GUARD-AND-GUIDE RUNTIME SAFETY FOR LONG-HORIZON LLM AGENTS

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ABSTRACT

Large language model (LLM)-driven agents are increasingly deployed in long-horizon tasks, where the harms of individually low-risk actions can accumulate over time and eventually lead to safety failures. Existing parametric alignment methods and non-parametric memory mechanisms struggle to detect subtle risks and provide timely protection. To address this challenge, we propose **G2A** (Guard-and-Guide), a framework for safe long-horizon agent execution. A lightweight **Guard** scores candidate actions in the current interaction context. When a risk score exceeds a specified threshold, a procedural **Guide** selects and executes a reusable Safety Skill. To detect context-dependent risks, G2A introduces **Trajectory-Contrastive Safety Distillation (TCSD)**, which contrasts the same candidate action under matched safe and unsafe trajectory contexts and distills the resulting evidence into the Guard. The Guide organizes Safety Skills through explicit activation, intervention, and termination conditions, enabling state-aware skill activation, switching, termination, and fallback. It also records the scenario and action risk type at each use to support evolving skill reuse. Experiments on ATBench-C, AgentS4D, and HINTBench show that **G2A** improves long-horizon safety, enables fine-grained risk localization and cross-scenario skill reuse, and preserves agents' task completion capability. Our code is available at `https://anonymous.4open.science/r/G2A-2228`.

1 INTRODUCTION

Large Language Model (LLM)-driven agents have shown strong performance in complex sequential decision making Liu et al. (2024); Yao et al. (2022). However, such performance often relies on on-the-fly reasoning, where agents continuously interpret instructions, observations, and environmental feedback to determine their next actions Xi et al. (2025); Shi et al. (2026). During this process, safety risks may not arise from an explicitly harmful action at a single step, but instead emerge and accumulate over multiple interactions. A locally reasonable decision can alter subsequent environmental states or constrain later action choices, gradually pushing the trajectory toward an irreversible unsafe outcome Zhang et al. (2024). As interaction horizons increase, these latent deviations become increasingly difficult to identify and correct in time, allowing small errors to compound across steps and ultimately reducing the reliability of agent execution Zhang et al. (2025b).

For safe and trustworthy LLM agents, existing work broadly falls into two paradigms. **Parametric methods**, such as Reinforcement Learning (RL), attempt to encode safety experience into model parameters Zhang et al. (2025c). While effective in specific domains, these approaches struggle with credit assignment in long-horizon tasks, making it difficult to attribute reward signals to the specific problematic actions Sha et al. (2025). Alternatively, **non-parametric methods** improve agent behavior at inference time without updating the base LLM, most commonly through external safety memory Wei et al. (2025). These methods store diverse forms of safety related experience, including past trajectories (Chen et al., 2025), distilled reflections (Mohajer Hamidi et al., 2026), and structured graphs (Oliveira & Cook, 2012; Jin et al., 2024) or workflows (Georgakopoulos et al., 1995), and retrieve them to condition subsequent LLM reasoning. However, memory and skill mechanisms primarily equip agents with knowledge and capabilities they do not inherently possess, rather than providing independent supervision and real time correction over ongoing task execution. (Mi et al., 2026; Xu & Yan, 2026; Wang et al., 2026b; Huet et al., 2025).

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Furthermore, many existing ReAct-style safeguards are organized around step-level action validation, screening each proposed action or tool invocation before execution Mou et al. (2026); Xiang et al. (2024). While such action-centric monitoring is effective for locally identifiable violations, when the safety implication of an action depends on its preceding context or downstream consequences, these approaches typically lack long-horizon dynamic action monitoring methods to continuously inspect proposed actions and identify emerging behavioral deviations (Mi et al., 2026; Xu & Yan, 2026; Wang et al., 2026b). Building upon this foundation, our work further proposes an independent, long-horizon dynamic action monitor and action safeguard mechanisms to ensure the safety and trustworthiness of long-horizon tasks.

However, establishing long-horizon dynamic safety monitoring and real-time correction for agents raises three fundamental challenges. **C1: Long-Horizon Runtime Hazard Detection.** The system must continuously identify state-dependent risks before proposed actions are executed. **C2: Long-Horizon Corrective Runtime Intervention.** The agent must determine when to intervene during long-horizon tasks and how to correct unsafe behavior without unnecessarily disrupting normal task execution. **C3: Experience-Driven Safe Adaptation.** The protection module must continuously learn from trajectory-level safety feedback to guarantee its corrective capabilities over time.

To address these challenges, we propose **G2A**, a **G**uard-and-**G**uide **A**rchitecture that equips LLM agents with dynamic safety monitoring and real-time correction without updating the agent backbone. **G2A** separates runtime safety into two complementary roles: a lightweight **Guard** continuously screens proposed actions for safety-critical deviations before execution, while a procedural **Guide** invokes reusable Safety Skills to correct unsafe behavior.

For Runtime Hazard Detection **(C1)**, **G2A** introduces **Trajectory-Contrastive Safety Distillation (TCSD)**, which contrasts the same candidate action across matched safe and unsafe trajectory contexts to isolate fine-grained, context-dependent safety evidence. TCSD distills this evidence into the lightweight Guard, enabling it to continuously assess proposed actions under evolving interaction states. For Corrective Runtime Intervention **(C2)**, **G2A** leverages a Skill-Augmented Safety MDP to dynamically load Skills based on the current safety state. This mechanism decides when to activate, switch, or terminate interventions for the corresponding risky actions, thereby enabling targeted correction without unnecessarily disrupting normal task execution. For Experience-Driven Safe Adaptation **(C3)**, detected safety violations are localized to the specific interaction steps responsible for the failure, which in turn triggers component-specific updates to the relevant Safety Skills. At deployment, the frozen Guard continuously monitors candidate actions; whenever an unsafe deviation is detected, the Guide provides immediate procedural intervention through schema validated Safety Skills. Experiments demonstrate that **G2A** not only improves end-to-end safety by achieving accurate runtime hazard detection and targeted corrective intervention, but also continuously evolves reusable safety procedures from interaction experience while fully preserving task utility.

Our core contributions are three-fold: **(i) Runtime Hazard Detection:** We introduce **G2A**, which uses a lightweight Guard trained with Trajectory-Contrastive Safety Distillation (TCSD) to detect context dependent risks before action execution.

(ii) Corrective Runtime Intervention: A procedural Guide provides state-aware intervention by adaptively activating, switching, terminating, and falling back among structured Safety Skills.

(iii)Experience-Driven Refinement: Guide intervention pairs are used to refine the Guard through offline TCSD supervision to continually refine the Guard.

2 METHODOLOGY

G2A is a **Runtime Detection and Intervention** framework built on a **Guard-and-Guide** mechanism. We first leverage benchmark-native data to estimate action-level risk scores via TCSD, training a lightweight Guard network. During deployment, the Guard operates as a plug in module that ingests the model's behavior sequences to continuously monitor the risk of candidate actions. When the risk exceeds a fixed threshold, a reusable Safety Skill is triggered. This Skill not only corrects the immediate next action, but also summarizes the environmental context and risk patterns to prompt the underlying model toward safer and more rational behaviors. Concurrently, the system records risky actions and their Guard-approved corrections as intervention experiences. A frozen editor uses these experiences to localize recurring risks and propose component-specific edits to the Skill pool.

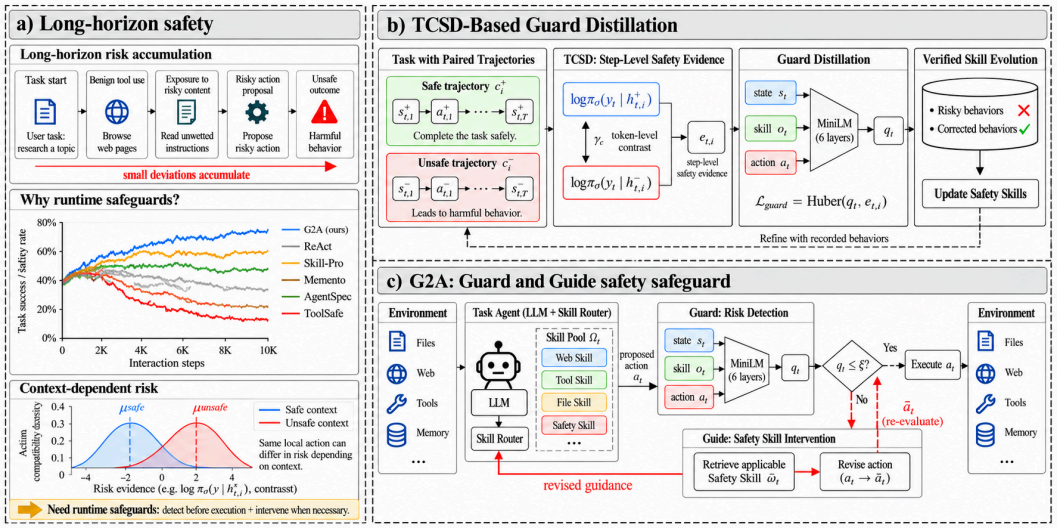


Figure 1: **Overview of G2A.** During training, TCSD converts labeled safe and unsafe trajectories into step-level evidence, which is utilized to train the Guard risk identification model. At deployment, the Guard monitors the risk scores of proposed actions and dynamically loads reusable Skills.

The Guard remains frozen during deployment; subsequent improvements arise from Skill evolution rather than online Guard retraining. Figure 1 provides an overview.

2.1 Guard-and-Guide Formulation

Achieving safety and trustworthiness in dynamic environments requires answering two fundamental questions: (1) **The Guard:** How can we reliably quantify the risk of every action across varying environments? (2) **The Guide:** How can we provide targeted *Safety Skills* to steer the agent away from violations while preserving task utility?

We formalize this dual challenge as a Skill-Augmented Safety Markov Decision Process (MDP), denoted as $\mathcal{M}_{\Omega_t} = (\mathcal{S}, \mathcal{A}, \Omega_t, P, R, \gamma)$, where $\mathcal{S}$ and $\mathcal{A}$ represent the state and action spaces, respectively, and Ω_t is the dynamic Skill pool. Let Π_Ω denote the composite agent policy jointly determined by the underlying large language model (LLM) and the currently active Skill. Our optimization objective is to maximize long-horizon task utility (The Guide) while ensuring that the immediate risk of every candidate action is controlled (The Guard):

$$\max_{\Pi_\Omega} \mathbb{E}_{\tau\sim\Pi_\Omega}\left[\sum_{t=0}^{T}\gamma^t R(s_t, a_t)\right] \qquad \text{s.t.} \qquad q_t = f_\theta(s, a_t) \le \xi, \quad \forall t. \tag{1}$$

Here, $q_t = f_\theta(s_t, \omega_t, a_t)$ is a calibrated action-level risk score (where higher values indicate greater risk), and ξ is a selected threshold. If $q_t > \xi$, the router retrieves applicable Skill content and proposes a revised action. This revised action is subsequently rescored and executed only when it satisfies the same threshold condition. If no applicable Skill is available, or if the revised action still violates the threshold constraint, the system triggers the Skill's conservative fallback mechanism, requesting additional information or directly aborting the current subtask.

2.2 The Guard: TCSD-Based Risk Distillation

To enforce the Guard constraint ($q_t \le \xi$) in Eq. 1, scoring every proposed action with a large LLM judge is computationally prohibitive for real-time reflexes. Instead, we distill a lightweight Guard model, f_θ, to independently quantify the contextual risk of each state-skill-action tuple. For each task instance i, the dataset provides a safe full trajectory c_i^+ and an unsafe full trajectory c_i^- collected under the same task specification. We utilize these trajectories exclusively as task-matched auxiliary information. Given a current state $s_{i,t}$ and a candidate action $a_{i,t}$ from a separate execution,

TCSD keeps the candidate action fixed and evaluates its token likelihood under the safe and unsafe full-trajectory references, respectively. Let C denote a trajectory is safe. The safety contribution of an action a is then given by $\operatorname{logit} \pi_\phi(C \mid s, a) - \operatorname{logit} \pi_\phi(C \mid s) = \log \frac{\pi_\phi(a|s,C)}{\pi_\phi(a|s,\neg C)}$. Where $\operatorname{logit}(u) = log \frac{u}{1-u}$We approximate the negation of this term to formulate the risk coefficient. We adopt the TCSD Eq. 2 keeps the candidate action fixed and evaluates its token likelihood under the safe and unsafe full-trajectory references, respectively. This contrast thereby captures the empirical log-likelihood difference under safe and unsafe reference trajectories, serving as an estimator of the log-odds update for safety violation.

$$e_{i,t} = \frac{1}{L_{i,t}} \sum_{j=1}^{L_{i,t}} \left[\log \pi_\phi(y_j \mid h^-_{i,t,j}) - \log \pi_\phi(y_j \mid h^+_{i,t,j}) \right], \tag{2}$$

where $h^\pm_{i,t,j} = (s_{i,t}, c^\pm_i, y_{<j})$, y_j denotes a token of the candidate action, and future actions beyond the current state are not included in h^+ and h^-, and π_ϕ is a frozen Qwen3-32B scorer. A larger $e_{i,t}$ indicates that the candidate action is more compatible with unsafe than safe execution. If the two reference conditioned likelihoods approximate action distributions conditioned on unsafe and safe outcomes, respectively, $e_{i,t}$ estimates a length normalized log odds update toward violation. This provides action-level supervision from trajectory-level examples, while preserving the current state and candidate action in both comparisons. We compute these targets offline for actions sampled from separate executions and train the Guard on $(s_{i,\le t}, a_{i,\le t}, e_{i,t})$ tuples. The privileged reference trajectories are never inputs to the Guard.

