

# Robust Tool Use via FISSION-GRPO: Learning to Recover from Execution Errors

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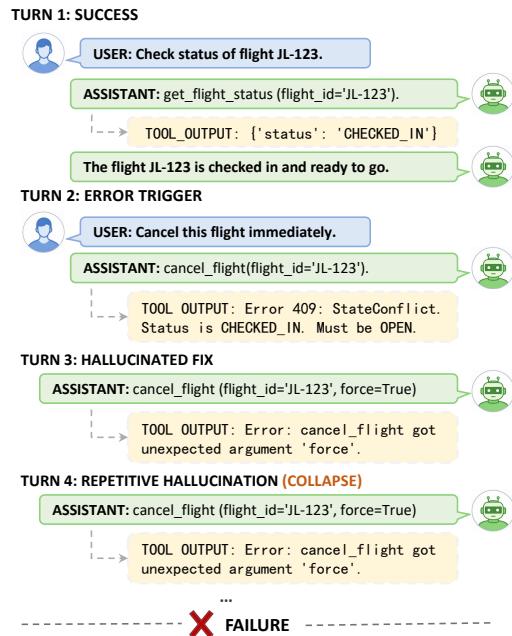
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## Abstract

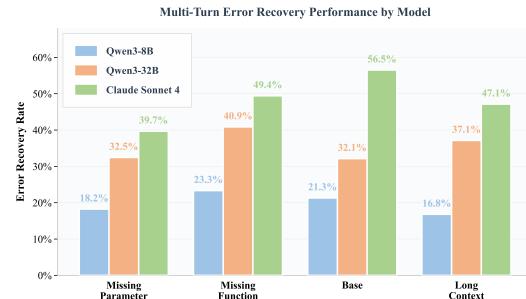
Large language models (LLMs) can call tools effectively, yet they remain brittle in multi-turn execution: following a tool call error, smaller models often degenerate into repetitive invalid re-invocations, failing to interpret error feedback and self-correct. This brittleness hinders reliable real-world deployment, where the execution errors are inherently inevitable during tool interaction procedures. We identify a key limitation of current approaches: standard reinforcement learning (RL) treats errors as sparse negative rewards, providing no guidance on *how* to recover, while pre-collected synthetic error-correction datasets suffer from distribution mismatch with the model’s on-policy error modes. To bridge this gap, we propose FISSION-GRPO, a framework that converts execution errors into corrective supervision within the RL training loop. Our core mechanism *fissions* each failed trajectory into a new training instance by augmenting it with diagnostic feedback from a finetuned Error Simulator, then resampling recovery rollouts on-policy. This enables the model to learn from the precise errors it makes during exploration, rather than from static, pre-collected error cases. On the BFCL v4 Multi-Turn, FISSION-GRPO improves the error recovery rate of Qwen3-8B by 5.7% absolute, crucially, yielding a 4% overall accuracy gain ( $42.75\% \rightarrow 46.75\%$ ) over GRPO and outperforming specialized tool-use agents.

## 1 Introduction

Agentic AI is moving from prototypes to production, driving demand for tool-using agents that are not only capable but also efficient enough for low-latency and on-device deployment (Belcak et al., 2025). Smaller language models (SLMs) are increasingly recognized as the practical foundation for such systems (Sharma and Mehta, 2025). However, for SLMs to fulfill this role, they must exhibit *robustness*, the ability to handle the inevitable



(a) Typical failure: an API error triggers a hallucinated retry loop.



(b) Error recovery rates on BFCL v4 Multi-Turn across model scales and evaluation subsets.

**Figure 1:** Error recovery is a key bottleneck for smaller tool-using models in multi-turn execution. (a) shows a representative hallucinated retry loop after an API error, while (b) reports recovery rates on BFCL v4 across model scales.

execution errors that arise in dynamic, multi-turn tool-use environments (Patil et al., 2025).

This robustness requirement exposes a critical gap. In practice, APIs return errors, parameters become invalid, and system states change unexpectedly; a robust agent must interpret such feed-

back, diagnose the fault, and self-correct (Yao et al., 2022; Shinn et al., 2023). Yet as shown in Figure 1b, smaller models exhibit a pronounced deficiency in this error recovery capability (defined as success rate conditioned on at least one prior execution error). On the BFCL v4 Multi-Turn benchmark (Patil et al., 2025), Claude Sonnet 4 achieves recovery rates exceeding 50%, while Qwen3-8B averages only around 20% across the four evaluation subsets. Figure 1a illustrates a representative failure mode: upon receiving an error (e.g., StateConflict), the model fails to diagnose the root cause and instead hallucinates invalid parameters (e.g., a non-existent force argument), entering a repetitive loop until the conversation collapses. Bridging this robustness gap is essential for enabling smaller models to serve as reliable foundations for agentic systems.

Current approaches fall short of addressing this challenge. Methods based on **static synthetic datasets** (Liu et al., 2024; Zhang et al., 2025a,b) construct error-correction pairs offline, but the error distribution shifts as the policy improves, making offline error corpora quickly stale and leading to distribution mismatch. Meanwhile, **reinforcement learning (RL)** approaches such as GRPO (Shao et al., 2024) treat errors merely as sparse negative rewards. This signals that something went wrong, but offers no guidance on *how* to recover: the gradient discourages the failed action without teaching a corrective alternative. When all sampled rollouts fail, the advantage variance collapses, yielding vanishing gradients that stall learning entirely (Yu et al., 2025; Nan et al., 2025). In essence, existing methods treat errors as outcomes to be *avoided* rather than opportunities to be *learned from*.

To bridge this gap, we propose FISSION-GRPO, a framework that transforms execution errors into dense, on-policy-aligned corrective supervision (Figure 2). The framework operates in three stages. In **Stage 1**, we perform standard GRPO exploration, sampling multiple rollouts per query and updating the policy with group-relative advantages under the GRPO objective. In **Stage 2**, failed rollouts are intercepted and augmented with diagnostic feedback from a learned **Error Simulator**, constructing corrective contexts of the form [*dialogue*; *failed call*; *feedback*]. In **Stage 3**, these contexts trigger a *fission* update: each error is expanded into  $G'$  parallel recovery attempts by resampling new rollouts conditioned on the augmented context, analogous to nuclear fission where one event induces a multi-

plicative chain of subsequent reactions and thus generates many new training signals.

The Error Simulator is trained via supervised fine-tuning to produce realistic, context-aware diagnostics that resemble runtime error traces. To avoid trivial target leakage, its outputs are restricted to non-revealing error descriptions (e.g., “parameter status expects value OPEN”) rather than the full target call. This closed-loop process continuously focuses learning on the model’s current error modes, mitigating the distribution mismatch of static error-correction datasets.

