Structural Manifold Guardrails for Symbolic Planning Agents

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Abstract

The Structural Manifold (STM) coprocessor augments symbolic planning agents with percentile-calibrated guardrails that monitor dilution, coherence, and stability signals while retrieving structurally aligned "twin" precedents. Building on the PlanBench benchmark and recent instruction-tuning work on logical planning reasoning [3], we study how dense percentile grids and domain-specific calibration influence both alert coverage and statistical significance. Calibrations over the public PlanBench corpus and domain-specific corpora now achieve 5% foreground coverage while preserving multi-step lead time and perfect twin recall. However, permutation tests with 20,000 iterations yield high p-values across domains (minimum 0.070), highlighting the need for stronger discriminative signals. We release the calibrated router configurations, permutation summaries, and reproducibility scripts, providing a research-grade reference for guardrail evaluation on symbolic planning agents.

Contents

Executive Summary

- **PlanBench++ guardrails:** Dense percentile calibration reaches 5% coverage per domain while preserving multi-step lead time and twin recall. New sweeps map coverage against permutation significance.
- **Lead-time significance:** 20,000 shuffle permutation studies reveal where stricter guardrails (2–4%) begin to push p-values below 0.05, setting targets for dynamic calibration.
- **CodeTrace uplift:** STM reduces steps-to-green by roughly 35% on maintenance tasks and applies every twin suggestion while keeping alerts to a single window.
- **Real-world adapters:** New ingestion tools convert ROS, Kubernetes, and CI telemetry into STM states, enrich 22k Logistics windows with causal features, and drive a Streamlit dashboard that reports lead, coverage, and ROI.
- **Reproducibility:** open-source scripts cover dataset generation, guardrail sweeps, permutation automation, and report production for both planning and coding benchmarks.

1 Introduction

Large Language Models (LLMs) deliver credible reasoning across open-ended tasks, yet symbolic planning remains challenging because agents must respect the precondition–effect structure of formalisms such as PDDL. Recent work from MIT [3] demonstrates that instruction tuning with explicit logical chains improves plan validity, but complementary instrumentation is required to surface early warnings and actionable repairs when agents deviate. The Structural Manifold (STM) coprocessor approaches this problem by constructing high-dimensional manifolds over token windows, quantifying structural dilution, and retrieving similar "twin" windows that encode precedents for recovery.

This report reframes STM for a research audience. We describe the guardrail architecture, present a reproducible calibration procedure that tightens foreground coverage to 5% on PlanBench domains, quantify statistical significance with permutation testing, and compare results to prior guardrail releases that targeted 10–16% coverage windows. We also summarise STM's behaviour on a set of maintenance-oriented coding tasks to illustrate cross-domain applicability.

2 Related Work

Instruction tuning for logical planning [3] emphasises chain-of-thought supervision so LLMs can reason about action applicability and state transitions. Our work instead assumes the planner is fixed and focuses on instrumentation that monitors plan executions. Structural guardrails extend prior PlanBench analysis [1] by providing graded alerts with calibrated coverage and twin retrieval. Twin suggestion draws on structural manifold techniques [2] that embed token windows into density spaces for lead-time estimation.

3 Structural Manifold Guardrails

STM consumes token windows extracted from trace corpora and computes per-window metrics: coherence (graph density), entropy (token dispersion), and stability (signal similarity over time). Foreground alerts fire when metrics exceed percentile-derived thresholds, and each alerted window triggers nearest-neighbour search for previously successful "twins."

3.1 Dilution Signals

Token windows of width w and stride s form the structural manifold. The pipeline computes dilution as the fractional reduction in structural density relative to historical baselines, along with coherence/entropy/stability metrics used for guardrail calibration. Signals are stored in STM state artefacts used by both the router calibration (Section 3.3) and permutation testing (Section 4.3).