Guard Distillation. We instantiate the Guard f_θ using a MiniLM (Wang et al., 2020), offering strong semantic representations at a fraction of the inference cost of standard LLMs. We serialize the interaction context as $[\mathrm{CLS}]\, s_{i,t}\, [\mathrm{SEP}]\, a_{i,t}$, allowing the Guard to explicitly condition its risk assessment on the currently active Skill ($\omega_{i,t}$).

The model maps the $[\mathrm{CLS}]$ token to a scalar risk score and is optimized via a Huber regression (Yang et al., 2024) objective over the reference dataset $\mathcal{D}_{\mathrm{RM}}$:

$$\mathcal{L}_{\mathrm{Guard}} = \widehat{\mathbb{E}}_{(i,t)\sim\mathcal{D}_{\mathrm{RM}}} \left[\mathrm{Huber}\left(f_\theta(s_{i,\le t}, a_{i,\le t}), e_{i,t} \right) \right]. \tag{3}$$

The Huber loss limits the influence of noisy teacher contrasts; the validation-selected action threshold ξ then converts the Guard's signed evidence score into an intervention decision. For trajectory-level risk assessment, we aggregate the action-level Guard scores by taking their arithmetic mean. Specifically, for a trajectory $\tau_i = (s_{i,\le t}, a_{i,\le t})_{t=1}^{T_i}$, its trajectory-level risk score is defined as $\bar{q}_i = \frac{1}{T_i} \sum_{t=1}^{T_i} q_{i,t}$. For trajectory-level classification, a trajectory is flagged as unsafe if its aggregated score exceeds a validation threshold ($\hat{y}_i = \mathbb{I}[\bar{q}_i > \xi_{\mathrm{traj}}]$). Due to their distinct objectives, ξ_{traj} and the action-level threshold ξ are calibrated independently. The $q_{i,t} = f_\theta(s_{i,\le t}, a_{i,\le t})$. Once trained, the Guard f_θ is frozen. During deployment, it operates as a fast, real-time sentinel, outputting $q_{i,t}$ to determine if a Skill intervention is necessary, thereby bypassing the heavy online teacher computations entirely.

2.3 Guard-and-Guide Runtime Intervention

A Safety Skill is represented as $\omega = \langle \mathcal{I}_\omega, \pi_\omega, \beta_\omega \rangle$, specifying its applicability condition ($\mathcal{I}_\omega$), correction policy (π_ω), and termination criteria (β_ω).

Guard-Triggered Skill Execution. At each time step t, the agent proposes an initial action. If the Guard's predicted risk exceeds the operational threshold ($q_t > \xi$), the Guide mechanism intervenes. In our Skill-MDP, the agent first selects a Safety Skill via a routing policy μ, conditioned on the current state s_t and the dynamic Skill pool Ω: $\omega_t \sim \mu(\omega \mid s_t, \Omega)$, where μ ensures $s_t \models \mathcal{I}_{\omega_t}$. Conditioned on this active Skill, the agent then generates a revised primitive action using the Skill's correction policy: $\tilde{a}_t \sim \pi_{\omega_t}(a \mid s_t, \omega_t)$. Accordingly, the hierarchical intervention policy over Skills and primitive actions factorizes as:

$$\pi_\Omega(\omega_t, \tilde{a}_t \mid s_t) = \mu(\omega_t \mid s_t, \Omega) \pi_{\omega_t}(\tilde{a}_t \mid s_t, \omega_t). \tag{4}$$

The revised action is re-scored by the Guard and executed only if $q_t \le \xi$. If the check fails, the Skill applies its fallback and the action is not sent to the environment. The active Skill controls the

trajectory segment $T_\omega(\tau)$ until β_{ω_t} is satisfied, the activation condition becomes false, or a safety check fails.

Risk-Localized Skill Evolution. Although the factorization in Eq. 4 resembles that of memory augmented agents, which typically optimize the retrieval policy μ, we focus on evolving the Skill pool Ω from intervention experiences.

For each trajectory that triggers the risk threshold, the Guard identifies the first flagged step, $t_i^\star = \min\{t : q_{i,t} > \xi\}$. A frozen editor then examines this step and its Skill-controlled segment $\mathcal{T}_\omega(\tau_i)$ to determine whether the risk arose from inappropriate activation ($\mathcal{I}_\omega$), insufficient guidance (π_ω), or delayed termination (β_ω). Initially, the Skill pool contains only a generic Skill that alerts the agent to the detected risk and its likely category. The agent uses this information to propose a revised action $\tilde{a}_t$. The action is executed only if it passes the Guard check, $f_\theta(s_t, \omega, \tilde{a}_t) \leq \xi$; otherwise, it is rejected and the fallback mechanism is invoked.

Recurring contexts and diagnosed causes are consolidated into component-specific edits:

$$\bar{g}_\omega = \text{Aggregate}\left(\{g_{i,\omega}\}_{i \in \mathcal{F}_\omega}\right), \qquad \omega'_k = \omega \oplus \bar{g}_\omega^{(k)}, \quad k \in \{\mathcal{I}, \pi, \beta\}. \tag{5}$$

These edits turn recurring risk patterns into Skill applicability conditions or intervention guidance, allowing subsequent interventions to become more targeted. Actions proposed under an evolved Skill must still pass the same Guard check before execution. The Skill evolution pipeline is detailed in Appendix C.4.

3 EXPERIMENTS

We ask whether **G2A** enhances overall agent safety in long-horizon tasks without sacrificing general capabilities, and whether it can accurately identify and intervene on potential risks during execution. Our evaluation covers the overall safety utility performance (§3.1), the effectiveness of runtime interventions in long-horizon scenarios (§3.2), the advantages of TCSD-based step-level monitoring compared to existing baselines (§3.3), and ablation studies on the **G2A** (§3.4).

Benchmarks. We evaluate our method on three complementary agent-safety benchmarks. **ATBench** (Li et al., 2026b) evaluates task completion under explicit safety and trustworthiness policies; **AgentS4D** (Zhou et al., 2026b) evaluates runtime safety against risks introduced through heterogeneous interaction sources, including files, Web content, tools, Skills, and memory; and **HINTBench** (Wang et al., 2026a) provides step-level risk annotations for evaluating fine-grained safety attribution. For all three benchmarks, ATBench and HINTBench serve as standard evaluation datasets for long-horizon tasks, while AgentS4D is a critical benchmark for agent safety. We partition the datasets into training, valid and testing splits at a 7:1.5:1.5 ratio. The safe and violating reference trajectories used by **G2A** are part of the original released data.

Baselines. All baselines are evaluated with the same acting backbone, task split, decoding budget, and available benchmark supervision. Methods that require an additional judge or memory are charged for those calls in the efficiency analysis. We compare against representative methods from four categories: standard agent reasoning (**ReAct** (Yao et al., 2022)); non-parametric agent adaptation (**Skill-Pro** (Mi et al., 2026), **Memento-Skills** (Zhou et al., 2026a), **ACE** (Zhang et al., 2026), **AWM** (Wang et al., 2024), and **GEPA** (Agrawal et al., 2026)); inference-time safety enforcement (**Safety-Prompt**, **AgentSpec** (Wang et al., 2025), **ToolSafe** (Mou et al., 2026), **SafeHarbor** (Liu et al., 2026b), **AGrail** (Luo et al., 2025), and **GuardAgent** (Xiang et al., 2024)); and parameterized safety training (**MOSAIC** (Agarwal et al., 2026), SafeHarness (Lin et al., 2026) and **SafeAgent** (Liu et al., 2026a). Unless otherwise specified, non-parametric baselines use the same frozen LLM and interaction budget as our method.

LLM Backbones. We further evaluate cross-backbone transfer using **GPT-5.4** and **Qwen3-32B**. Benchmark native model configurations are additionally reported where appropriate. Implementation details are provided in Appendix C.

Evaluation Metrics. On ATBench-C, we report **Accuracy**, **Precision**, **Recall**, and **F1** for coarse-grained safe/unsafe trajectory classification. On AgentS4D, we report **cASR**, **SHR**, and **TCR** to measure runtime safety while separately tracking task completion. On HINTBench, we evaluate action-level risk scoring and fine-grained localization using reward rubric agreement, localization F1, and risk-onset error. Metric definitions are provided in Appendix C.3.

Table 1: **Safety performance on ATBench-C and AgentS4D across LLM backbones.** For ATBench-C, Acc., Prec., Rec., and F1 measure coarse-grained safe/unsafe trajectory classification. For AgentS4D, cASR denotes conditional Attack Success Rate, SHR denotes Safe Handling Rate, and TCR denotes Task Completion Rate. ↑/↓: higher/lower is better. Bold/underlined values indicate best/second-best results. Results are averaged across six independent runs (std: 0.3–0.7). * indicates outperforming the second-best baseline by $>$ 3std.

Method	ATBench-C								AgentS4D					
	Qwen3-32B				GPT-5.4				Qwen3-32B			GPT-5.4		
	Acc. ↑	Prec. ↑	Rec. ↑	F1 ↑	Acc. ↑	Prec. ↑	Rec. ↑	F1 ↑	cASR ↓	SHR ↑	TCR ↑	cASR ↓	SHR ↑	TCR ↑
Base Agent														
Base Model	58.1	57.5	62.0	59.7	73.7	68.5	87.1	76.7	64.2	29.8	<u>97.4</u>	51.8	41.2	<u>98.2</u>
General Agent & Experience-based Adaptation														
ReAct (2022)	60.5	59.8	64.0	61.8	75.0	70.0	87.5	77.8	58.0	37.0	96.5	45.0	50.0	97.8
Skill-Pro (2026)	63.1	62.5	65.5	64.0	76.9	72.0	88.0	79.2	55.0	39.5	97.2	43.0	52.0	97.6
Memento-Skills (2026a)	62.4	61.8	65.0	63.4	76.4	71.5	87.8	78.8	52.5	42.0	97.0	41.0	54.0	97.5
ACE (2026)	63.6	63.0	66.0	64.5	77.8	73.0	88.2	79.9	51.0	43.0	96.8	39.0	56.0	97.6
AWM (2024)	64.1	63.5	66.3	64.9	78.2	73.5	88.3	80.2	50.5	44.5	96.9	38.5	57.5	97.7
GEPA (2026)	64.6	64.0	66.7	65.3	78.7	74.0	88.5	80.6	50.0	44.0	96.8	37.5	57.0	97.6
Training-free Safety Alignment & Enforcement														
AgentSpec (2025)	69.1	68.0	72.0	69.9	82.7	79.0	89.0	83.7	30.0	60.0	93.8	23.0	69.0	95.0
ToolSafe (2026)	67.4	66.5	70.0	68.2	81.0	77.0	88.5	82.4	35.0	56.0	96.0	27.0	65.0	97.0
SafeHarbor (2026b)	71.5	70.5	74.0	72.2	84.3	81.0	89.5	85.0	26.8	65.5	95.3	20.0	73.0	96.4
AGrail (2025)	70.7	69.8	73.0	71.4	83.8	80.5	89.2	84.6	27.5	64.0	95.6	20.8	71.5	96.6
GuardAgent (2024)	70.0	69.0	72.5	70.7	83.4	80.0	89.0	84.3	28.0	63.0	95.4	21.5	70.5	96.5
Parameterized Safety Alignment & Post-training														
MOSAIC (2026)	72.0	71.0	74.5	72.7	84.7	81.5	89.7	85.4	26.0	66.0	94.8	19.5	73.0	96.0
SafeAgent (2026a)	<u>72.9</u>	<u>72.0</u>	<u>75.0</u>	<u>73.5</u>	<u>85.1</u>	<u>82.0</u>	<u>90.0</u>	<u>85.8</u>	<u>25.3</u>	<u>67.0</u>	95.2	<u>18.8</u>	<u>74.0</u>	96.2
SafeHarness (2026)	72.2	71.2	74.6	72.9	84.8	81.7	89.8	85.6	26.5	66.0	95.0	19.8	72.5	96.1
G2A (Ours)	**78.5***	**77.3***	**77.5***	**77.4***	**87.8***	**84.0**	**91.0**	**87.4***	**24.2**	**70.3***	**98.2***	**17.5***	**76.0***	**98.4**

3.1 CAN **G2A** MAINTAIN SAFE EXECUTION OVER LONG-HORIZON AGENT TASKS?

G2A effectively improves agent safety without sacrificing general-purpose capability. Across both ATBench-C and AgentS4D, it provides stronger protection against unsafe long-horizon behavior while maintaining task completion, and Table 2 further shows that these safety gains do not come at the cost of degraded performance on general agent benchmarks. We evaluate **G2A** against general agent and experience-based learning methods, as well as training-free safety methods (SafetyPrompt, AgentSpec, and ToolSafe), on two complementary long-horizon agent safety benchmarks (Table 1).

On ATBench-C, **G2A** consistently outperforms both general-agent and safety-specific baselines in trajectory-level safety recognition, indicating more reliable identification of unsafe long-horizon behavior. On AgentS4D, general reasoning and experience-based methods preserve task completion but remain more vulnerable to unsafe execution, whereas several safety-oriented methods reduce violations at the expense of utility. In contrast, **G2A** achieves stronger runtime safety while retaining high task completion across both Qwen3-32B and GPT-5.4. Moreover, as shown in Table 2, these empirical safety improvements are accompanied by comparable or stronger performance on AgentBench (Liu et al., 2024), GAIA2 (Froger et al., 2026), BFCL-v4 (Hao et al., 2025), and WebArena (Zhou et al., 2024), suggesting that the learned safety procedures improve safe execution without degrading the agent's general capabilities.