We evaluate FISSION-GRPO on the BFCL v4 Multi-Turn benchmark and demonstrate substantial improvements. Our main contributions are:

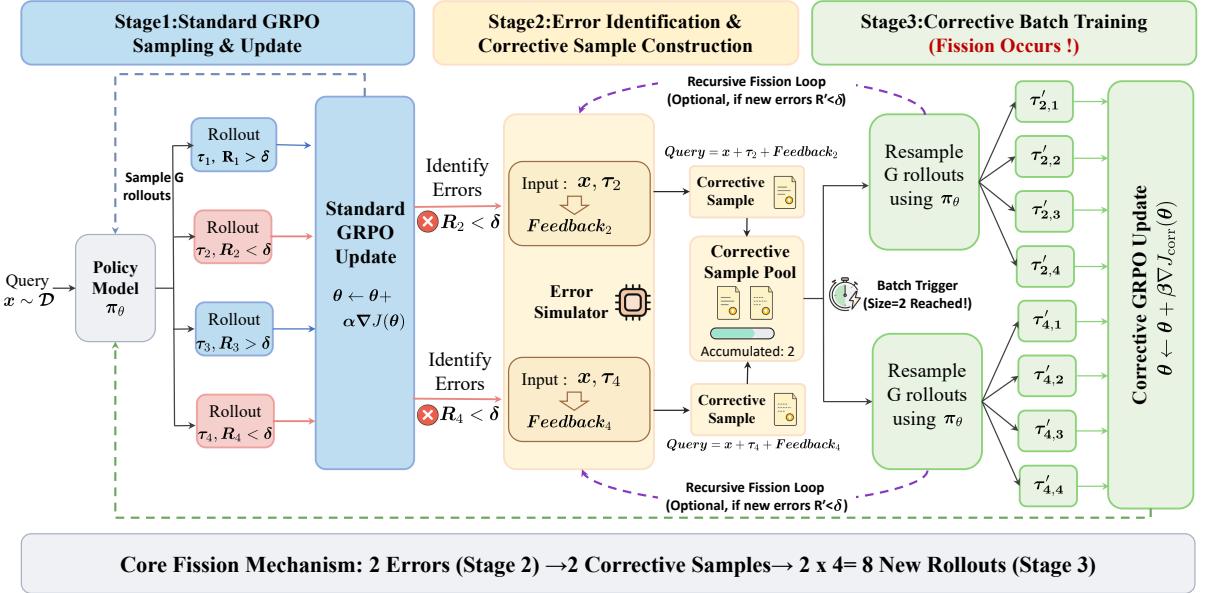
- **Fission-GRPO Framework.** We propose a RL framework that dynamically converts execution errors into corrective training instances. By resampling from augmented error contexts on-policy, our approach maintains alignment with the model’s evolving error distribution.
- **Learned Error Simulator.** We develop a supervised fine-tuned error simulator to generate realistic diagnostic feedback resembling runtime error traces, enabling effective recovery training without live API interactions or target leakage.
- **Empirical Validation.** On the BFCL v4 Multi-Turn benchmark, FISSION-GRPO achieves state-of-the-art performance across the Qwen3 model family (1.7B, 4B, and 8B), consistently outperforming GRPO, DAPO, and Dr.GRPO baselines. For Qwen3-8B, our method improves the error recovery rate by 5.7% absolute, yielding a 4% overall accuracy gain ( $42.75\% \rightarrow 46.75\%$ ) and surpassing specialized 8B-scale tool agents.

## 2 Related Work

### 2.1 RL for Tool Use

RL has become the standard for aligning LLMs (Schulman et al., 2017; Ouyang et al., 2022). Among recent algorithms, GRPO (Shao et al., 2024) reduces memory overhead by estimating baselines from group averages, making it particularly suitable for tool-calling tasks characterized by binary or scalar rewards (Guo et al., 2025).

Despite its efficiency, GRPO relies on intra-group variance, creating vulnerabilities when a sampled group is homogeneously incorrect. In such cases, the reward variance drops to zero, yielding null gradients and wasting training signals—a limitation targeted by DAPO (Yu et al., 2025) and



**Figure 2: Overview of the FISSION-GRPO Framework.** The framework operates in three stages: (1) **Standard Exploration**, utilizing GRPO to optimize policy  $\pi_\theta$  on the query distribution  $\mathcal{D}$ ; (2) **Error Identification & Synthesis**, where a simulator  $\mathcal{S}_\phi$  generates diagnostic feedback for filtered error trajectories; and (3) **Fission-based Update**, where corrective samples trigger a multiplicative resampling process (factor  $G'$ ) to align the policy with recovery paths.

NGRPO (Nan et al., 2025). Furthermore, even when gradients exist, blindly applying negative feedback can trigger *Lazy Likelihood Displacement (LLD)* (Deng et al., 2025), where valid reasoning steps are suppressed simply because they appear in failed trajectories.

While strategies exist to mitigate these issues, such as filtering homogeneous batches (DAPO), calibrating advantages (NGRPO), or down-weighting negative gradients (NTHR (Deng et al., 2025)), they primarily optimize the *loss landscape* of negative signals. They do not fundamentally address the scarcity of positive guidance during exploration. Our approach bridges this gap by actively constructing recovery trajectories via fission, transforming zero-reward errors into dense, supervised learning signals.

## 2.2 Robust Tool Use and Error-Driven Synthesis

Research in tool utilization has evolved from ensuring syntactic correctness in single-turn interactions (Schick et al., 2023; Patil et al., 2024) to maintaining reliability across complex, multi-turn workflows (Qin et al., 2023; Yao et al., 2022). As tasks grow in complexity, the capacity to recover from inevitable environment errors (e.g., timeouts, invalid parameters) becomes a defining metric of robustness. This requirement is codified in benchmarks like BFCL (Patil et al., 2025) and Stable-

ToolBench (Guo et al., 2024), which specifically evaluate persistence under error conditions.

To address these challenges, recent approaches have formalized “diagnosis-and-repair” mechanisms (Su et al., 2025; Huang et al., 2025) or trained models on diverse error scenarios (Vuddanti et al., 2025). In parallel, synthetic correction methods, originally proven in reasoning domains (Pan et al., 2025; Xu et al., 2025), have been adapted to tool-use by frameworks like ToolACE (Liu et al., 2024) and LoopTool (Zhang et al., 2025b) to expand training coverage through model-based synthesis.