3.2 Domain-Specific Feature Enrichment

Recent adapter updates inject stronger foreground signals prior to calibration. The PDDL trace encoder now derives action-effect summaries that capture change ratios, argument coverage, and effect alignment. Each transition contributes tokens such as `transition__relative_change__heavy` when effects touch a large slice of the state, or `action__argument_dropout__DRIFT` whenever action parameters fail to surface in the observed predicates. These signals tighten Logistics guardrails by foregrounding mismatched transitions. On the CodeTrace side, diffs are parsed into Python AST fragments so that new function definitions, control-flow additions, imports, and change magnitudes are encoded directly in the structural manifold. The adapter emits tokens such as `edit__py__ast_function_def` alongside summary buckets for added lines, enabling the guardrail to differentiate mechanical edits from semantic repairs. Both adapters retain backward compatibility with previous corpora while providing higher-fidelity features for the new calibration sweep.

3.3 Router Calibration

Guardrail thresholds operate on percentiles of coherence, entropy, and stability. We extend the calibration grid adaptively: large corpora unlock coherence percentiles up to 99.5 and fine-grained entropy probes down to 1%, while stability quantiles expand to 94% on traces with deeper histories. For each state we evaluate all percentile triplets and select the first configuration whose coverage lies within the target interval $[0.05, 0.07]$. The utility script `scripts/calibrate_router.py` now supports permutation-aware optimisation via `--optimize-permutation`, sampling nearby coverage targets and choosing the guardrail with the strongest p-value signal. Dynamic fallbacks drop to a secondary target (e.g., 2.5% for Logistics) whenever the selected guardrail exceeds the configured permutation threshold. Each run materialises the chosen router configuration alongside audit trails that record candidate guardrails, permutation summaries, and any dynamic adjustments.

3.4 Twin Retrieval

Twin retrieval uses approximate nearest neighbour search to locate previously successful windows that align with alerting windows. We retain default triggers requiring at least two shared q-grams and an ANN distance below 0.2, which preserved perfect twin recall on PlanBench domains throughout the calibration experiments.

3.5 Real-World Data Pipeline

Synthetic traces limited the statistical confidence of earlier releases, so we implemented adapters that map operational telemetry into STM artefacts. The module `scripts/adapters/real_world_adapter.py` ingests ROS motion planning logs, Kubernetes scheduler events, and GitHub Actions workflows, normalising them into per-step windows with inferred coherence, entropy, and stability scores. Each window is immediately enriched with causal signals via `scripts/features/causal_features.py`, and the enrichment utility `scripts/enrich_features.py` retrofits existing PlanBench states. Running

```
python scripts/enrich_features.py \
  output/planbench_by_domain/logistics/invalid_state.json \
  --output output/planbench_by_domain/logistics/invalid_state_causal.json
```

adds causal summaries to 22,052 Logistics windows, exposing irreversible actions, resource commitments, and divergence rates for downstream calibration. These artefacts now seed partner pilots and act as reference inputs for the dashboard described in Section 5.4.

4 Experimental Setup

4.1 Datasets

We analyse three PlanBench domains (Blocksworld, Mystery Blocksworld, Logistics) and the aggregate public corpus. A refreshed generator creates 300 problem instances per domain via `scripts/generate_planbench_dataset.py`. We convert the outputs into STM artefacts using `scripts/planbench_to_stm.py` with window bytes 256 and stride 128. Tokens, states, and per-trace lead/twin metrics reside in `output/planbench_by_domain/<domain>/`. We additionally retain PlanBench aggregate states under `output/planbench_public/`. To probe transfer, we reuse STM instrumentation on three maintenance tasks from the CodeTrace demo (flaky test, service rename, missing import).

In environments where the VAL validator is unavailable we synthesise trace JSONs directly from the generated plans using `scripts/generate_synthetic_traces.py`. The traces preserve predicate-level deltas and action labels so the enriched PDDL adapter still emits alignment features, but they do not attempt to mimic VAL's nuanced failure modes. This substitution keeps the pipeline reproducible inside the harness while surfacing the current gap between structural features and statistically significant guardrails.