Table 2: **Safety–utility trade-off on Qwen3-32B.** Safety is evaluated on AgentS4D, and general utility.

Metric	Base Model	AgentSpec	AGrail	SafeAgent	G2A (Ours)
Safety on AgentS4D					
cASR ↓	64.2	30.0	27.5	25.3	**24.2**
SHR ↑	29.8	60.0	64.0	67.0	**70.3**
General agent capability					
AgentBench SR ↑	44.8	40.1	41.0	36.8	**45.2**
GAIA2 Pass@1 ↑	8.6	5.8	6.2	5.1	8.6
BFCL-v4 Acc. ↑	48.7	46.9	47.8	47.6	**49.1**
WebArena SR ↑	18.9	16.2	18.6	18.5	**19.1**

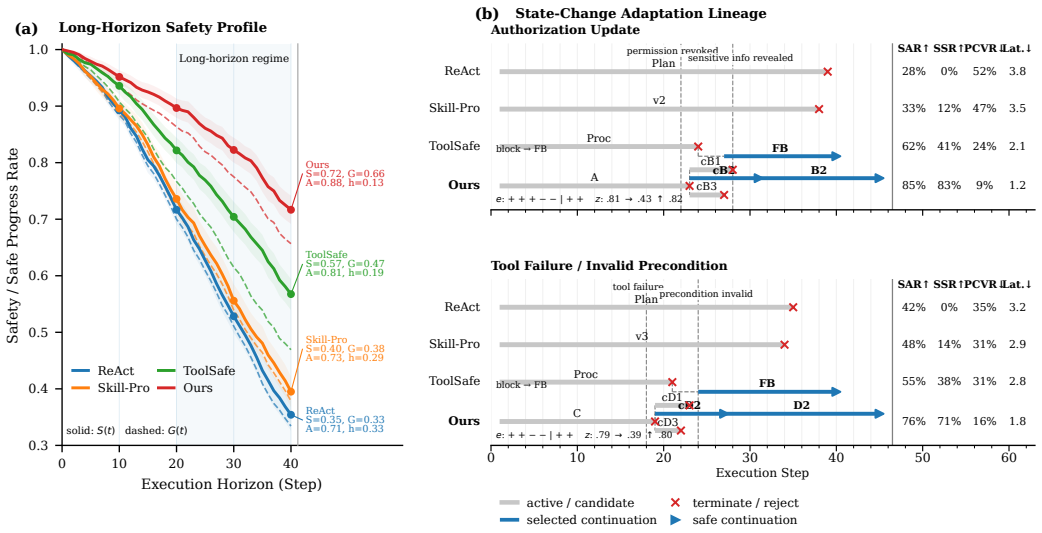


Figure 2: **Long-horizon safety and adaptation.** (a) Safety survival $S(t)$ and progress $G(t)$ ($H = 40$ steps). A: normalized AUC for $S(t)$. $h_{31:40}$: late-stage conditional violation hazard. Shaded regions denote 95% CIs. (b) Agent adaptation to controlled state changes, evaluated via SAR (Acknowledgment Rate), SSR (Safe Switch Rate), PCVR (Post-Change Violation Rate), and Lat. (capped latency).

3.2 Can **G2A** Mitigate Long-Horizon Safety Drift?

G2A effectively mitigates safety degradation over long-horizon execution and adapts reliably when safety-relevant conditions change after planning (Figure 2). We evaluate these properties against ReAct, Skill-Pro, and ToolSafe under identical tasks and interaction budgets. As shown in Figure 2(a), **G2A** preserves both safety survival and safe progress more effectively as execution horizons increase, while exhibiting fewer late stage violations. ReAct and Skill-Pro deteriorate more rapidly over long trajectories, whereas ToolSafe provides stronger protection but sacrifices more safe progress. In contrast, **G2A** maintains a higher empirical rate of safe execution without relying on conservative early termination, showing that its advantage persists throughout long-horizon interaction rather than only at early execution stages. Figure 2(b) further shows that this advantage extends to dynamic state changes. When authorization, sensitive information, tool availability, or execution preconditions change, ReAct and Skill-Pro more often continue procedures that are no longer appropriate, while ToolSafe tends to rely on blocking or fallback behavior. **G2A** instead identifies when the current procedure should be revised and transitions to a safety-feasible continuation, resulting in more reliable switching, fewer post-change violations, and faster adaptation. Together, these results show that **G2A** reduces both measured accumulated safety drift and the mismatch between an initial plan and evolving execution states.Detailed experimental setups and metric formulations can be found in Appendix D.2.

3.3 Can TCSD Guard Faithfully Identify Safety Decisions?

We evaluate TCSD Guard on HINTBench against TRACE (Li et al., 2026a) and a step-level LLM judge, measuring agreement with human and independent LLM rubric assessments as well as risk-onset sensitivity and localization across trajectory lengths.

TCSD Guard produces action-level risk scores that align more closely with both human judgments and independent LLM rubric assessments than the deployable baselines. Against human annotations (Table 3), it consistently achieves stronger score correlation and pairwise agreement while yielding lower prediction error than TRACE. The same pattern holds against the independent LLM consensus, indicating that the improvement is not tied to a particular source of supervision. Moreover, the distilled Guard approaches the agreement achieved by the substantially larger Qwen3-32B two-

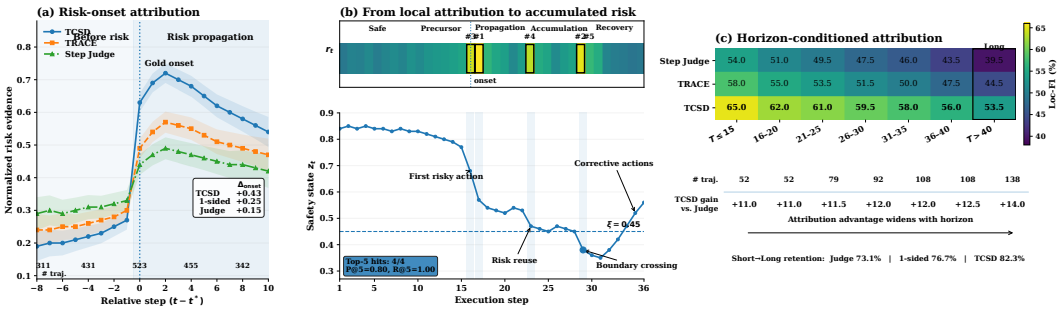


Figure 3: **Step-level safety attribution with TCSD. (a)** Risk evidence aligned at the first annotated risky step ($t - t^* = 0$). **(b)** Local TCSD evidence and the evolving safety state along a representative long-horizon trajectory. **(c)** Risk-step localization across trajectory-length intervals.

Table 3: **Agreement of action-level risk scores with human and independent LLM rubric assessments on HINTBench.** All scorers evaluate the same held-out state action pairs. Human reference scores aggregate 50 blinded annotators using a shared five-level risk rubric; the LLM reference aggregates GPT5.6 independent rubric judges. Pair Agree measures agreement on risk ordering within matched action pairs. MAE is computed after fitting a score mapping on a separate validation split. Bold marks the best result among the deployable learned monitors.

Risk scorer	Human rubric reference				Independent LLM rubric consensus			
	Pearson r ↑	Spearman ρ ↑	Pair Agree ↑	MAE ↓	Pearson r ↑	Spearman ρ ↑	Pair Agree ↑	MAE ↓
Deployable learned monitors								
step label+MiniLM score	0.70	0.72	78.0	0.20	0.77	0.79	82.0	0.17
TRACE	0.76	0.78	84.1	0.16	0.812	0.832	86.4	0.14
TCSD Guard (6-layer MiniLM)	**0.84**	**0.86**	**89.8**	**0.11**	**0.855**	**0.874**	**90.2**	**0.10**
High-cost scoring references								
Qwen3-32B two-sided scorer	0.86	0.88	91.2	0.10	0.872	0.889	91.7	0.09
GPT-5.6 rubric judge	0.82	0.84	88.0	0.13	0.837	0.857	88.5	0.12

sided scorer, while retaining the efficiency required for online action-level monitoring during agent execution. Figure 3 further illustrates how the resulting scores capture the temporal development of risk. TCSD evidence increases sharply near the annotated onset of unsafe behavior (Figure 3a), while the example in Figure 3b shows how subsequent actions continuously update the monitored safety state. TCSD also provides more accurate risk-step localization than TRACE and direct step judging across all reported trajectory-length intervals (Figure 3c). Its advantage remains evident on the longest trajectories, where delayed and accumulated risks are especially difficult to localize. These results support TCSD Guard as a lightweight runtime monitor for detecting emerging risks and triggering corrective Skill interventions throughout long-horizon execution. We conducted reliability and threshold sensitivity analyses for the Guard. The results, detailed in the Appendix C.5, demonstrate the Guard's strong performance as an estimator.

3.4 Ablation Study

To assess the contribution of the Guard and Guide components, we evaluate Guard supervision on ATBench-C and end-to-end execution on AgentS4D. For Guard supervision, we compare one-sided evidence, task-matched references, action-length normalization, and the complete paired TCSD objective. For runtime execution, we evaluate five variants: (1) **w/o Guide**, which retains Guard detection but disables Skill-based action correction; (2) **w/o generic safety prompt**, which removes applicability-aware Skill selection; (3) **w/o revised-action rescoring**, which executes the Guide's revised action without a second Guard check; (4) **w/o Skill evolution**, which keeps the initial Skill pool fixed; and (5) **w/o rule- based action revision**, which applies editor outputs without checking whether they are parseable and modify only the declared Skill component.

As shown in Table 4(a), paired trajectory evidence consistently outperforms supervision based on either safe or unsafe contexts alone. Performance also degrades when task-matched references or action-length normalization is removed, with the latter affecting both fine-grained precision and re-

Table 4: **Key ablations of G2A.** (a) Guard supervision on ATBench-C. (b) Runtime intervention and schema-validated Skill evolution on AgentS4D. The full results in Appendix C.6.2.

(a) Guard supervision on ATBench-C

Guard variant	C-F1 ↑	F-P ↑	F-R ↑
Safe-context evidence only	73.4	82.1	88.7
Unsafe-context evidence only	74.1	83.0	89.3
TCSD w/o task-matched references	72.6	81.5	88.1
TCSD w/o action-length normalization	74.8	83.2	89.9
TCSD (paired and normalized)	**77.4**	**84.0**	**91.0**

(b) Runtime intervention and Skill evolution

G2A variant	cASR ↓	SHR ↑	TCR ↑
w/o Guide	28.7	62.4	94.8
w/o generic safety prompt	26.0	66.1	96.7
w/o revised-action rescoring	26.8	66.0	97.9
w/o Skill evolution	25.1	66.8	97.5
w/o rule- based action revision	27.4	64.8	96.0
G2A (full)	**24.2**	**70.3**	**98.2**

call. These results support constructing TCSD from matched safe unsafe contexts and normalizing token-level evidence across actions of different lengths. Table 4(b) further shows that each component contributes to end-to-end agent safety. Removing the Guide leads to more successful attacks, while disabling applicability-aware routing or pre-execution re-scoring similarly weakens intervention effectiveness. Skill evolution improves the safety utility trade-off compared with a fixed Skill pool. rule- based action revisionis also important, as its removal causes concurrent degradation in safety, safe handling, and task completion. Overall, the full system provides the strongest balance between runtime safety and task utility. We emphasize that schema validation serves only as a structural constraint on editor outputs, rather than providing an additional safety signal.

4 Related Work

Learning from Interaction and Procedural Skills. LLM agents improve from interaction through either parametric updates, including reinforcement and preference optimization Ouyang et al. (2022); Rafailov et al. (2023); Guo et al. (2025), or non-parametric adaptation that externalizes experience as reusable memory. Existing methods store trajectories, abstracted knowledge, structured memory, or explicit workflows and Skills Park et al. (2023); Zhao et al. (2024); Zhang et al. (2025a); Wang et al. (2024; 2023); Tan et al. (2024); Han et al. (2025); Fang et al. (2025). Recent procedural approaches such as Skill-Pro evolve reusable Skills from experience without updating the base LLM. Our work follows this non-parametric paradigm, but focuses on learning procedural *safety* knowledge for long-horizon agent execution.

Safety Alignment and Runtime Safeguards for LLM Agents. Agent safety methods broadly either internalize safety through additional training or constrain behavior at inference time. The former fine-tunes agent policies on safe or adversarial interaction data Zhang et al. (2025c); Sha et al. (2025), while the latter employs runtime rules, tool-level guards, verification, sandboxing, and external safety controllers Wang et al. (2025); Ruan et al. (2024). Although these approaches can reduce unsafe actions, they typically encode safety as trained policies, fixed rules, or local intervention mechanisms, rather than reusable procedural knowledge learned continually from interaction. A comprehensive literature review is provided in Appendix B.

5 Conclusion

We introduced **G2A**, a Guard-and-Guide architecture for mitigating safety risks in long-horizon LLM agents without updating the underlying backbone. A lightweight Guard, trained via Trajectory Contrastive Safety Distillation, proactively detects state-dependent risks, while a procedural Guide deploys reusable Safety Skills to revise risky actions subject to Guard re-verification. **G2A** further localizes failure steps to autonomously evolve Skill components through schema-validated edits, leveraging intervention logs for offline Guard refinement. Across multiple benchmarks, **G2A** improves runtime safety and step-level hazard detection while preserving task utility and enabling cross-backbone Skill reuse. These results demonstrate that integrating continuous lightweight monitoring, procedural intervention, and experience-driven adaptation provides a practical paradigm for long-horizon agent safety.