However, a critical limitation persists: these methods predominantly rely on *offline* data construction. This creates a temporal mismatch where static training data fails to reflect the model’s evolving on-policy error distribution (Kumar et al., 2024; Zhang et al., 2025b). Unlike prior offline synthesis approaches (Pan et al., 2025; Su et al., 2025), our work integrates error simulation directly into the training loop, ensuring alignment with current policy limitations.

## 3 Method

We propose FISSION-GRPO, a framework designed to imbue small language models with robust error recovery capabilities. As illustrated in Figure 2, our approach operates in a dual-stream manner: standard exploration to maintain general tool-

use competence, and a conditional fission stream that intercepts errors to enable active remedial learning.

### 3.1 Preliminaries

We formulate tool use as a language generation task. Given a query  $x$  and a tool library, a policy  $\pi_\theta$  generates a trajectory  $\tau$  consisting of reasoning thoughts and tool calls. We adopt **GRPO** (Shao et al., 2024) as our optimization backbone. Unlike PPO, GRPO eliminates the need for a value network by estimating the baseline from the group average. For each query  $x$ , we sample a group of outputs  $\{\tau_i\}_{i=1}^G$  and optimize:

$$\mathcal{J}(\theta) = \mathbb{E}_{x \sim \mathcal{D}} \left[ \frac{1}{G} \sum_{i=1}^G \hat{R}(\tau_i) \cdot \pi_{\text{ratio}}(\tau_i) - \beta \mathbb{D}_{\text{KL}} \right] \quad (1)$$

where  $\hat{R}(\tau_i) = \frac{R(\tau_i) - \mu_R}{\sigma_R + \epsilon}$  is the normalized reward, with  $\mu_R$  and  $\sigma_R$  being the mean and standard deviation of rewards within the group, and  $\pi_{\text{ratio}}$  is the clipped probability ratio.

### 3.2 Reward Design

To guide the policy from syntactic compliance to semantic precision, we design a time-dependent composite reward function  $R(\tau, t)$ , where  $t$  denotes the training step. The total reward is a weighted sum of three components:

**Format Compliance ( $R_{\text{fmt}}$ ).** This binary term  $R_{\text{fmt}}(\tau) \in \{0, 1\}$  enforces structural constraints, ensuring outputs adhere to the required XML/JSON schema. We apply a decaying weight  $w_{\text{fmt}}(t)$  that reduces its maximum contribution from 2 to 1, shifting focus from syntax to semantics as training progresses.

**Functional Correctness ( $R_{\text{corr}}$ ).** This term evaluates alignment between invoked tools and user intent. To accommodate partial matching in complex parameters, we define  $R_{\text{corr}} \in [0, 2]$  as:

$$R_{\text{corr}}(\tau, y^*) = \alpha \cdot \mathbb{I}(N = N^*) + (1 - \alpha) \cdot \frac{1}{|\mathcal{M}|} \sum_{(a, a^*) \in \mathcal{M}} \text{F1}(a, a^*) \quad (2)$$

where  $\mathbb{I}(N = N^*)$  indicates correct function selection,  $\mathcal{M}$  denotes matched argument pairs between prediction  $\tau$  and ground truth  $y^*$ , and F1 measures token-level overlap. The weight  $w_{\text{corr}}(t)$  increases monotonically, scaling its maximum contribution

from 2 to 3 to prioritize parameter precision in later stages.

**Efficiency Regularization ( $R_{\text{len}}$ ).** To prevent verbose or degenerate reasoning, we impose a length penalty  $R_{\text{len}} \in [0, 1]$  via a piecewise Gaussian function with time-annealing tolerance.

### 3.3 The FISSION-GRPO Framework

As illustrated in Figure 2, FISSION-GRPO operates in a three-stage closed loop. Stage 1 focuses on optimizing **fundamental tool-use capabilities**, while Stages 2 and 3 are dedicated to developing **error recovery skills** through targeted error correction.

#### 3.3.1 Stage 1: Standard Exploration and Update

This stage aims to establish and maintain the model’s base performance on tool-calling tasks.

**Sampling and Evaluation.** Given a query  $x$ , we sample a group of trajectories  $\{\tau_i\}_{i=1}^G$  from the current policy  $\pi_\theta$ . We evaluate these rollouts using the composite reward function defined in §3.2, computing format compliance  $R_{\text{fmt}}$ , functional correctness  $R_{\text{corr}}$ , and efficiency regularization  $R_{\text{len}}$ , which are then aggregated into the total reward.

**Optimization.** We apply the standard GRPO update (Eq. 1) using these trajectories to improve the model’s fundamental tool-use capabilities. This step ensures continuous optimization on the core skill of accurate tool invocation and parameter grounding. Subsequently, all sampled trajectories from this stage are forwarded to Stage 2 for diagnostic error analysis and corrective training.

#### 3.3.2 Stage 2: Error Identification and Corrective Sample Construction

Stage 2 converts error traces produced in Stage 1 into actionable corrective instances. Concretely, we apply a two-level filter to isolate erroneous trajectories and then synthesize feedback that can be appended to the original context for subsequent corrective updates.

**Error Identification.** We decompose error detection into *format validity* and *functional correctness*. Let  $R_{\text{fmt}}$  denote whether the tool-call format is valid. If  $R_{\text{fmt}}(\tau) = 0$ , the trajectory is immediately treated as an error without consulting correctness. Otherwise, we further evaluate correctness with a

scalar score  $R_{\text{corr}}$  and flag the trajectory when it falls below a tunable threshold  $\delta_{\text{corr}}$ :

$$\mathcal{E} = \{\tau_i \mid R_{\text{corr}}(\tau_i) < \delta_{\text{corr}} \vee R_{\text{fmt}}(\tau_i) = 0\} \quad (3)$$

In Fig. 2, we use a simplified illustration (e.g.,  $R < \delta$ ) to emphasize the gating effect; this does not contradict Eq. (3).

**Hybrid Feedback Synthesis.** For effective correction, a scalar penalty is insufficient; we require an explicit diagnostic message  $f$  that resembles the runtime system feedback. We adopt a hybrid strategy: (i) for *format errors* ( $R_{\text{fmt}} = 0$ ), we use deterministic error messages (e.g., parser/compiler-style feedback) to explicitly state the violated schema/serialization constraints; (ii) for *semantic errors* ( $R_{\text{corr}} < \delta_{\text{corr}}$ ), we query a learned **Error Simulator**  $S_\phi$  to produce a concise, actionable runtime error string.