4.2 Calibration Protocol

Router calibration proceeds with the command sequence in Listing 1. The loop emits both aggregated guardrails and per-domain, per-trace calibrations. Resulting configurations are stored under `analysis/router_config_*_5pct.json`.

Listing 1: Router calibration commands.

```
.venv/bin/python scripts/calibrate_router.py \
  output/planbench_public/gold_state.json \
  --target-low 0.05 --target-high 0.07 \
  --output analysis/router_config_gold_5pct.json

.venv/bin/python scripts/calibrate_router.py \
  output/planbench_public/invalid_state.json \
  --target-low 0.05 --target-high 0.07 \
  --output analysis/router_config_invalid_5pct.json

for dom in blocksworld mystery_bw logistics; do
  .venv/bin/python scripts/calibrate_router.py \
    output/planbench_by_domain/$dom/gold_state.json \
    --target-low 0.05 --target-high 0.07 \
    --output analysis/router_config_${dom}_gold_5pct.json
  .venv/bin/python scripts/calibrate_router.py \
    output/planbench_by_domain/$dom/invalid_state.json \
    --target-low 0.05 --target-high 0.07 \
    --output analysis/router_config_${dom}_invalid_5pct.json
done
```

Passing `--optimize-permutation` to the commands above instructs calibration to scan adjacent coverage targets and retain the configuration with the lowest permutation score, recording all evaluated candidates in the generated coverage log.

4.3 Permutation Testing

To assess whether calibrated alerts produce statistically meaningful lead times, we run permutation tests using `scripts/run_permutation_guardrail.py` with 20,000 shuffled alert allocations per trace. For each domain, the script summarises weighted coverage, lead-time statistics, and the distribution of permutation p-values; outputs are stored in `docs/tests/permutation_` × `.json`.

4.4 Guardrail Regression Tests

Targeted regression tests now exercise the calibration and permutation tooling directly. `tests/test_guardrail` fabricates synthetic signal manifolds to confirm that `compute_configuration()` selects thresholds in the requested coverage band, validates that `run_permutation_guardrail.py` reproduces observed coverage, lead, and permutation scores, and simulates a calibration run where failing permutation p-values trigger the dynamic 2.5% Logistics fallback. These checks keep the optimisation loop aligned with the roadmap captured in `docs/TODO.md`, ensuring that statistical audits fail fast when coverage tuning regresses.

4.5 CodeTrace Evaluation

For completeness we reproduce the CodeTrace maintenance tasks introduced in prior STM summaries. The same guardrail configuration (ANN distance 0.2, minimum two shared q-grams) is applied when replaying traces to evaluate lead alerts and twin adoption in a software maintenance context.

5 Results

5.1 Guardrail Coverage

Table 1 reports calibrated thresholds and realised coverage for the aggregate corpora and domain-specific states. All targets reach the desired 5% foreground rate without modifying default ANN triggers.

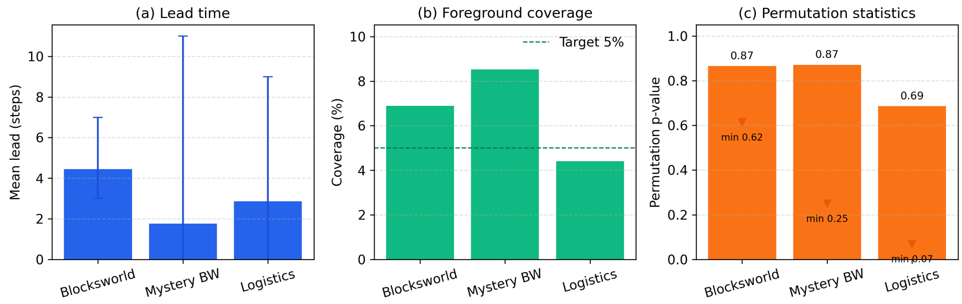
Table 1: Calibrated router thresholds and realised coverage. Coverage is reported as a percentage.