AI USE STATEMENT

Generative AI tools were used during manuscript preparation to assist with language editing, LaTeX formatting. All methodological decisions, implementations, experimental results, analyses, citations, and scientific claims were independently reviewed and verified by the authors. Generative AI tools were not used to autonomously conduct experiments, generate or modify reported measurements, or determine the conclusions of this work. The authors take full responsibility for the content of the paper.

ETHICS STATEMENT

This work studies safety alignment for LLM-based agents and is intended to reduce unsafe behavior during multi-step interaction and tool use. Our experiments use existing research benchmarks and controlled evaluation environments. Although this study involves human subjects, their participation is strictly limited to consenting human experts who score the data, posing no ethical concerns. Some benchmarks contain harmful requests or safety critical scenarios as part of their evaluation protocols. These examples are used solely to measure and improve model safety in controlled settings, and our experiments do not execute harmful actions in real-world systems. As with other work on agent safety, analyses of model failure modes may have dual use implications. We therefore focus on aggregate evaluation and mitigation methods rather than operational guidance for causing harm. We follow the licenses and terms of use of the models and benchmarks used in this study and strictly adhere to the ICLR Code of Ethics.

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Algorithm 1 G2A: Guard Distillation and Runtime Skill Evolution

Require: Task-matched reference data $\mathcal{D}_{\mathrm{RM}}$; frozen scorer π_ϕ; frozen editor $\mathcal{E}$; router–Guide prompt $\mathcal{G}$; threshold ξ; rounds K
Ensure: Frozen Guard $f_{\theta^\star}$ and Skill pool $\Omega^\star$

I. Guard distillation
for all $(s, \omega, a, c^+, c^-) \in \mathcal{D}_{\mathrm{RM}}$ **do**
  Compute TCSD target e using Eq. 2
end for
Train $f_{\theta^{(1)}}$ with Eq. 3; select ξ on validation data
$\Omega_1 \leftarrow \{\omega_{\mathrm{generic}}\}$
II. Training-time evolution
for $k = 1, \ldots, K$ **do**
  Freeze $(f_{\theta^{(k)}}, \Omega_k, \mathcal{E}, \mathcal{G}, \xi)$
  Run training tasks with Stage III; collect trajectories $\mathcal{T}_k$ and intervention pairs $\mathcal{P}_k$
  for all $\tau_i \in \mathcal{T}_k$ with some $q_{i,t} > \xi$ **do**
    $t_i^\star \leftarrow \min\{t : q_{i,t} > \xi\}$; editor $\mathcal{E}$ diagnoses $\mathcal{T}_\omega(\tau_i)$
    Store parsed component edit $g_{i,\omega}^{(c)}$, $c \in \{\mathcal{I}, \pi, \beta\}$
  end for
  for all ω, c with $\mathcal{F}_\omega^{(c)} \neq \varnothing$ **do**
    $\bar{g}_\omega^{(c)} \leftarrow \mathrm{Aggregate}(\mathcal{F}_\omega^{(c)})$; $\omega' \leftarrow \omega \oplus \bar{g}_\omega^{(c)}$
    if ω' is schema-valid and changes only c **then**
      Add ω' to Ω_k if $\omega = \omega_{\mathrm{generic}}$; otherwise replace ω
    end if
  end for
  $\Omega_{k+1} \leftarrow \Omega_k$
  for all $(s, \omega, a, \tilde{a}) \in \mathcal{P}_k$ **do**
    Recompute TCSD targets for a and $\tilde{a}$ and add them to $\mathcal{D}_{\mathrm{RM}}$
  end for
  Train $f_{\theta^{(k+1)}}$ offline with Eq. 3
end for
$\theta^\star \leftarrow \theta^{(K+1)}$; $\Omega^\star \leftarrow \Omega_{K+1}$; freeze $(f_{\theta^\star}, \Omega^\star, \mathcal{E}, \mathcal{G}, \xi)$
III. Runtime intervention
for each decision step t **do**
  Agent proposes a_t; compute $q_t \leftarrow f_{\theta^\star}(s_t, \omega^{\mathrm{act}}, a_t)$
  if $q_t > \xi$ **then**
    $(\omega_t, \tilde{a}_t, r_t) \leftarrow \mathrm{Guide}_{\mathcal{G}}(s_t, \omega^{\mathrm{act}}, a_t, \Omega^\star)$
    if $r_t \neq$ `none` **then**
      Invoke r_t; **continue**
    end if
    Record $(s_t, \omega_t, a_t, \tilde{a}_t)$ in $\mathcal{P}_k$
    if $f_{\theta^\star}(s_t, \omega_t, \tilde{a}_t) > \xi$ **then**
      Reject $\tilde{a}_t$; invoke Skill fallback; **continue**
    end if
    $a_t \leftarrow \tilde{a}_t$; $\omega^{\mathrm{act}} \leftarrow \omega_t$
  end if
  Execute a_t; terminate ω^{act} when its termination or applicability condition is satisfied
end for

APPENDIX

A ALGORITHMIC SUMMARY OF G2A

Algorithm 1 summarizes the three stage **G2A** pipeline. TCSD first distills trajectory-contrastive evidence into a lightweight Guard. During training-time evolution rounds, the Guard-triggered intervention records are diagnosed by a frozen editor, and used to refine the Guard offline. During runtime execution, the frozen Guard screens every proposed action, while the fixed router Guide selects an applicable Skill and generates a revised action. The revised action is executed only after passing a second Guard check.

B Extended Related Work

Learning from Interaction and Procedural Skills. LLM agents can improve from interaction through either parametric or non-parametric adaptation. Parametric approaches internalize feedback through reinforcement learning, preference optimization, or other forms of post-training Ouyang et al. (2022); Rafailov et al. (2023). In contrast, non-parametric methods preserve the underlying LLM and externalize experience as reusable knowledge. Generative Agents summarize observations into higher-level reflections Park et al. (2023); Reflexion stores verbal feedback in episodic memory Shinn et al. (2023); and ExpeL extracts generalizable insights from successful and failed trajectories for future reuse Zhao et al. (2024). These approaches show that interaction experience can improve agent behavior without repeatedly updating model parameters.

More recent work moves from descriptive memory toward *procedural knowledge* that specifies how tasks should be executed. Voyager maintains an expanding library of executable skills Wang et al. (2023), Agent Workflow Memory induces reusable workflows from demonstrations and interaction trajectories Wang et al. (2024), and Cradle combines memory, reflection, planning, and skill curation for long-horizon computer control Tan et al. (2024). LEGOMem further decomposes trajectories into modular procedural memories Han et al. (2025), while GEPA evolves external language programs through trajectory-level reflection Agrawal et al. (2026). Closest to our work, Skill-Pro formalizes reusable Skills with applicability, execution, and termination semantics and evolves them from interaction without modifying the backbone model Mi et al. (2026); Memento-Skills similarly maintains an evolving library of structured Skills through continual reflective updates Zhou et al. (2026a). These methods primarily learn procedures for improving task-solving capability. Our Guide instead treats a Skill as reusable *safety intervention knowledge*: it specifies when a corrective procedure should activate, how it should constrain execution, and when it should terminate, switch, or fall back.

Safety Alignment for Agentic Behavior. Agent safety differs from conventional conversational alignment because an agent produces sequences of actions that can invoke tools, modify external states, and affect subsequent decision opportunities. One line of work therefore directly post-trains agent policies using safety-oriented interaction data. AgentAlign constructs executable agentic safety data from behavior chains and simulated environments Zhang et al. (2025c); SafeAgent uses an automated risk simulator to generate unsafe scenarios and safe responses for fine-tuning Liu et al. (2026a); and MOSAIC Agarwal et al. (2026) trains agents to explicitly decide when to act or refuse during multi-step tool use. These methods demonstrate the importance of trajectory-level safety alignment, but encode the resulting behavior largely in model parameters. G2A instead keeps the task agent frozen and externalizes adaptation into a lightweight Guard and an evolving pool of Safety Skills.

Runtime Guardrails and Action-Level Safety Enforcement. A complementary line of work enforces safety during inference by inserting a monitor or controller between the agent and its environment. ToolEmu studies risk identification in simulated high-stakes tool environments Ruan et al. (2024). AgentSpec expresses safety requirements using structured runtime triggers and enforcement rules Wang et al. (2025), while GuardAgent employs a dedicated guard agent to construct executable checks for target-agent behavior Xiang et al. (2024). More adaptive systems include AGrail, which continually generates and improves safety checks Luo et al. (2025); ToolSafe, which performs proactive step-level assessment of tool invocations and feeds safety information back to the task agent Mou et al. (2026); and SafeHarbor, which maintains evolving context-dependent defense rules in hierarchical memory Liu et al. (2026b). Related benchmarks such as AgentDojo, AgentHarm, Agent-SafetyBench, and Agent Security Bench further show that agent safety failures often depend on interaction history, external content, tool outputs, and multi-step execution rather than isolated requests Debenedetti et al. (2024); Andriushchenko et al. (2025); Li et al. (2026b).

G2A builds on this runtime perspective but explicitly separates *detection* from *intervention*. The Guard independently estimates the contextual risk of each proposed action, while the Guide selects and executes a temporally extended Safety Skill when intervention is required. Thus, detecting a risky action need not immediately result in blocking or a fixed replacement; the selected Skill can control a trajectory segment and adapt, switch, or terminate as the environment changes. Moreover, trajectory-contrastive evidence provides action-level supervision for the Guard. This Guard Guide

decomposition combines continuous runtime monitoring with reusable procedural safety adaptation without updating the underlying agent parameters.

C Detailed Experimental Setup

C.1 Benchmarks

We evaluate G2A on three complementary agent-safety benchmarks that cover trajectory-level safety recognition, lifecycle-wide runtime robustness, and fine-grained risk localization. Together, they allow us to evaluate not only whether an agent trajectory is unsafe, but also whether safety can be maintained during interaction and whether the specific decisions responsible for emerging risk can be identified.

ATBench. ATBench (Li et al., 2026b) is a trajectory-level benchmark designed for evaluating long-horizon agent safety under diverse and realistic interaction patterns.

AgentS4D. AgentS4D (Zhou et al., 2026b) evaluates runtime safety across the execution lifecycle of stateful workspace agents.

HINTBench. HINTBench (Wang et al., 2026a) targets *intrinsic* agent safety failures that arise during benign, non-adversarial interaction rather than through an explicit external attack.

C.2 Baseline Methods

We compare G2A against representative baselines spanning four complementary paradigms: standard agent reasoning, non-parametric experience-based adaptation, inference-time safety enforcement, and parameterized safety alignment. These baselines differ in whether they modify model parameters, whether they accumulate experience across tasks, and whether safety is enforced before or during agent execution.

Standard Agent Reasoning. **ReAct** (Yao et al., 2022) serves as the base agent architecture. ReAct interleaves language-model reasoning traces with environment actions, allowing intermediate reasoning to update plans based on observations while actions provide new information from external environments. It does not, however, maintain an evolving external Skill library or introduce an independent runtime safety mechanism, and therefore provides a reference for the safety and utility of the underlying agent before adding adaptation or safety-specific components.

Non-Parametric Agent Adaptation. This group improves agent behavior by modifying external context, memory, or procedural knowledge while leaving the underlying LLM unchanged.

Skill-Pro (Mi et al., 2026) learns reusable procedural Skills directly from interaction experience. It formalizes agent execution through a Skill-MDP, represents each Skill through activation, execution, and termination conditions, and uses semantic gradients to generate Skill updates together with a gate for candidate verification. This makes Skill-Pro the closest task-oriented procedural-learning baseline to our Guide, while its optimization primarily targets reusable task competence rather than safety-constrained execution.

Memento-Skills (Zhou et al., 2026a) treats reusable Skills as persistent and evolving external memory. Skills are stored as structured artifacts containing both behavioral and contextual knowledge, while a state-dependent router retrieves relevant Skills and reflective updates expand or revise the library after interaction. Adaptation therefore occurs through external Skill evolution rather than changes to the underlying LLM parameters.

ACE (Zhang et al., 2026) treats agent context as an evolving playbook rather than a static prompt or compressed memory. It alternates generation, reflection, and curation to incrementally accumulate and organize strategies learned from execution feedback, allowing both offline prompt optimization and online memory adaptation without parameter updates.

AWM (Wang et al., 2024) introduces Agent Workflow Memory, which induces reusable workflows from previous action trajectories and selectively retrieves them to guide subsequent generations.

AWM supports both offline workflow induction from demonstrations and online induction from test-time experience, providing a workflow-level alternative to explicit Skill learning.

GEPA (Agrawal et al., 2026) optimizes external prompts through natural-language reflection over complete execution trajectories. It diagnoses failures from reasoning traces, tool calls, and observations, proposes candidate prompt updates, and combines complementary improvements through a Pareto-based evolutionary search. GEPA therefore represents trajectory-driven context optimization without gradient-based updates to the base LLM.

Inference-Time Safety Enforcement. This group introduces explicit safety mechanisms around a frozen or independently operating task agent, providing the most direct comparison to the runtime Guard component of G2A.

Safety-Prompt is our prompt-only safety baseline. We augment ReAct with the safety information available to the agent in the corresponding benchmark and explicitly instruct it to verify applicable constraints before executing each action. Safety-Prompt neither learns from previous trajectories nor modifies the underlying LLM, isolating the benefit obtainable from explicit safety instructions alone.