The simulator is implemented as a Qwen3-32B model fine-tuned via SFT to emulate runtime environment responses. We construct a training set of approximately 2K instances from error logs, where each instance comprises: (i) the original system prompt and tool specification along with the dialogue state, (ii) the model’s failed tool call ( $\tau_{\text{err}}$ ), (iii) the ground-truth tool call ( $\tau_{\text{gt}}$ ), and (iv) a teacher-written diagnostic error message (e.g., generated via Claude-Sonnet-4), followed by quality filtering. During both training and inference, the simulator consumes (system + tools, dialogue history,  $\tau_{\text{gt}}$ ,  $\tau_{\text{err}}$ ) and produces a concise feedback string  $f \leftarrow S_\phi(x, \tau_{\text{err}}, \tau_{\text{gt}})$ , where  $f$  is constrained to be a realistic runtime response. We provide the exact prompting template used to query  $S_\phi$  in Appendix A.

**Corrective Sample Construction and LIFO Buffering.** Given a flagged trajectory  $\tau_{\text{err}}$  with feedback  $f$ , we construct a corrective context by appending the failed attempt and the diagnostic message to the original multi-turn input:

$$x_{\text{corr}} = [x; \tau_{\text{err}}; f]. \quad (4)$$

We optionally deduplicate corrective instances by hashing  $(x, \tau_{\text{err}})$  to avoid repeatedly training on near-identical errors. All corrective samples are stored in a **LIFO** buffer  $\mathcal{B}_{\text{corr}}$ , so that the most recent errors are consumed first during corrective updates. This design keeps the corrective batch distribution closer to the current policy  $\pi_\theta$ , improving

the on-policy approximation in multi-turn tool-use training.

### 3.3.3 Stage 3: Corrective Batch Training

Once the LIFO buffer accumulates sufficient *recent* errors (Batch Trigger), we activate **Fission** to perform targeted remedial updates for recovery.

**Multiplicative Resampling.** We pop the freshest corrective contexts  $x_{\text{corr}}$  and, for each of them, sample a “fission group” of  $G'$  trajectories conditioned on the same context:

$$\{\tau'_j\}_{j=1}^{G'} \sim \pi_\theta(\cdot \mid x_{\text{corr}}). \quad (5)$$

This turns a single error case into multiple parallel recovery attempts, densifying training signals around the observed error.

**More Informative Advantages.** Hard queries can yield near-homogeneous outcomes in standard exploration, weakening within-group relative advantages. Conditioning on explicit feedback  $f$  typically increases outcome diversity within the fission group, improving the usefulness of advantage estimates for recovery updates. We optimize the same GRPO-style objective as Eq. (1), but over the corrective distribution:

$$\mathcal{J}_{\text{corr}}(\theta) = \mathbb{E}_{x_{\text{corr}}} \left[ \frac{1}{G'} \sum_{j=1}^{G'} \hat{A}(\tau'_j) \nabla \log \pi_\theta(\tau'_j \mid x_{\text{corr}}) \right]. \quad (6)$$

**Summary.** These three stages form a continuous loop; detailed pseudocode and hyperparameters are provided in Algorithm 1 (Appendix B).

## 4 Experiments

### 4.1 Experimental Setup

**Data Construction** Diverging from prevalent tool-learning paradigms that emphasize extensive scaling of synthetic corpora (e.g., ToolACE (Liu et al., 2024), XLAM (Zhang et al., 2025a)), we prioritize *data quality* and *trajectory correctness*. We implement a three-stage pipeline to construct a compact yet rigorous training set:

(1) **Domain Schema Curation:** We curated a diverse schema library spanning 11 domains (e.g., *Healthcare*, *Smart Home*, *Vehicle Control*), prompting Claude-4-Sonnet to generate realistic API definitions grounded in BFCL characteristics.

(2) **Trajectory Synthesis:** Utilizing Claude-4-Sonnet, we first synthesized multi-turn user queries

Model	Method	Overall Acc	Base	Miss Func	Miss Param	Long Context
Qwen3-1.7B	Base	7.80%	10.00%	11.00%	8.00%	2.50%
	GRPO	17.12%	22.00%	<b>18.50%</b>	15.50%	12.50%
	DAPO	16.00%	22.00%	17.00%	14.00%	11.00%
	Dr.GRPO	16.12%	19.50%	17.50%	14.50%	13.00%
	<b>FISSION-GRPO (Ours)</b>	<b>20.38%</b>	<b>29.00%</b>	<b>18.50%</b>	<b>16.00%</b>	<b>18.00%</b>
Qwen3-4B	Base	19.37%	24.50%	19.00%	14.50%	19.50%
	GRPO	36.38%	46.50%	34.50%	27.50%	37.00%
	DAPO	38.25%	48.50%	36.50%	28.00%	<b>40.00%</b>
	Dr.GRPO	34.75%	43.00%	34.50%	27.50%	34.00%
	<b>FISSION-GRPO (Ours)</b>	<b>40.87%</b>	<b>51.50%</b>	<b>42.50%</b>	<b>30.50%</b>	39.00%
<b>External 8B Agent Models</b>						
ToolACE-2-8B	–	37.00%	47.00%	31.00%	28.00%	42.00%
	BitAgent-8B	37.75%	46.50%	37.50%	24.00%	43.00%
Qwen3-8B	Base	28.75%	35.50%	37.00%	22.50%	20.00%
	GRPO	42.75%	50.50%	41.00%	36.00%	43.50%
	DAPO	43.12%	54.50%	44.50%	29.00%	44.50%
	Dr.GRPO	44.88%	55.00%	<b>45.00%</b>	32.50%	47.00%
	<b>FISSION-GRPO (Ours)</b>	<b>46.75%</b>	<b>57.50%</b>	43.50%	<b>38.00%</b>	<b>48.00%</b>

**Table 1:** Performance comparison on BFCL V4 Multi-Turn benchmark across model scales and training methods.

based on these schemas, followed by generating full interaction trajectories that fulfill the requests.

**(3) Hierarchical Filtering and Factorization:** To ensure rigorous quality control, we applied a hierarchical protocol. First, raw trajectories underwent a global coherence check via Claude-4-Sonnet. Validated trajectories of length  $K$  were then factorized into discrete decision instances  $\{(h_t, a_t)\}_{t=1}^K$ , where  $h_t$  denotes the cumulative context history. Finally, these decomposed instances underwent a double-blind verification via Qwen3-235B-A22B-Instruct-2507 (Team, 2025) and Kimi K2 (Team et al., 2025). Only samples achieving unanimous consensus were retained, distilling an initial pool of  $\sim 2,000$  trajectories down to 630 high-quality training instances.

