds the resulting record to $\mathcal{D}_{\text{pair}}$. CIEL parameters are then trained on the designated training split and frozen before benchmark evaluation. No paired replay, effect-model update, or decision-head update is performed on evaluation tasks.

The complete learning and execution flow is offline paired execution $\longrightarrow \widetilde{\Gamma}_t^{\text{pair}} \longrightarrow \widehat{\Gamma}_\phi \longrightarrow \iota_t^*$, trajectory evidence $\longrightarrow \left(z_t^*, y_t^{\text{chg},*}, b_t^*\right)$, frozen CIEL predictions $\longrightarrow$ ARCO realization $\longrightarrow$ authorized execution.

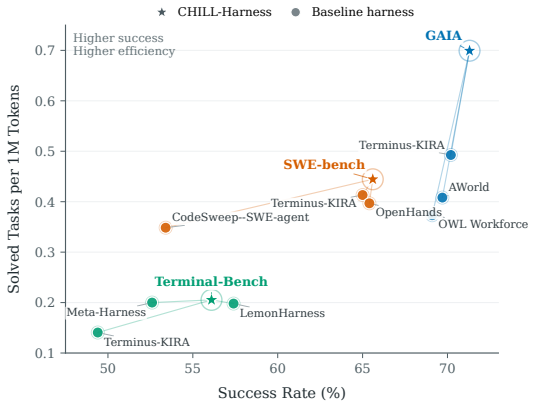


Figure 2: Joint effectiveness–efficiency comparison on GAIA, SWE-bench Verified, and Terminal-Bench 2.0. The horizontal axis reports task success and the vertical axis reports solved tasks per one million tokens; higher values on both axes are preferred. Stars denote CHILL-Harness, circles denote public baseline harnesses, and colors group methods evaluated on the same benchmark.

D Experimental Metrics and Additional Visualization

This appendix collects evaluation definitions and the secondary effectiveness–efficiency visualization moved from the main paper for space while preserving the complete experimental specification.

D.1 Evaluation Metrics

Let m denote a method, N_m the number of valid evaluation instances reported for method m, and $y_i^{(m)} \in \{0,1\}$ whether m solves instance i. Effectiveness is measured by $\mathrm{Success}(m) = \frac{1}{N_m}\sum_{i=1}^{N_m} y_i^{(m)} \times 100\%$. Reasoning cost is measured by $\mathrm{Tokens}(m) = \sum_{i=1}^{N_m}\sum_{k\in\mathcal{K}_m}\left(\mathrm{Tok}_{i,k}^{\mathrm{in}} + \mathrm{Tok}_{i,k}^{\mathrm{out}}\right)$, $\mathrm{Tokens/Solved}(m) = \frac{\mathrm{Tokens}(m)}{\sum_{i=1}^{N_m} y_i^{(m)}}$, where $\mathcal{K}_m$ includes all model-based harness components. Let $T_i^{(m)}$ be the end-to-end runtime of method m on task i, including inference, orchestration, tools, interaction, and verification: $\mathrm{RelativeRuntime}(m; b_T) = \frac{\sum_{i=1}^{N_m} T_i^{(m)}}{\sum_{i=1}^{N_m} T_i^{(b_T)}}$. For $X \in \{\mathrm{Tokens}, T\}$, resource gain is $\mathrm{Gain}_X(m; b_X) = \left(1 - \frac{X(m)}{X(b_X)}\right) \times 100\%$. Here, b_T and b_X denote the runtime and resource reference baselines, respectively.

D.2 Joint Effectiveness–Efficiency Visualization

Figure 2 provides a joint view of task effectiveness and token efficiency across the three evaluated benchmarks, complementing the numerical comparisons reported in the main text. The visualization highlights the relative trade-off between success rate and solved tasks per one million tokens, allowing the effectiveness–efficiency position of CHILL-Harness to be compared directly with the corresponding public baselines.