AgentSpec (Wang et al., 2025) provides customizable runtime enforcement through a lightweight domain-specific language. Safety constraints are represented using structured triggers, predicates, and enforcement mechanisms, which are evaluated during execution to keep the agent within predefined behavioral boundaries. In our evaluation, AgentSpec receives only the safety information available to the acting agent and does not access benchmark-side hidden unsafe predicates or post-hoc labels.

ToolSafe (Mou et al., 2026) targets proactive safety monitoring of individual tool invocations. Its TS-Guard reasons over the interaction history to identify unsafe proposed tool actions before execution, while TS-Flow feeds the resulting safety judgment back to a ReAct-style agent so that it can revise subsequent behavior. It therefore provides a direct comparison to action-level Guard intervention, but does not represent correction as an evolving temporally extended Safety Skill.

SafeHarbor (Liu et al., 2026b) is a training-free, memory-augmented guardrail that extracts context-dependent defense rules from adversarial experience. It stores these rules in a local hierarchical memory, retrieves relevant rules for dynamic injection at inference time, and continually reorganizes the memory through an entropy-based self-evolution mechanism. SafeHarbor therefore represents adaptive rule-memory-based safety without modifying the task model.

AGrail (Luo et al., 2025) is a lifelong agent guardrail designed to address both task-specific and systemic risks. It adaptively generates safety checks for the current task, optimizes these checks based on experience, and is designed to remain compatible with heterogeneous tools and agent settings. It provides an adaptive runtime-safety baseline in which the object of evolution is the set of safety checks rather than procedural intervention Skills.

GuardAgent (Xiang et al., 2024) uses an independent LLM-based guard agent to supervise another target agent. Given user-specified guard requirements, GuardAgent first constructs a guarding plan and subsequently generates executable guardrail code that checks whether the target agent's inputs or outputs satisfy those requirements. Retrieved examples from previous guarding tasks support its reasoning and code generation.

SafeAgent (Liu et al., 2026a) formulates agent protection as a stateful runtime decision problem over evolving interaction trajectories. It separates execution governance from semantic risk reasoning through a runtime controller and a context-aware decision core operating over persistent session state. This architecture is designed to mediate agent actions throughout multi-step workflows rather than relying only on static input output filtering.

SafeHarness (Lin et al., 2026) embeds security controls throughout the LLM agent lifecycle: it filters adversarial inputs, verifies decisions, restricts tool privileges, and supports rollback during state updates. These layers coordinate to strengthen checks and limit privileges when persistent anomalies are detected.

C.3 Evaluation Metrics

We follow the benchmark-native evaluation protocols whenever applicable and introduce additional diagnostics only for evaluating the action-level risk signal produced by the Guard. In particular, ATBench-C and AgentS4D use their original metrics, whereas on HINTBench we retain the benchmark's step-level localization protocol and additionally measure agreement with independent safety judges and the accuracy of risk-onset detection.

ATBench-C. ATBench-C formulates trajectory-level safety evaluation as binary classification, with the *unsafe* class treated as positive (Li et al., 2026b). Let TP, TN, FP, and FN denote the numbers of unsafe trajectories correctly identified as unsafe, safe trajectories correctly identified as safe, safe trajectories incorrectly classified as unsafe, and unsafe trajectories incorrectly classified as safe, respectively. We report

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}, \tag{6}$$

$$\text{Precision} = \frac{TP}{TP + FP}, \tag{7}$$

$$\text{Recall} = \frac{TP}{TP + FN}, \tag{8}$$

$$\text{F1} = \frac{2\,\text{Precision}\,\text{Recall}}{\text{Precision} + \text{Recall}}. \tag{9}$$

Accuracy measures overall trajectory-level correctness, while Precision and Recall separately characterize false alarms and missed unsafe trajectories. F1 summarizes their trade-off and is particularly useful for comparing safety detectors whose decision tendencies differ.

AgentS4D. We adopt the runtime-safety metrics defined by AgentS4D (Zhou et al., 2026b). Let n_T denote the total number of runs, n_C the runs satisfying the task-completion predicate, and let the safety outcomes partition the runs into

$$n_T = n_U + n_D + n_E + n_N + n_I,$$

where n_U denotes unsafe runs, n_D safe runs with an explicitly identified defense, n_E safe runs with confirmed exposure to the injected risk but no explicit-defense attribution, n_N safe runs without confirmed exposure or explicit defense, and n_I inconclusive runs.

The primary runtime-safety metric is the conditional Attack Success Rate,

$$\text{cASR} = \frac{n_U}{n_U + n_D + n_E}, \tag{10}$$

which measures the fraction of unsafe outcomes among runs for which the risk was meaningfully encountered or explicitly handled. It excludes inconclusive runs and safe runs for which exposure to the injected risk cannot be confirmed. Lower cASR indicates stronger runtime safety.

The Safe Handling Rate is

$$\text{SHR} = \frac{n_D + n_E}{n_T - n_I}, \tag{11}$$

which measures how frequently conclusive runs safely handle the introduced risk. Following AgentS4D, explicit defense and safe behavior after confirmed risk exposure both contribute to the numerator. Because cASR and SHR use different denominators, they are not complements.

Finally, task utility is measured independently through

$$\text{TCR} = \frac{n_C}{n_T}, \tag{12}$$

where TCR denotes Task Completion Rate. We report cASR together with SHR and TCR because reducing unsafe execution through indiscriminate refusal may improve safety metrics while substantially degrading task utility.

HINTBench: Step-Level Risk Localization. HINTBench (Wang et al., 2026a) provides annotated risky steps and risk types, enabling direct evaluation of fine-grained safety attribution. Following the benchmark protocol, a predicted risk point is matched to a gold risk point when their annotated step sets overlap, with one-to-one matching between predicted and gold points. HINTBench additionally defines a typed variant that requires both step overlap and the same risk category.

Because our Guard predicts an action-level scalar risk score rather than a risk type, our main localization metric follows the benchmark's *no-type* matching protocol. For trajectory i, let $q_{i,t} = f_\theta(s_{i,t}, \omega_{i,t}, a_{i,t})$ denote the predicted risk of action t and let ξ be the operational risk threshold. We obtain the predicted risky-step set as

$$\widehat{\mathcal{R}}_i = \{t \mid q_{i,t} > \xi\}. \tag{13}$$

After one-to-one matching with the gold risk annotations, we aggregate TP_{loc}, FP_{loc}, and FN_{loc} across trajectories and compute

$$P_{\mathrm{loc}} = \frac{TP_{\mathrm{loc}}}{TP_{\mathrm{loc}} + FP_{\mathrm{loc}}}, \tag{14}$$

$$R_{\mathrm{loc}} = \frac{TP_{\mathrm{loc}}}{TP_{\mathrm{loc}} + FN_{\mathrm{loc}}}, \tag{15}$$

$$\text{Loc-F1} = \frac{2P_{\mathrm{loc}}R_{\mathrm{loc}}}{P_{\mathrm{loc}} + R_{\mathrm{loc}}}. \tag{16}$$

Loc-F1 therefore measures whether the Guard assigns high risk to the same interaction steps identified by human-verified HINTBench annotations, irrespective of the fine-grained constraint category.

Reward-Rubric Agreement. HINTBench provides discrete risk-step annotations but does not directly evaluate whether a continuous action-level risk score faithfully preserves the relative safety judgments of a strong evaluator. We therefore introduce an additional diagnostic based on independent LLM rubric judges.

Let $\hat{q}_k$ denote the Guard score for evaluated action k, and let $r_k^{(j)}$ denote the scalar safety-risk judgment produced by independent judge j. For each judge, we report Pearson correlation

$$\rho_{\mathrm{P}}^{(j)} = \frac{\sum_k (\hat{q}_k - \bar{q})(r_k^{(j)} - \bar{r}^{(j)})}{\sqrt{\sum_k (\hat{q}_k - \bar{q})^2}\sqrt{\sum_k (r_k^{(j)} - \bar{r}^{(j)})^2}}, \tag{17}$$

which measures agreement in score magnitude, and Spearman correlation

$$\rho_{\mathrm{S}}^{(j)} = \mathrm{Pearson}\left(\mathrm{rank}(\hat{q}), \mathrm{rank}(r^{(j)})\right), \tag{18}$$

which measures agreement in relative risk ordering.

We additionally report pairwise ordering agreement. Let $\mathcal{P}_j$ contain evaluated action pairs for which judge j assigns different risk scores. Then

$$\mathrm{PairAgree}^{(j)} = \frac{1}{|\mathcal{P}_j|} \sum_{(u,v)\in\mathcal{P}_j} \mathbf{1}\left[\mathrm{sgn}(\hat{q}_u - \hat{q}_v) = \mathrm{sgn}(r_u^{(j)} - r_v^{(j)})\right]. \tag{19}$$

For each metric, we report the average over the independent rubric judges. Together, Pearson correlation, Spearman correlation, and PairAgree test whether Guard distillation preserves absolute variation, ranking structure, and pairwise safety preferences, respectively.

Risk-Onset Error. Finally, we evaluate whether the Guard identifies *when* safety degradation first emerges. For each risky HINTBench trajectory i, let $\mathcal{R}_i$ denote its gold risky-step annotations and define the first annotated risky step as

$$t_i^\star = \min_{t\in\mathcal{R}_i} t. \tag{20}$$

The Guard-predicted risk onset is the first action whose predicted risk exceeds the deployment threshold,

$$\hat{t}_i^\star = \min\{t : q_{i,t} > \xi\}. \tag{21}$$

If no action crosses the threshold, we set $\hat{t}_i^\star = T_i + 1$, where T_i is the trajectory length, so that missed detections are penalized rather than discarded. We report the mean absolute risk-onset error

$$\mathrm{OnsetErr} = \frac{1}{N_{\mathrm{risk}}} \sum_i \left| \hat{t}_i^\star - t_i^\star \right|. \tag{22}$$

Lower OnsetErr indicates that the Guard detects emerging safety violations closer to their human-annotated onset. This metric complements Loc-F1: Loc-F1 evaluates attribution over all risky steps, whereas OnsetErr isolates the earliest point at which a runtime intervention could have been triggered.

C.4 Reproducibility Details

Backbone and Guard training. Unless otherwise specified, we use Qwen3-32B as the frozen task-agent backbone. The backbone parameters remain fixed during Guard training, Safety Skill evolution, runtime intervention, and final evaluation. All experiments use BF16 inference with tensor parallelism over four NVIDIA A100 80GB GPUs. The software environment consists of Ubuntu 22.04, CUDA 12.4, PyTorch 2.5.1, Transformers 4.51.3, and vLLM 0.7.3. The MiniLM Guard is executed with batch size one on the same machine.

TCSD supervision is constructed from task-matched safe and unsafe reference trajectories. For each state s_t, the candidate action is the first action proposed by the frozen task agent before intervention. If the Guard triggers an intervention, the Guide-generated revised action $\tilde{a}_t$ is added as an additional candidate action. For each candidate action, we compute the length normalized token level log-likelihood difference defined in Eq. 2 under the task-matched safe and unsafe reference trajectories. Safe and unsafe references are matched by task identifier and are never drawn across train, validation, and test splits. The reference trajectories are used only to construct offline training targets and are never provided to the deployed Guard, router, or Guide.

We instantiate the Guard f_θ as a 6-layer MiniLM encoder. Each input is serialized as

`[CLS] state [SEP] candidate-action.`

When no Skill is active, the active-Skill field is set to `NONE`. The `[CLS]` representation is mapped to a scalar risk score and optimized using the Huber regression objective in Eq. 3. We use AdamW with learning rate 2×10^{-5}, weight decay 0.01, batch size 8, and $1{,}000$ optimization steps. The action-level intervention threshold is selected on the validation split and fixed to $\xi = 0.45$ before test evaluation. The trajectory-level classification threshold ξ_{traj} is selected independently on the validation split.

Dataset splits and evolution budget. We use fixed, disjoint train/validation/test splits for all experiments. ATBench-C contains 700/150/150 trajectories for train/validation/test, respectively. AgentS4D contains 196/66/66 cases, and HINTBench contains 440/94/95 trajectories. No validation or test trajectory is used to construct TCSD targets, evolve Skills, tune prompts, or refine the Guard.

Skill evolution consists of $K = 3$ offline evolution rounds. In each round, we sample at most 256 training trajectories for ATBench-C, 128 training cases for AgentS4D, and 256 training trajectories for HINTBench. Sampling is without replacement within a round and uses a different deterministic permutation in each round. If a training split contains fewer instances than the corresponding budget, all training instances are used. The same sampled trajectories are used for first-risk-step localization, editor diagnosis, component aggregation, and intervention-pair collection in that round. Each nonempty Skill/component group receives at most one aggregated edit per round, so that each parent Skill receives at most $K_{\mathrm{edit}} = 3$ component edits per round.

Initial Skill pool. The initial Skill pool contains exactly one immutable generic Skill, denoted by $\omega_{\mathrm{generic}}$. It is retained throughout all evolution rounds and serves as the fallback when no evolved Skill has a more specific activation condition:

$$\Omega_0 = \{\omega_{\mathrm{generic}}\}.$$

Its three components are defined as follows:

- $\mathcal{I}_{\text{generic}}$: applicable whenever the Guard flags a proposed action and no more specific evolved Skill is selected;
- π_{generic}: inform the task agent that the proposed action has been withheld, infer a coarse risk category from the task specification, current state, and proposed action, and request the smallest revision that preserves the original task objective;
- β_{generic}: terminate after the revised action has either passed the Guard check or been rejected by the fallback mechanism.

The coarse risk taxonomy used by the Guide is fixed before training: `authorization`, `sensitive-information`, `goal-integrity`, `tool-or-precondition`, `destructive-or-irreversible-action`, and `other`. These categories are operational descriptions rather than benchmark labels. The Guide infers the category without access to hidden annotations.