**Training Details** All models are trained using the **Verl** framework (Sheng et al., 2024) on a single node with  $8 \times$ H800 80GB GPUs. For GRPO training, we use a learning rate of 1e-6 with cosine warmup, a batch size of 8, and sample 8 rollouts per query ( $G = 8$ ). The maximum prompt length is set to 12,800 tokens and the maximum response length to 4,096 tokens. We use temperature 0.95 and top- $k$  50 for sampling. For FISSION-GRPO, we set the correctness threshold  $\delta_{\text{corr}} = 1$  for error identification (Eq. 3), determined empirically as a stable threshold across multiple runs.

**Benchmarks.** We evaluate on the BFCL V4 Multi-Turn benchmark (Patil et al., 2025), specifi-

cally chosen for its stress-testing of state tracking and robustness. A distinctive feature of this benchmark, crucial to our study, is its interactive error feedback mechanism: upon execution error, the environment provides explicit error traces and permits the agent up to 20 retries to correct its action. This setup directly aligns with our research objective, allowing us to measure how improved error recovery dynamics translate to overall success rates in tool use.

**Baselines.** We compare FISSION-GRPO against advanced RL baselines implemented on the Qwen3 series (1.7B/4B/8B), including: (1) **GRPO** (Shao et al., 2024), utilizing group-normalized advantages; (2) **DAPO** (Yu et al., 2025), incorporating dynamic sampling constraints; and (3) **Dr.GRPO** (Liu et al., 2025), employing mean-centered estimators to mitigate length bias. For broader context, we also report performance of specialized 8B-scale tool agents such as ToolACE (Liu et al., 2024) and BitAgent.

## 4.2 Main Results

Table 1 presents the performance on the BFCL v4 Multi-Turn benchmark. As shown, FISSION-GRPO achieves consistent state-of-the-art (SOTA) performance across all Qwen3 model scales (1.7B, 4B, and 8B) when compared to other GRPO-based post-training methods.

**Scalability and Subset Performance.** Our method demonstrates superior scalability and ro-

bustness. On Qwen3-1.7B, FISSION-GRPO yields a substantial improvement, elevating overall accuracy to **20.38%**, a relative gain of over 160% compared to the Base model (7.80%) and surpassing standard GRPO (17.12%). As the model scale increases, the performance gap remains distinct: on Qwen3-4B and Qwen3-8B, our method achieves **40.87%** and **46.75%** accuracy respectively, outperforming strong baselines like DAPO and Dr.GRPO. Notably, FISSION-GRPO excels in the *Base* and *Miss Param* categories, achieving the highest scores across most settings (e.g., 57.50% on 8B Base and 30.50% on 4B Miss Param), indicating a precise understanding of function calls and parameters.

**Comparison with Specialized Agents.** Furthermore, we compare our generalist approach with specialized 8B-scale tool agents. FISSION-GRPO (Qwen3-8B) significantly outperforms both ToolACE-2-8B (37.00%) and BitAgent-8B (37.75%) by margins of 9.75 and 9.00 percentage points, respectively. This underscores the efficacy of our method in enhancing tool-use capabilities beyond varying baselines.

### 4.3 Error Recovery Analysis

To identify the source of performance gains, we decouple the overall success rate into two components: *One-Shot Success* (success achieved without triggering any errors) and *Error Recovery Rate* (conditional probability of success after an error occurs).

Figure 3 illustrates this breakdown for the Qwen3-8B model. The results clearly indicate that the performance improvement is primarily driven by enhanced error recovery capabilities. FISSION-GRPO yields an average improvement of **5.7%** in Error Recovery Rate across all categories, with particularly substantial gains in *Long Context* (+11.8%) and *Base* (+5.5%) scenarios. This enhanced recovery capability serves as the primary contributor to the overall accuracy improvement from 42.75% to 46.75%.

Crucially, this gain does not come at the expense of fundamental capabilities. The One-Shot Success Rate is preserved and even modestly improved by an average of 1.75%, with notable gains in *Long Context* (+3.5%) and *Base* (+2.0%). This confirms that our framework effectively equips the model with robust recovery skills while simultaneously enhancing its standard tool-use competence, demonstrating that the fission mechanism provides com-



**Figure 3:** Performance decomposition on BFCL v4 Multi-Turn (Qwen3-8B).

Method	Avg.	Base	M.Func	M.Param	Long
<i>Qwen3-1.7B</i>					
GRPO	17.12	22.00	18.50	15.50	12.50
Static	17.75	23.50	21.00	15.50	11.00
<b>Dynamic</b>	<b>20.38</b>	<b>29.00</b>	<b>18.50</b>	<b>16.00</b>	<b>18.00</b>
<i>Qwen3-4B</i>					
GRPO	36.38	46.50	34.50	27.50	37.00
Static	37.25	50.50	34.00	28.50	36.00
<b>Dynamic</b>	<b>40.87</b>	<b>51.50</b>	<b>42.50</b>	<b>30.50</b>	<b>39.00</b>
<i>Qwen3-8B</i>					
GRPO	42.75	50.50	41.00	36.00	43.50
Static	44.00	53.50	43.00	35.50	44.00
<b>Dynamic</b>	<b>46.75</b>	<b>57.50</b>	<b>43.50</b>	<b>38.00</b>	<b>48.00</b>

**Table 2: Ablation on Feedback Quality.** *Static* denotes Fission training with generic error prompts; *Dynamic* uses our simulated feedback. *Avg.* denotes Overall Accuracy; *M.Func* and *M.Param* denote Missing Function and Missing Parameter errors, respectively.

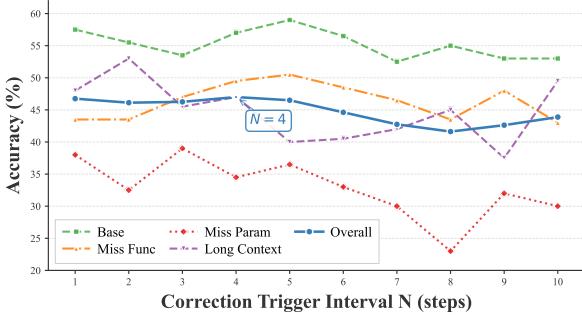
plementary benefits to both error prevention and error correction.

### 4.4 Impact of Feedback Quality

To disentangle the contribution of the *Fission* mechanism from the informational gain of the Error Simulator, we conduct an ablation study across three settings: (1) **GRPO**: The standard baseline without explicit recovery training. (2) **Fission-Static**: Applies the fission update but uses a fixed, generic error message for all errors.<sup>1</sup> (3) **Fission-Dynamic**: Our full method using the Error Simulator for context-aware feedback.

Results in Table 2 reveal a hierarchical improvement. First, Fission-Static consistently outperforms GRPO. Even with uninformative feedback, the explicit process of re-sampling and penalizing failed trajectories forces the model to refine its internal state tracking (e.g., +1.25% on Qwen3-8B Overall Acc). This validates that the *structural* intervention

<sup>1</sup>The static prompt is: “ERROR: Function call failed. Please verify your output format, function name, required parameters, and parameter values are correct.”



**Figure 4:** Multi-turn performance across different correction trigger intervals ( $N$ ) on BFCL v4 Multi-Turn.

of the fission mechanism is inherently valuable.

Second, Fission-Dynamic yields significant marginal gains. The gap between Static and Dynamic (e.g., +3.62% on Qwen3-4B) underscores the necessity of precise supervision. Generic signals fail to guide the model through complex errors, whereas simulated feedback effectively directs the gradient towards correcting specific semantic errors, particularly in the *Miss Param* and *Long Context* subsets.

#### 4.5 Sensitivity to Correction Trigger Frequency

To investigate how frequently correction updates should be triggered in training, and to balance timely suppression of recurring error patterns with scheduling overhead and potential training instability, we conduct a sensitivity study on the minimum trigger interval, denoted by  $N$  (in global steps). Here  $N$  controls how often correction can be inserted by limiting correction updates to occur no more than once every  $N$  global steps. We fix the total training budget to 234 global steps and vary only  $N$ , enforcing the constraint that at most one correction update occurs every  $N$  global steps. We further adopt a LIFO sampling strategy to prioritize the most recent correction samples, which keeps updates better aligned with the current policy distribution and therefore closer to the on-policy assumption.

**Results.** Figure 4 shows Multi-turn Overall Accuracy and category-wise metrics as a function of  $N$ . Performance remains relatively stable when correction is triggered frequently, corresponding to small  $N$ , but declines noticeably as updates become sparse, corresponding to large  $N$ , with consistent degradation across subcategories. The drop is most pronounced on *Miss Param* and is also evident on *Long Context*, indicating that parameter-

level errors and long-context interactions particularly benefit from timely correction signals. These results suggest that standard policy optimization alone does not reliably prevent error patterns from accumulating and reappearing over long horizons, whereas correction updates serve as a stabilizing mechanism for multi-turn reliability. At the same time, the stability observed over a small-to-moderate range of  $N$  indicates that correction does not need to be inserted extremely often to remain effective, highlighting a practical trade-off between correction timeliness and scheduling cost.

#### 4.6 Case Study: Error Recovery Behaviors

To qualitatively illustrate the robustness improvements, we compare three Qwen3-8B variants (Base, GRPO, FISSION-GRPO) on a representative multi-turn file manipulation task (from BFCL V4 Multi-Turn Base) requiring state tracking across directory changes and file moves (full logs in Appendix C).

We observe three distinct error-recovery patterns. The **Base** model exhibits *collapse*: it fails to update internal state after partial command success, entering repetitive invalid retries until conversation breakdown. **GRPO** shows *hallucination*: it recognizes errors but lacks grounding—when a file path becomes invalid, it invents non-existent parameters (e.g., a path argument for 1s) rather than verifying the actual state. In contrast, **FISSION-GRPO** demonstrates *active diagnosis*: it employs a diagnose-then-correct strategy, deploying verification tools (e.g., find) to resolve state uncertainty before reattempting the task. This comparison shows that FISSION-GRPO transforms error signals into active diagnostic capabilities rather than brittle heuristics.

### 5 Conclusion

We presented FISSION-GRPO, a framework that transforms execution errors into on-policy corrective supervision for multi-turn tool use. By intercepting errors, augmenting them with simulated feedback, and resampling recovery attempts, our approach enables smaller models to learn robust self-correction rather than collapsing into repetitive loops. On BFCL v4 Multi-Turn, Qwen3-8B achieves a 5.7% gain in error recovery and 4% overall accuracy improvement, outperforming specialized tool agents. The fission paradigm may generalize to other iterative refinement domains such as code debugging and mathematical reasoning.

## Limitations

Our work has several limitations that suggest directions for future research.

**Evaluation Scope.** We evaluate FISSION-GRPO exclusively on the BFCL v4 Multi-Turn benchmark. We chose this benchmark because it is one of the few that features an interactive error feedback mechanism permitting retry attempts, which directly aligns with our focus on error recovery. Most existing tool-use benchmarks emphasize single-turn correctness without explicit retry mechanisms. Extending evaluation to other domains with error-retry dynamics (e.g., interactive code debugging or web navigation with fallback) is a promising direction for future work.

**Computational Overhead.** The fission mechanism introduces additional computational cost by resampling  $G'$  rollouts for each intercepted error. We partially mitigate this through a configurable trigger interval  $N$  (Section 4.5), which allows trading off correction frequency against training efficiency. Our analysis shows that moderate intervals maintain effectiveness while reducing overhead, though further optimization of this trade-off remains an open direction.

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## A Prompt Template for the Error Simulator

To improve reproducibility, we provide the prompting template used to query the error simulator  $S_\phi$ . We use a two-message chat format: a system prompt that specifies the simulator role and output constraints, followed by a user prompt that injects the original context, ground-truth tool calls, and the model’s failed attempt.

## B Training Algorithm Details

Algorithm 1 outlines the detailed execution flow of the FISSION-GRPO framework. The process alternates between standard exploration (to maintain general capability and mine errors) and fission-based updates (to learn specific recovery strategies).

## C Extended Case Study Analysis

In this section, we provide a detailed breakdown of the case study referenced in Section 4.6. Figure 6 visualizes the trajectories of Qwen3-8B under three training conditions on a multi-turn file manipulation task (Sample ID: `multi_turn_base_1`).

**Scenario Overview.** The user requests to verify the current directory, move a `log.txt` file into a new archive folder, and then search for a keyword within that file. The key challenge arises in Turn 2: `mkdir archive` fails (directory already exists), but `cd workspace` and `mv log.txt` succeed. This partial-success state requires careful tracking—in Turn 3, since the file was moved to `archive`, a direct `grep` will fail, requiring the agent to locate the file first.

## Detailed Behavioral Comparison.

**1. Qwen3-8B (Base): State Awareness Collapse.** The Base model correctly issues the initial batch command [cd, mkdir, mv]. However, it fails to update its internal state to reflect that it is already inside workspace after the successful cd. When attempting to handle the mkdir error, it redundantly retries cd workspace, which fails (“No such directory” within the current directory). Confused by this feedback, it spirals into a loop of invalid operations, ultimately failing to realize the file was already moved.