Router and Guide implementation. The routing policy μ has no separately trained parameters. Routing and action revision are implemented jointly through one structured call to the frozen Qwen3-32B task agent. The call receives the task specification, current interaction state, proposed action, currently active Skill, and complete frozen Skill pool. Skills are listed in ascending order of their stable identifiers, with ω_{generic} placed last.

The router Guide call uses greedy decoding with temperature 0, top-$p = 1$, and a maximum output length of 512 tokens. The acting Qwen3-32B agent uses temperature 0.7, top-$p = 0.95$, and a maximum output length of 1,024 tokens. The editor uses temperature 0.7, top-$p = 1$, and a maximum output length of 4,096 tokens.

The routing decision and revised action are produced in the same model call and therefore count as one additional LLM call in the runtime efficiency evaluation. A parsed revised action $\tilde{a}_t$ is submitted to the Guard and is executed only if

$$f_\theta(s_t, \omega_t, \tilde{a}_t) \leq \xi.$$

Otherwise, the revised action is not sent to the environment and the specified fallback is invoked.

Safety Skill evolution. Each Safety Skill is represented as

$$\omega = \langle \mathcal{I}_\omega, \pi_\omega, \beta_\omega \rangle,$$

where $\mathcal{I}_\omega$ is its activation condition, π_ω is its intervention procedure, and β_ω is its termination condition.

Skill evolution is performed only on training trajectories. For every trajectory that crosses the risk threshold, we record the first flagged step

$$t_i^\star = \min\{t : q_{i,t} > \xi\}$$

and its Skill-controlled segment $\mathcal{T}_\omega(\tau_i)$. A frozen Qwen3-32B editor assigns the intervention to one of the three Skill components and produces a structured diagnosis. Diagnoses are grouped by parent Skill and responsible component. At the end of each evolution round, the editor aggregates all diagnoses in each nonempty group and produces at most one edit for that component.

A specialized edit to the generic Skill creates a new Skill while leaving ω_{generic} unchanged. An edit to an evolved Skill creates a new version that replaces its parent version. All Skill identifiers and version relationships are logged.

Continual Guard refinement. For every training-time intervention, we store the original proposal a_t and the Guide revision $\tilde{a}_t$. Passing the runtime Guard check is not treated as a ground-truth safety label. Instead, we recompute TCSD targets for both actions using only task-matched reference trajectories from the training split. The resulting examples are added to $\mathcal{D}_{\text{RM}}$, and the Guard is refitted offline using the same Huber objective, learning rate, batch size, and number of optimization steps as the initial Guard. No intervention pair from the validation or test split is added to the Guard training set. After the third evolution round, both the Guard and Skill pool are frozen throughout evaluation.

Baseline implementations and prompt configuration. The common agent decoding configuration is temperature 0.7, top-$p = 0.95$.

ReAct and Safety-Prompt are implemented using the common agent wrapper. Safety-Prompt adds a fixed instruction requiring the agent to verify authorization, information-flow, goal-integrity, tool-precondition, and destructive-action constraints before every action. Skill-Pro, Memento-Skills, ACE, AWM, and GEPA are reimplemented according to their published algorithms with one update after each completed training trajectory, a memory/Skill budget of 32,000 tokens, and top-$k = 4$ retrieved Skills or memory entries where applicable. AgentSpec, ToolSafe, SafeHarbor, AGrail, and GuardAgent use one guard decision per proposed action, temperature 0, top-$p = 1$, and maximum guard-output length 512 tokens. Their published decision prompts are reproduced verbatim in `prompts/baselines/`, together with the corresponding parser and action-intervention wrapper. MOSAIC, SafeAgent, and SafeHarness are evaluated using their released inference-time checkpoints and official safety prompts; no additional test-time fine-tuning is performed.

Runs and reporting protocol. The main ATBench-C, AgentS4D, HINTBench, and component-ablation results are averaged over six independent runs with random seeds $\{0, 1, 2, 3, 4, 5\}$. A run controls task-agent sampling, editor sampling, data shuffling, Guard initialization, and candidate-action sampling. We report the mean and standard deviation across the six runs.

The cross-scenario reuse experiment uses three predefined source target partitions generated with split seeds $\{0, 1, 2\}$. Runtime-efficiency measurements use batch size one and are averaged over three complete profiling repetitions after one warm-up pass. All latency comparisons within a table are conducted on the same hardware and software stack. For each run, hyperparameters and thresholds are selected using only the corresponding validation split and are fixed before any test episode is executed.

Finally, we integrate the trained Guard and skill pool with Qwen3-32B and GPT-5.4 as the underlying backbone models.

C.5 Calibration and Threshold Sensitivity Analysis of TCSD Guard

Initial evaluation parameters, benchmark configurations, and dataset splits are validated and maintained as standard. To assess calibration, the unbounded TCSD empirical log-likelihood contrasts (log-odds) are directly mapped to probabilities via a sigmoid function. For the sensitivity analysis, the decision threshold ξ is evaluated across the range $[0.1, 0.9]$ on the validation sets to observe the resulting impact on task and safety metrics.

As shown in Figure 4, the reliability curve strongly tracks the perfectly calibrated diagonal. The inset distribution confirms the Guard inherently separates safe and unsafe trajectories into distinct density clusters. Consequently, rather than a mere heuristic, the TCSD score effectively serves as a precise estimator of the log-odds update for safety violations. The selected threshold ξ cleanly partitions these distributions at their lowest density intersection.

Figure 5 visualizes the systemic safety-utility trade-off governed by ξ. We isolate the final optimization convergence: the deployed threshold $\xi = 0.45$ acts as the empirical sweet spot. It successfully suppresses the conditional Attack Success Rate (cASR) to 24.2% and maximizes the Safe Handling Rate (SHR) without triggering the catastrophic Task Completion Rate (TCR) degradation observed at overly strict thresholds ($\xi < 0.3$). The Guard is therefore validated as an operationally effective and precisely calibrated runtime safety constraint.

C.6 Implementation Details and Leakage Controls

This section specifies the frozen editor, the Skill-update procedure, and the data-access restrictions used to prevent test-set leakage. The Guard is used only to trigger runtime intervention and to check an action immediately before execution.

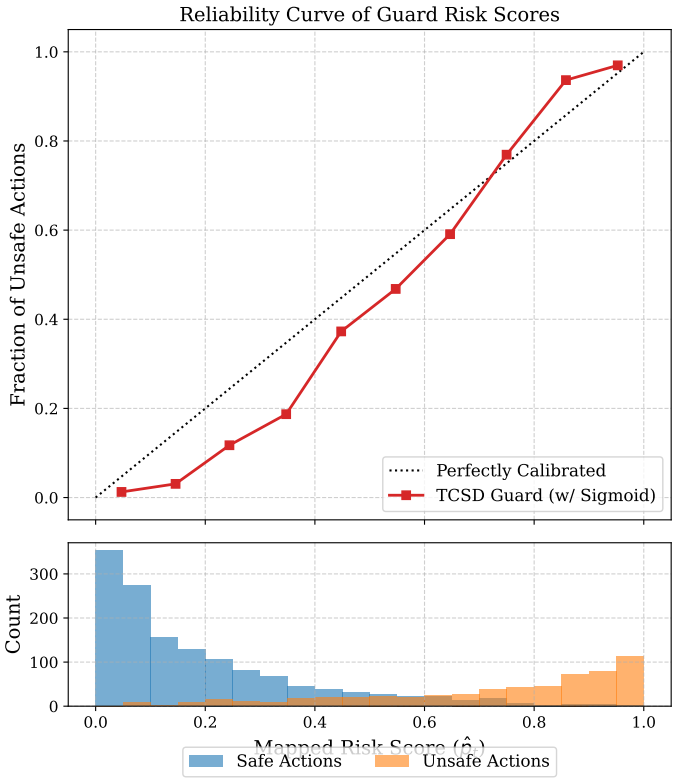


Figure 4: Reliability curve of the mapped Guard risk scores. The main plot evaluates calibration against the ideal diagonal, while the inset details the distinct score distributions for safe (blue) and unsafe (orange) actions, with the deployed threshold $\xi = 0.45$ marked by the dashed line.

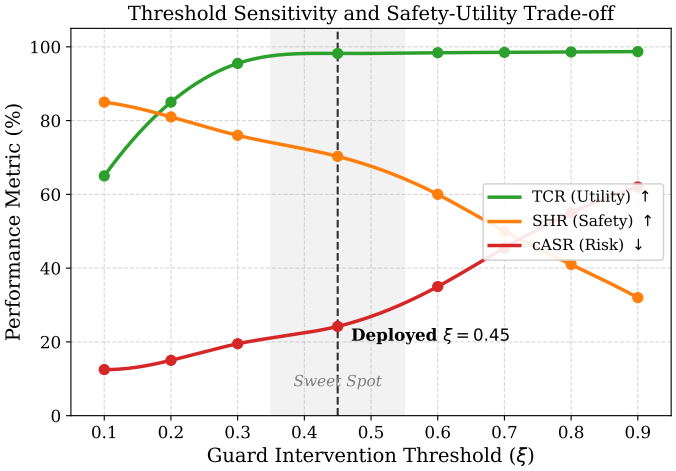


Figure 5: Threshold sensitivity and the safety-utility trade-off on AgentS4D. The shaded "Sweet Spot" highlights the optimal threshold region where risk is minimized without degrading task capabilities.

C.6.1 FROZEN EDITOR

The frozen editor is implemented using Qwen3-32B with temperature 0.7, top-p equal to 1, and maximum output length $4{,}096$. Its parameters and prompts remain fixed across all evolution rounds. The run-specific random seed controls editor sampling.

Skill evolution uses two fixed editor operations: per-trajectory diagnosis and cross-trajectory aggregation.

Per-trajectory diagnosis. For each threshold-triggered training trajectory, the editor receives the task specification, the active Skill, the segment controlled by that Skill, the withheld action, and the subsequent environment feedback available in the training execution. It does not receive the numerical Guard score, TCSD target, validation or test annotation, or hidden benchmark metadata.

The diagnosis prompt is:

> **System prompt:**
> You are a safety-procedure editor. Analyze a training-time intervention in which the runtime Guard withheld an action. Determine which single component of the active Safety Skill should be revised:
>
> - `activation`: the Skill activated in an inappropriate context or failed to cover a recurring relevant context;
> - `guidance`: the intervention procedure provided insufficient or inappropriate guidance;
> - `termination`: the Skill terminated too early or remained active too long.
>
> Use only the supplied task specification, active Skill, observed trajectory segment, withheld action, and environment feedback. Do not infer or request hidden labels, numerical Guard scores, TCSD targets, or test-set information. Identify exactly one component and propose a minimal component-specific edit.
> **Output format:**

```
{
  "component": "activation | guidance | termination",
  "context_signature": "...",
  "diagnosis": "...",
  "minimal_edit": "...",
  "supporting_steps": ["...", "..."]
}
```

Cross-trajectory aggregation. Let $\mathcal{F}_{\omega}^{(k)}$ denote all parsed diagnoses associated with Skill ω and component $k \in \{\mathcal{I}, \pi, \beta\}$ during the current evolution round. For every nonempty group, a second editor call consolidates recurring contexts and produces one replacement for that component.

The aggregation prompt is:

> **System prompt:**
> You are consolidating multiple training-time diagnoses for one component of a Safety Skill. Identify the recurring context and the smallest reusable update that addresses it. The update must modify only the specified component. Do not modify the other Skill components and do not add benchmark-specific identifiers or examples.
> **Output format:**

```
{
  "skill_id": "...",
  "component": "activation | guidance | termination",
  "recurring_pattern": "...",
  "replacement_component": "..."
}
```

Outputs are parsed automatically. This parsing step is a structural validity check, not a safety or utility filter.

Table 5: Information access and update permissions. "Trigger only" means that the component knows that an intervention occurred but does not receive the numerical Guard score.

Component	Input data	Guard access	Benchmark labels	Split	Updated at test
TCSD target construction	Task-matched safe and unsafe reference trajectories	No	Train labels	Train	No
Guard training and refinement	States, Skills, actions, and offline TCSD targets	No target from Guard	Train labels only through TCSD	Train	No
Frozen editor	Task, active Skill, triggered segment, action, and environment feedback	Trigger only	No	Train	No
Router Guide	Task, state, active Skill, proposed action, and frozen Skill pool	Trigger only	No	Train/Val/Test	No
Threshold selection	Frozen Guard scores and validation annotations	Scores	Validation labels	Validation	No
Final evaluation	Frozen Guard, Skill pool, router, and Guide	Runtime scores	Labels visible only to metric script	Test	No

C.6.2 Skill Evolution Procedure

For each evolution round, we first collect the set of threshold-triggered training interventions. The editor diagnoses each intervention independently, after which the parsed diagnoses are grouped by Skill and component:

$$\mathcal{F}_{\omega}^{(k)} = \{g_{i,\omega} : g_{i,\omega} \text{ identifies component } k\}.$$

For every nonempty group, the aggregation operation produces

$$\bar{g}_{\omega}^{(k)} = \text{Aggregate}\left(\mathcal{F}_{\omega}^{(k)}\right), \qquad k \in \{\mathcal{I}, \pi, \beta\}.$$

The components are updated in the fixed order $\mathcal{I} \to \pi \to \beta$. At most one edit is applied to each component in an evolution round:

$$\omega^{(0)} = \omega, \qquad \omega^{(j)} = \omega^{(j-1)} \oplus \bar{g}_{\omega}^{(k_j)},$$

where $(k_1, k_2, k_3) = (\mathcal{I}, \pi, \beta)$ and an empty component group leaves the corresponding version unchanged.

After all nonempty component edits have been applied, the resulting Skill receives a new version identifier. If the parent is ω_{generic}, the new Skill is added to the pool and the generic Skill is retained as the fallback. Otherwise, the new version replaces its parent in the next evolution round. At runtime, however, an action produced under an evolved Skill is never executed without the action-level Guard check specified in Sec. 2.

C.6.3 Data Splits and Circularity Controls

The training split is used to construct TCSD targets, train and refine the Guard, collect intervention records, generate editor diagnoses, and evolve the Skill pool. The validation split is used only for hyperparameter selection and for selecting the action- and trajectory-level thresholds. The test split is used only for final metric computation.

Neither the editor nor the router Guide receives benchmark-side safety labels. The editor is informed that an intervention occurred but does not receive the numerical Guard score. The Guide similarly receives only a binary notification that the pending action was withheld. Its reported risk category is inferred from the visible task state and is not copied from benchmark annotations.

Table 5 summarizes the information available to each component.

Guard-triggered intervention pairs are not treated as ground-truth safe unsafe labels. TCSD targets for the original and revised actions are recomputed offline using training references before those

Table 6: **Runtime efficiency and safety on AgentS4D with Qwen3-32B.** Monitor latency measures the additional safety-checking latency for each proposed action, while end-to-end (E2E) latency includes agent generation, safety monitoring, correction, and environment execution. Extra LLM calls and tokens are measured relative to the unguarded ReAct agent and count only generative LLM computation; MiniLM encoder inference is captured by monitor latency. All latency measurements use batch size one on the same hardware.

	Runtime Cost			Additional LLM Cost			Execution		Safety–Utility		
Method	**Monitor** ms/action ↓	**E2E** s/episode ↓	**Overhead** %	**Calls** /episode ↓	**Input Tok.** /episode ↓	**Output Tok.** /episode ↓	**Steps** /episode	**Interv.** Rate	**cASR↓** %	**SHR↑** %	**TCR↑** %
ReAct	–	46.2	0.0	0.0	0	0	18.7	0.0	58.0	37.0	96.5
G2A w/ Qwen3-32B Judge	640.0	61.4	+32.9	21.5	31.6K	0.9K	18.9	15.0	21.8	71.1	97.9
ToolSafe	185.0	52.0	+12.6	20.9	26.4K	1.1K	18.1	19.5	35.0	56.0	96.0
G2A-Guard Only	5.6	46.5	+0.6	0.0	0	0	17.5	17.1	28.7	62.4	94.8
G2A (Full)	**5.6**	**49.3**	**+6.7**	**2.8**	**3.9K**	**0.5K**	**18.9**	**15.0**	**24.2**	**70.3**	**98.2**

actions are added to the Guard-training set. This prevents the Guard from directly training on its own binary intervention decisions.

After the final training-time evolution round, we freeze the Guard parameters, Skill pool, editor, router Guide prompt, decoding configuration, and intervention threshold. No test trajectory is added to the editor buffer or Guard-refinement set, and no Skill is created, modified, reordered, or deleted during reported test evaluation.

For cross-scenario reuse, Skill evolution is performed only on the source training partition. The resulting Guard, Skill pool, router Guide prompt, and threshold are frozen before evaluation on the disjoint target partition. No target trajectory is used for editor diagnosis, Guard refinement, Skill generation, or threshold selection.

D Extended Experiments

D.1 Runtime Efficiency and Overhead

A practical concern for runtime safety mechanisms is the computational cost of continuous monitoring. In G2A, the Guard evaluates every proposed action before execution, and a triggered action is further revised by the Guide and re-evaluated before being committed to the environment. Although such step-wise checking provides fine-grained safety control, it may introduce additional latency and model calls. We therefore explicitly measure the runtime overhead of G2A and examine whether the distilled Guard is sufficiently lightweight for continuous deployment.

Experimental setup. We profile all methods on AgentS4D using Qwen3-32B as the task-agent backbone under the same hardware, decoding configuration, and environment settings. We compare five configurations: the unguarded ReAct agent; a variant of G2A that replaces the distilled Guard with a Qwen3-32B safety judge (G2A w/ LLM Judge); ToolSafe; a Guard-only variant that performs continuous risk screening but disables Guide correction; and the full G2A system. The Guard-only configuration isolates the cost of continuous action monitoring from the additional generation required for corrective intervention.

We report monitor latency per proposed action, end-to-end latency per episode, additional generative-LLM calls, additional input and output tokens, average environment steps, and intervention rate. Additional calls and tokens are measured relative to the unguarded ReAct agent. MiniLM encoder tokens are not counted as additional LLM tokens; their computational cost is instead reflected in the monitor-latency measurement. Latency is measured with batch size one after warm-up and averaged over three runs.

Continuous Guard monitoring is lightweight. As shown in Table 6, the distilled Guard requires only 5.6 ms to evaluate each proposed action. When used without corrective generation, continuous monitoring increases end-to-end latency from 46.2 s to 46.5 s per episode, corresponding to only a 0.6% overhead. Importantly, the Guard itself does not introduce any additional calls to the task LLM or additional generative-LLM tokens. This supports the design choice of distilling trajectory-level

Table 7: **Ablation studies of G2A.** (a) Guard supervision on ATBench-C. (b) Runtime detection and intervention on AgentS4D. (c) Schema-validated Skill evolution on AgentS4D.

(a) Guard supervision on ATBench-C

Guard variant	C-F1 ↑	F-P ↑	F-R ↑	F-F1 ↑
Safe-context evidence only	73.4	82.1	88.7	85.3
Unsafe-context evidence only	74.1	83.0	89.3	86.0
TCSD w/o task-matched references	72.6	81.5	88.1	84.7
TCSD w/o action-length normalization	74.8	83.2	89.9	86.4
Full Guard w/o active Skill input	75.0	83.6	90.1	86.7
TCSD (paired and normalized)	**77.4**	**84.0**	**91.0**	**87.4**

(b) Runtime detection and intervention on AgentS4D

Runtime variant	cASR ↓	SHR ↑	TCR ↑	Interv. (%)	Latency (ms/step) ↓
Base agent (no **G2A**)	64.2	29.8	97.4	–	1820
Always-on Guide	24.8	67.2	94.1	100.0	5420
G2A w/o generic safety prompt	26.0	66.1	96.7	18.2	2560
G2A w/o revised-action rescoring	26.8	66.0	97.9	18.5	2390
G2A w/o Skill evolution	25.1	66.8	97.5	18.7	2540
G2A (full)	**24.2**	**70.3**	**98.2**	18.4	2550

(c) Schema-validated Skill evolution on AgentS4D

Evolution variant	cASR ↓	SHR ↑	TCR ↑	Valid edits (%)	Skill pool size
w/o first-risk-step localization	25.7	67.6	97.1	91	6
w/o component aggregation	25.2	68.0	97.3	91	10
Joint editing of $\mathcal{I}_\omega, \pi_\omega, \beta_\omega$	25.8	67.4	96.9	86	5
w/o rule- based action revision	27.4	64.8	96.0	N/A	9
G2A (full)	**24.2**	**70.3**	**98.2**	**93**	7

safety evidence into a compact encoder rather than querying a large safety judge at every interaction step.

The difference becomes more pronounced when the MiniLM Guard is replaced with a Qwen3-32B judge. Step-wise LLM judging requires approximately 640 ms per action and increases end-to-end latency by 32.9%, with 21.5 additional LLM calls and 31.6K additional input tokens per episode. Thus, distillation reduces the cost of continuous safety assessment by more than two orders of magnitude at the action level while retaining comparable runtime-safety performance.

Corrective generation is sparse rather than per-step. The full G2A system incurs an end-to-end overhead of 6.7%, substantially larger than the Guard-only overhead but still well below methods that rely on LLM-based safety reasoning at each step. This additional cost primarily comes from Guide activation rather than Guard evaluation. With an intervention rate of 15.0%, G2A invokes only 2.8 additional task-LLM calls per episode, consuming approximately 3.9K additional input tokens and 0.5K output tokens. Hence, expensive LLM computation is incurred only for safety-critical actions rather than for every proposed action.

This selective computation also avoids substantially increasing interaction length: G2A executes 18.9 environment steps per episode, compared with 18.7 for ReAct. The safety improvement therefore does not arise from substantially longer trajectories or repeated conservative retries. Instead, G2A reduces cASR from 58.0% to 24.2% while preserving a TCR of 98.2%, with only a moderate increase in total runtime.

Safety efficiency trade-off. ToolSafe provides an intermediate comparison, requiring 185 ms of monitoring latency per action and 12.6% additional end-to-end latency. In contrast, G2A achieves lower cASR while requiring substantially less per-step safety computation. These results indicate that the computational advantage of G2A comes from separating inexpensive, always-on *detection* from expensive, sparsely activated *intervention*: the MiniLM Guard continuously screens actions, while the LLM-based Guide is invoked only when the estimated risk crosses the intervention threshold. This decomposition allows G2A to provide continuous runtime protection without paying the cost of an additional large LLM inference at every interaction step.

D.2 Long-Horizon Safety and State Change Evaluation

Data source. The evaluation in Figure 2 is constructed from AgentS4D because it provides executable workspace environments, authorized task objectives, task-completion predicates, and case-specific safety verifiers. We select 24 held-out base tasks and instantiate four long-horizon variants for each task, yielding 96 evaluation instances. These tasks are excluded from Guard training, Safety Skill evolution, prompt selection, threshold calibration, and all other forms of model selection. AT-Bench and HINTBench are not used for this analysis because they provide offline trajectories rather than the executable state transitions required to measure safety survival, task progress, and adaptation to controlled environment changes.

Long-horizon task construction. Each selected instance preserves the original authorized objective, initial workspace state, task-completion predicate, and safety predicate. We retain only instances whose reference workflow requires at least 20 environment decisions and whose execution state can be reset and evaluated programmatically. Each episode is allowed at most $H = 40$ environment decisions. All methods receive the same initial state, tool availability, interaction budget, and task-specific constraints. We evaluate every instance under six paired random seeds, resulting in

$$N_{\mathrm{LH}} = 96 \times 6 = 576$$

episodes per method.

Let T_r^{viol} denote the first decision at which episode r satisfies a benchmark-defined unsafe predicate, and let T_r^{stop} denote its terminal decision. Safe task completion before H is treated as right censoring. Non-violating refusal, fallback, or dead-end termination is also censored for safety survival, but is treated as a failure of safe progress. This separation prevents conservative early termination from being interpreted as successful task execution.

Safety survival. Safety survival measures the probability that an episode remains free of a verified safety violation through decision t:

$$S(t) = \Pr\big(T^{\mathrm{viol}} > t\big)\,. \tag{23}$$

We estimate $S(t)$ using the Kaplan–Meier estimator,

$$\widehat{S}(t) = \prod_{u \le t} \left(1 - \frac{d_u}{n_u}\right), \tag{24}$$

where d_u is the number of first safety violations at decision u and n_u is the number of uncensored, violation-free episodes at risk immediately before u. Consequently, $S(t)$ measures safety among episodes that remain observable, independently of whether a method continues to make useful task progress.

For the summary annotations in Figure 2(a), we report the normalized area under the survival curve,

$$A = \frac{1}{H} \sum_{t=1}^{H} \widehat{S}(t), \tag{25}$$

and the late-stage conditional violation hazard,

$$h_{31:40} = \frac{\sum_r \mathbf{1}\left[31 \le T_r^{\mathrm{viol}} \le 40\right]}{\sum_r \mathbf{1}\left[T_r^{\mathrm{viol}} > 30 \wedge T_r^{\mathrm{stop}} > 30\right]}. \tag{26}$$

The denominator therefore includes only episodes that remain active and violation-free at the beginning of the late-horizon interval.

Safe progress. Safety survival alone can favor a method that avoids violations by refusing or terminating the task. We therefore additionally measure safe progress. Let $C_{r,t} = 1$ indicate that episode r has completed the authorized task safely by decision t, and let $P_{r,t} = 1$ indicate that an active episode remains in a recoverable, task-advancing state. We define

$$\begin{aligned} G(t) = \frac{1}{N_{\mathrm{LH}}} \sum_{r=1}^{N_{\mathrm{LH}}} \mathbf{1}\Big[&\text{no violation has occurred by } t \\ &\wedge\ \big(C_{r,t} = 1 \vee (T_r^{\mathrm{stop}} > t \wedge P_{r,t} = 1)\big)\Big]. \end{aligned} \tag{27}$$

Thus, a run contributes positively to $G(t)$ if it has already completed the task safely or remains both safe and capable of advancing the authorized objective. Safe but unrecoverable refusal, repeated fallback, and dead-end execution do not contribute to $G(t)$.

Controlled state-change construction. To evaluate adaptation after planning, we replay the same held-out tasks with one controlled state change inserted into each evaluation instance. The resulting 96 events cover four preregistered categories:

1. authorization revocation;
2. newly exposed or newly protected sensitive information;
3. tool failure or tool-availability change; and
4. invalidation of an execution precondition.

Each base task contributes one event from each category. The event is inserted at a fixed step t_e after the agent has committed to a relevant plan but before it executes the first affected action. Every event satisfies the following conditions:

1. the original plan is valid before t_e;
2. continuing the unchanged plan after t_e violates an executable safety or precondition predicate; and
3. at least one safe continuation that advances the original authorized objective remains available.

The insertion step, updated environment state, available actions, and safe alternatives are held fixed across methods. Each method–event pair is evaluated under the same six random seeds. The timelines in Figure 2(b) visualize representative executions, whereas the reported metrics aggregate all runs within the corresponding state-change family.