**2. Qwen3-8B + GRPO: Latent State Mismatch & Hallucination.** The GRPO model succeeds in Turn 2 (the file is moved), but fails to track the consequence—specifically, that log.txt is no longer in the current directory but in the archive subdirectory. This latent state mismatch surfaces in Turn 3: it first tries grep("log.txt") (fails), then attempts a heuristic guess grep("archive/log.txt") (also fails). Lacking a grounded fallback strategy, it resorts to hallucination, inventing a non-existent path parameter for ls.

**3. Qwen3-8B + FISSION-GRPO: Active Diagnosis.** Our model handles the Turn 2 state transition correctly. More importantly, in Turn 3, when faced with the same “No such file” error, it demonstrates a superior recovery mechanism: instead of guessing, it deploys find(name="log.txt", path="workspace") to empirically verify the file’s location. Using the confirmed path, it performs a precise state update via cd(folder="archive"), then executes grep successfully. This confirms that FISSION-GRPO learns to bridge state gaps through active diagnosis rather than relying on fragile internal memory or hallucinated corrections.

---

### Algorithm 1 Detailed Training Procedure of FISSION-GRPO

---

```

Require: Policy  $\pi_\theta$ , Reference Policy  $\pi_{\text{ref}}$ , Error Simulator  $\mathcal{S}_\phi$ 
Require: Training dataset  $\mathcal{D}$ 
Require: Hyperparameters: Learning rate  $\eta$ , KL coefficient  $\beta$ , Clip ratio  $\epsilon$ 
Require: Group sizes:  $G$  (Exploration),  $G'$  (Fission/Correction)
Require: Thresholds: Buffer trigger  $B_{\text{trig}}$ , Success score  $R_{\text{thresh}} = 1.0$ 
1: Initialize Corrective Sample Pool  $\mathcal{B} \leftarrow \emptyset$   $\triangleright$  Implemented as LIFO Stack
2: for iteration  $k = 1, \dots, K$  do
3:   // STAGE 1: STANDARD EXPLORATION & MINING
4:   Sample batch of user queries  $x \sim \mathcal{D}$ 
5:   Generate exploration group  $\{\tau_i\}_{i=1}^G \sim \pi_\theta(\cdot|x)$ 
6:   Compute rewards for each trajectory:  $r_i \leftarrow R_{\text{corr}}(\tau_i) + R_{\text{fmt}}(\tau_i)$ 
7:   Compute GRPO Advantages:
8:    $\mu_R \leftarrow \frac{1}{G} \sum r_i, \quad \sigma_R \leftarrow \text{Std}(r_i)$ 
9:    $\hat{A}_i \leftarrow \frac{r_i - \mu_R}{\sigma_R + \epsilon}$ 
10:  Update Policy (Standard):
11:   $\mathcal{L}_{\text{GRPO}} \leftarrow \frac{1}{G} \sum_{i=1}^G [\min(\rho_i \hat{A}_i, \text{clip}(\rho_i, 1 \pm \epsilon) \hat{A}_i) - \beta \mathbb{D}_{\text{KL}}(\pi_\theta \parallel \pi_{\text{ref}})]$ 
12:   $\theta \leftarrow \theta + \eta \nabla_\theta \mathcal{L}_{\text{GRPO}}$ 
13:  // STAGE 2: SYNTHESIS & ACCUMULATION
14:  Identify error set  $\mathcal{E} = \{\tau_i \mid R_{\text{corr}}(\tau_i) < R_{\text{thresh}} \vee R_{\text{fmt}}(\tau_i) = 0\}$ 
15:  for each error trajectory  $\tau_{\text{err}} \in \mathcal{E}$  do
16:    if  $R_{\text{fmt}}(\tau_{\text{err}}) == 0$  then
17:       $f \leftarrow \text{GetFormatError}(\tau_{\text{err}})$ 
18:    else
19:       $f \leftarrow \mathcal{S}_\phi(x, \tau_{\text{err}})$   $\triangleright$  Generate diagnostic feedback
20:    end if
21:    Construct corrective context  $x_{\text{corr}} \leftarrow [x; \tau_{\text{err}}; f]$ 
22:    Compute Deduplication Key  $k \leftarrow \text{Hash}(x, \tau_{\text{err}}, f)$ 
23:    if  $k \notin \text{Keys}(\mathcal{B})$  then
24:      Push( $x_{\text{corr}}$ )  $\rightarrow \mathcal{B}$   $\triangleright$  LIFO Push
25:    end if
26:  end for
27:  // STAGE 3: FISSION-BASED REMEDIAL UPDATE
28:  if  $|\mathcal{B}| \geq B_{\text{trig}}$  then
29:     $X_{\text{batch}} \leftarrow \text{Pop}(B_{\text{trig}})$  items from top of  $\mathcal{B}$   $\triangleright$  LIFO: Fetch freshest errors
30:    Initialize batch loss  $\mathcal{L}_{\text{total}} \leftarrow 0$ 
31:    for each corrective context  $x_{\text{corr}} \in X_{\text{batch}}$  do
32:      Fission Resampling:
33:      Generate recovery group  $\{\tau'_j\}_{j=1}^{G'} \sim \pi_\theta(\cdot|x_{\text{corr}})$ 
34:      Compute rewards  $\{r'_j\}$  for recovery attempts
35:      Compute Corrective Advantages:
36:       $\mu'_R \leftarrow \frac{1}{G'} \sum r'_j, \quad \sigma'_R \leftarrow \text{Std}(r'_j)$ 
37:       $\hat{A}'_j \leftarrow \frac{r'_j - \mu'_R}{\sigma'_R + \epsilon}$   $\triangleright$  Variance restored via Fission
38:      Accumulate Gradients:
39:       $\mathcal{L}_{\text{corr}} \leftarrow \frac{1}{G'} \sum_{j=1}^{G'} [\min(\rho'_j \hat{A}'_j, \dots) - \beta \mathbb{D}_{\text{KL}}]$ 
40:       $\mathcal{L}_{\text{total}} \leftarrow \mathcal{L}_{\text{total}} + \mathcal{L}_{\text{corr}}$ 
41:    end for
42:     $\theta \leftarrow \theta + \eta \nabla_\theta \mathcal{L}_{\text{total}}$   $\triangleright$  Apply corrective update
43:  end if
44: end for

```

---

## Prompt Templates

### Prompt 1: System prompt for querying the error simulator.

You are a Runtime Environment Simulator for an AI Agent.  
Your role is to act as the API Server or Operating System that executes tool calls.

IMPORTANT CONTEXT:  
You are receiving a tool call from an Agent that has ALREADY FAILED validation or logic checks against the Ground Truth.  
Your task is NOT to judge correctness. Your task is to generate the specific ERROR MESSAGE that the system would return to the Agent.

GOAL:  
Generate a short, realistic, and actionable error message (starting with "ERROR: ")  
that will help the Agent understand why its call failed compared to the expected Ground Truth.

PRIORITY ERROR CATEGORIES:  
- Dependency & Sequence Violations  
- Parameter Hallucination  
- Schema & Parameter Errors  
- Business Logic Errors

EVALUATION LOGIC:  
- Reference the Ground Truth: ground\_truth is usually correct and serves as the primary standard.  
- Verify Context: cross-check the Agent output against the User Request in the Original Context.  
- Ambiguity Rule: if the Agent output differs from ground\_truth but is still plausible, note missing validation.

OUTPUT RULES:  
- Start with "ERROR: " (case-sensitive)  
- Be specific: mention actual parameter names/values from the failed attempt  
- Sound like a system/API response  
- Keep it concise (1--2 sentences)  
- Return ONLY the error string (no JSON, no markdown, no extra explanation)

ERROR MESSAGE EXAMPLES (Real error style):  
<<ERROR\_EXAMPLES\_SNIPPET>>

CRITICAL REMINDERS:  
- Do NOT output JSON like {"error": "..."}; output plain text only  
- Do NOT add any preamble; only the "ERROR: ..." line  
- Do NOT fabricate placeholders unless they appear in the failed attempt  
- The error should be what the runtime system returns, not an analysis

### Prompt 2: User prompt template (simulation input).

```
## Simulation Task
The Agent attempted to execute a tool call, but it was INCORRECT compared to the Ground Truth.
Generate the system error message triggered by the Agent's specific mistake.

1) Original Context (what the Agent saw)

[System instructions & tools]
<<SYSTEM_AND_TOOLS>>

[Dialogue history before this attempt (non-system turns)]
<<DIALOGUE_HISTORY>>

2) Execution Comparison

[Ground-truth tool call(s)]
<<GROUND_TRUTH_TOOL_CALLS>>

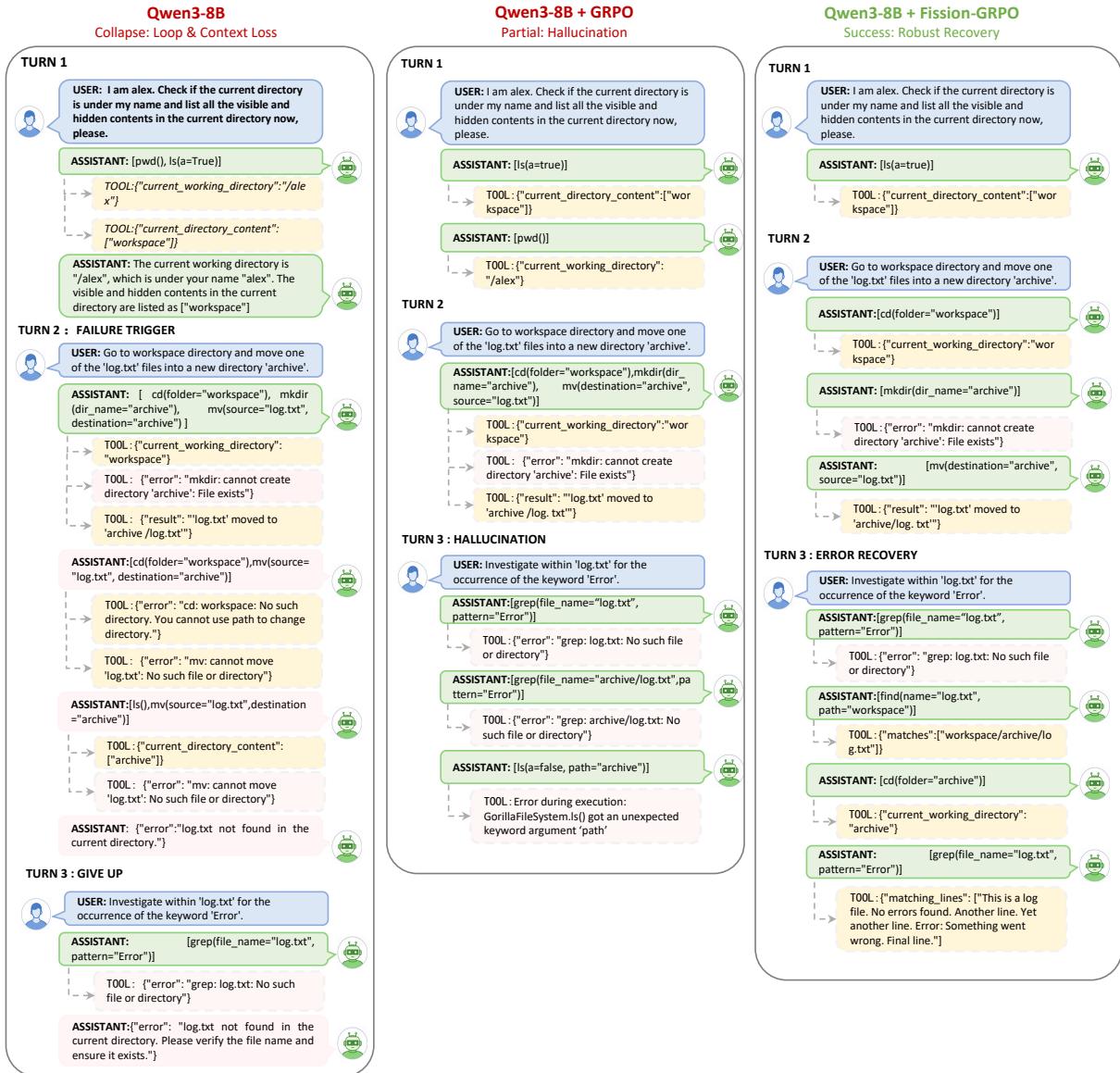
[Failed tool call(s) extracted from the model output]
<<FAILED_TOOL_CALLS>>

3) Instruction

Compare the failed attempt against the ground truth under the given context.
Identify the first critical failure and generate the runtime error.

Output:
Return ONLY one error string starting with "ERROR:".
```

**Figure 5:** Two-message prompting format used to query the error simulator  $S_\phi$ .



**Figure 6: Detailed visualization of Multi-turn Error Recovery.** Comparisons of trajectories generated by Qwen3-8B under different training regimes. The Base model collapses due to immediate state loss; the GRPO model suffers from latent state mismatch leading to hallucination in later turns; FISSION-GRPO overcomes this by employing diagnostic tools (`find`) to actively resolve state uncertainties.