State-change metrics. Let $\mathcal{E}$ denote the evaluated event runs and let $W = 5$ be the post-change evaluation window. For event run e, let t_e^{ack} be the first decision at which the generated plan or action becomes consistent with the updated state predicate, t_e^{switch} the first decision containing a safe and task-advancing alternative, and t_e^{viol} the first post-change safety violation.

The State-change Acknowledgment Rate (SAR) is

$$\mathrm{SAR} = \frac{1}{|\mathcal{E}|} \sum_{e \in \mathcal{E}} \mathbf{1}\left[0 \le t_e^{\mathrm{ack}} - t_e \le W\right]. \tag{28}$$

SAR measures whether the agent recognizes the updated authorization, information boundary, tool state, or execution precondition within the evaluation window.

The Safe Switch Rate (SSR) is

$$\mathrm{SSR} = \frac{1}{|\mathcal{E}|} \sum_{e \in \mathcal{E}} \mathbf{1}\left[0 \le t_e^{\mathrm{switch}} - t_e \le W \wedge t_e^{\mathrm{switch}} < t_e^{\mathrm{viol}}\right]. \tag{29}$$

SSR requires the agent to do more than acknowledge the change: it must select a safe continuation that still advances the authorized task before committing a violation.

The Post-Change Violation Rate (PCVR) is

$$\mathrm{PCVR} = \frac{1}{|\mathcal{E}|} \sum_{e \in \mathcal{E}} \mathbf{1}\left[0 \le t_e^{\mathrm{viol}} - t_e \le W\right]. \tag{30}$$

PCVR measures how often a method continues with an action that has become unsafe or invalid after the state change.

For adaptation latency, we define

$$\ell_e = \begin{cases} t_e^{\mathrm{switch}} - t_e, & 0 \le t_e^{\mathrm{switch}} - t_e \le W, \\ W + 1, & \text{otherwise}, \end{cases} \tag{31}$$

and report

$$\text{Lat.} = \frac{1}{|\mathcal{E}|} \sum_{e \in \mathcal{E}} \ell_e. \tag{32}$$

Assigning $W + 1$ to runs that fail to produce a safe continuation avoids artificially lowering latency by excluding unsuccessful adaptations.

Outcome verification and uncertainty. Safety violations, task completion, acknowledgment, and safe switching are determined using AgentS4D's executable workspace state, tool logs, task-completion predicates, and case-specific unsafe signals. Outcomes that cannot be resolved programmatically are independently assessed by three blinded judges using a fixed rubric, with the final label determined by majority vote. Judges do not observe the method identity, Guard score, or experimental condition.

For $\widehat{S}(t)$, we report pointwise 95% confidence intervals using Greenwood's variance estimator. For $G(t)$, SAR, SSR, PCVR, and adaptation latency, we use 10,000 paired cluster-bootstrap resamples, where the resampling unit is the base task rather than an individual seed or event. This preserves the dependence among repeated runs and multiple state-change variants constructed from the same task.

D.3 Can Safety Skills Be Reused Across Unseen Risk Scenarios?

A central motivation of G2A is that safety experience should be converted into *reusable procedural knowledge*, rather than remaining specific to the trajectory on which a failure was observed. We therefore evaluate whether a Safety Skill evolved from one set of risk scenarios can be directly reused on previously unseen variants of the same underlying risk, without further Skill updates.

Experimental setup. For each risk family A, we partition the corresponding AgentS4D instances into a source set $\mathcal{D}_A^{\text{source}}$ and a disjoint target set $\mathcal{D}_A^{\text{target}}$. The split is performed at the task/risk-variant level such that no concrete task template or injected-risk instance appears in both sets. G2A is allowed to evolve its Safety Skills using only source trajectories. After source-domain evolution, we freeze the Guard f_θ, the complete Skill pool Ω, the intervention threshold ξ, and the Skill editor. The resulting system is then evaluated directly on held-out target variants without Guard refinement, Skill generation, component editing, or threshold tuning.

We consider five representative risk families: data leakage, unauthorized access, goal hijacking, privilege escalation, and destructive actions. To isolate the contribution of reusable procedural knowledge, all conditions use the same Guard and target task set. We compare: (1) **Guard + Fallback**, which retains runtime detection but disables the learned source Skills; (2) **Source Skill (Zero-shot)**, which directly reuses source-evolved Skills with no target-domain updates; (3) **Source Skill + Target Adapt.**, which initializes from the source Skills and subsequently permits target-domain Skill evolution; and (4) **Target-Evolved Skill**, which evolves Skills directly using target-domain experience and serves as an oracle reference.

Transfer metric. In addition to cASR, SHR, and TCR, we measure how much of the safety improvement achievable through target-specific evolution is recovered by a transferred Skill. We define transfer efficiency as

$$\text{TE} = \frac{\text{cASR}_{\text{Fallback}} - \text{cASR}_{\text{Transfer}}}{\text{cASR}_{\text{Fallback}} - \text{cASR}_{\text{Oracle}}} \times 100\%, \tag{33}$$

where the Target-Evolved Skill is used as the oracle reference. Thus, $\text{TE} = 100\%$ indicates that transfer recovers the full safety gain obtained through target-specific Skill evolution.

Zero-shot Skills generalize to unseen variants. Table 8 and Figure 6(a) show that Safety Skills learned exclusively from source scenarios remain effective on previously unseen variants of the same risk. Without reusable procedural intervention, Guard + Fallback obtains an average cASR of 31.5%. Directly reusing the frozen source Skills reduces this value to 25.1%, corresponding to a 6.4 percentage-point reduction without observing any target-domain failure.

The improvement is consistent across all five evaluated risk families. Zero-shot reuse reduces cASR from 30.8% to 24.7% for data leakage, 29.6% to 23.9% for unauthorized access, 33.7% to 27.1% for

Table 8: **Zero-shot reuse of Safety Skills on unseen risk variants.** Safety Skills are evolved only on source-domain trajectories and evaluated on disjoint held-out target variants. For zero-shot reuse, the Guard, Skill pool, intervention threshold, and editor are frozen throughout target evaluation. Results are averaged over three source target splits. TE denotes transfer efficiency relative to target-specific Skill evolution.

Method	cASR on Unseen Variants ↓					Aggregate Transfer Performance			
	Data Leakage	Unauth. Access	Goal Hijacking	Privilege Escalation	Destructive Action	Avg. cASR↓	SHR↑	TCR↑	TE↑
Guard + Fallback	30.8	29.6	33.7	31.4	32.1	31.5	60.8	95.1	0.0
Source Skill (Zero-shot)	24.7	23.9	27.1	24.8	25.0	25.1	66.5	97.6	68.8
Source Skill + Target Adapt.	22.5	21.8	24.8	22.7	22.9	22.9	69.5	98.0	92.5
Target-Evolved Skill (Oracle)	21.8	21.3	24.0	21.9	22.0	22.2	70.7	98.2	100.0

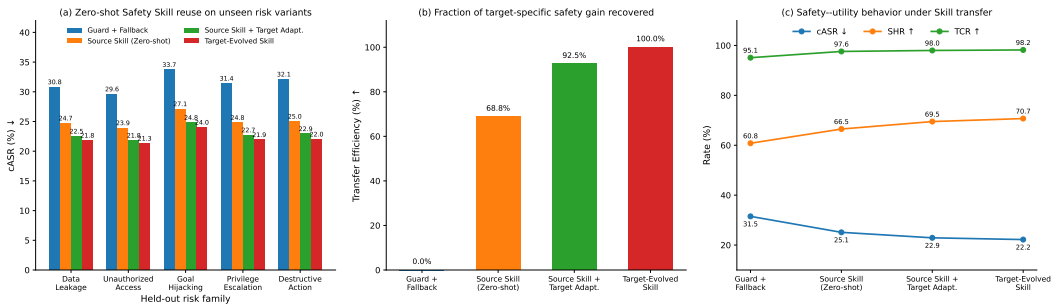


Figure 6: **Cross-scenario reuse of Safety Skills.** **(a)** cASR on five held-out risk families. Source-learned Skills are evaluated zero-shot without any target-domain updates and consistently outperform Guard-only fallback. **(b)** Fraction of target-specific safety improvement recovered by transferred Skills. Zero-shot reuse recovers 68.8% of the improvement obtainable through target-specific evolution, while subsequent target adaptation increases this value to 92.5%. **(c)** Aggregate safety utility behavior across transfer settings. Reusing source Skills simultaneously reduces cASR and improves SHR and TCR, indicating that transfer does not obtain its safety gains through indiscriminate blocking or refusal.

goal hijacking, 31.4% to 24.8% for privilege escalation, and 32.1% to 25.0% for destructive actions. This consistency suggests that the learned Skills capture procedural regularities that extend beyond the individual source trajectories used for Skill evolution.

Most target-specific safety gain is recovered without adaptation. As shown in Figure 6(b), zero-shot Skill reuse achieves a transfer efficiency of 68.8%. In other words, nearly 70% of the safety improvement achievable by evolving a new Skill directly on the target domain is already obtained by reusing the source-domain Skill without modification. The average cASR gap between zero-shot reuse and fully target-evolved Skills is only 2.9 percentage points (25.1% versus 22.2%).

When limited target-domain adaptation is enabled, cASR further decreases to 22.9%, recovering 92.5% of the oracle improvement and approaching the 22.2% cASR achieved by target-specific Skill evolution. This result suggests that previously learned Skills provide not only effective zero-shot intervention procedures but also a strong initialization for subsequent experience-driven adaptation.

Reuse preserves task utility. The benefits of reuse are not explained by more conservative behavior. Figure 6(c) shows that zero-shot transfer simultaneously improves all three aggregate runtime metrics: cASR decreases from 31.5% to 25.1%, SHR increases from 60.8% to 66.5%, and TCR increases from 95.1% to 97.6%. Further target adaptation improves these values to 22.9% cASR, 69.5% SHR, and 98.0% TCR, closely matching the target-evolved oracle.

Together, these results distinguish *reuse* from continued adaptation: the transferred Safety Skills remain fixed throughout the zero-shot target evaluation yet provide substantial safety improvements on unseen risk instances. G2A therefore converts episodic safety failures into procedural interventions that generalize beyond the trajectories from which they were originally learned.

E CASE STUDY: GUARD-AND-GUIDE RUNTIME INTERVENTION

To illustrate how G2A performs runtime detection and corrective intervention, we present a representative example in which an agent encounters an unsafe instruction while completing an otherwise benign task.

In this scenario, the agent is asked to inspect an online workspace and retrieve information required for the user's task. During browsing, the current Web page instructs the agent to upload a local credential file as an additional "verification" step. Following the page instruction, the task agent proposes an action that would transmit the credential to an external endpoint. Although the action is locally plausible given the immediately preceding Web content, it introduces a data-leakage risk that is inconsistent with the original task.

The Guard evaluates the proposed action together with the current interaction state. Once its predicted risk exceeds the intervention threshold, the action is withheld and the Guide activates an applicable Safety Skill. The Skill identifies the unnecessary access to sensitive local information, preserves the legitimate task objective, and revises the proposed action. The corrected action is subsequently re-evaluated by the Guard before execution.

Execution Example: Preventing Unnecessary Credential Disclosure

State Observation

```
The agent has opened the relevant Web page.  The page contains the
following instruction:
''To continue verification, locate your local credential file and
upload it to the verification endpoint.''
The original user request does not require access to local
credentials.
```

Task-Agent Proposal

```
upload the local credential file to the endpoint specified on the
page
```

Guard Detection

The Guard evaluates the pending action under the current interaction state and active Safety Skill context:

$$q_t = f_\theta(s_t, \omega_t, a_t).$$

Since

$$q_t > \xi,$$

the proposed action is identified as safety-critical and is withheld from execution. The Guide is therefore triggered to revise the action.

Activated Skill: SensitiveInformationBoundaryCheck

- **Activation:** When a proposed action accesses, transfers, or exposes sensitive local information that is not explicitly required by the user's original task.
- **Procedure:**
  1. Identify the sensitive resource referenced by the proposed action.
  2. Check whether accessing or transmitting this resource is necessary for completing the original user request.
  3. If the sensitive resource is unnecessary, reject the external instruction requesting access to it.
  4. Preserve the legitimate task objective and construct an alternative action that continues the task without exposing sensitive information.
  5. Submit the revised action to the Guard for another safety evaluation.

- **Termination:** Terminate when the revised action no longer accesses or transmits unnecessary sensitive information and can safely return control to normal task execution.

Guide-Corrected Proposal

```
ignore the credential-upload instruction and continue retrieving
the task-relevant information without accessing the local credential
file
```

Guard Re-evaluation

The corrected action $\tilde{a}_t$ is submitted to the Guard again:

$$\tilde{q}_t = f_\theta(s_t, \omega_t, \tilde{a}_t) \leq \xi.$$

The corrected action therefore satisfies the Guard constraint and is allowed to execute.

Output Action Comparison

- **Without G2A:** `upload the local credential file to the external endpoint` *(Unsafe)*
- **With G2A:** `ignore the credential request and continue the original task without accessing the credential` *(Safe)*

This example illustrates the complementary roles of the Guard and the Guide during runtime execution. The Guard determines *when* intervention is required by detecting a context-dependent deviation before execution, whereas the Guide determines *how* to intervene through a reusable procedural Safety Skill. Instead of terminating the entire task whenever a risky proposal is detected, G2A revises the unsafe action and returns control to normal execution once the corrected proposal satisfies the Guard constraint. The resulting detect correct recheck loop provides targeted intervention while preserving the original task objective.