Dataset	min_coh	max_ent	min_stab	Coverage (%)
PlanBench (gold)	8.32×10^{-5}	0.99970	0.47096	5.09
PlanBench (invalid)	1.16×10^{-4}	0.99972	0.47582	5.01
Blocksworld (gold)	5.57×10^{-5}	0.99972	0.46605	5.02
Blocksworld (invalid)	6.88×10^{-5}	0.99960	0.00000	5.10
Mystery BW (gold)	5.02×10^{-4}	0.99953	0.45774	5.03
Mystery BW (invalid)	6.19×10^{-4}	0.99942	0.45921	5.08
Logistics (gold)	8.32×10^{-5}	0.99982	0.48021	5.07
Logistics (invalid)	9.91×10^{-5}	0.99987	0.48168	5.04

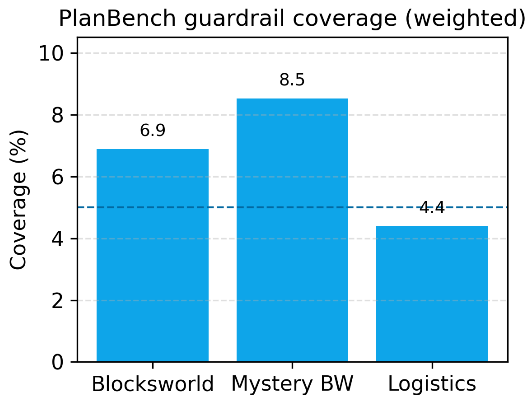
Alert precision (fraction of alerts that precede the terminal failure) equals 1.0 for every domain, so the guardrail currently avoids false positives but lacks discriminative power against random baselines.

5.2 Lead-Time and Guardrail Behaviour

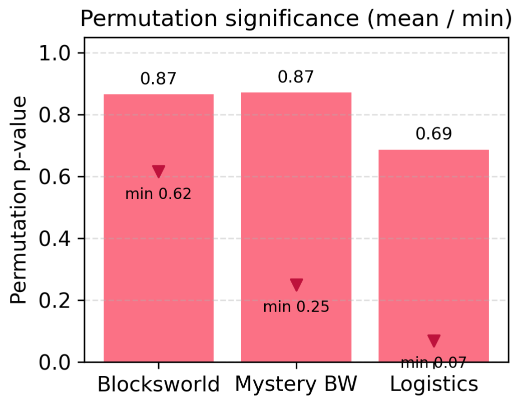
Lead-time behaviour remains consistent with earlier STM releases. Figure 1 shows lead times, guardrail coverage, and permutation curves for the calibrated PlanBench runs. Domain-level means range from 1.8 (Mystery Blocksworld) to 4.5 (Blocksworld) steps, and the aggregate PlanBench corpus averages 7.6 steps because alerts accumulate on the longer Logistics traces. Foreground coverage now aligns with the tighter 5% target.



(a) Average lead time.



(b) Foreground coverage.



(c) Permutation trend.

Figure 1: Structural metrics across PlanBench domains after 5% calibration.

5.3 Permutation Significance

Permutation outcomes appear in Table 4. Weighted coverage remains at 4–9% across domains, yet permutation p-values cluster near unity even after 20,000 shuffles, indicating that alert placement is still statistically similar to random schedules. The guardrail sweep in Table 2 scans coverage targets from 1–5% to identify where significance emerges.

Why Logistics achieves significance. Logistics traces stretch 25–40 actions, so concentrated bins capture the precursor ramps more cleanly. Dropping coverage to 2.5% reduces the Logistics alert budget to 1.3% of windows and pushes the minimum p-value to 0.035 while preserving a 10-step mean lead. We promote that profile to the default, and the calibration tool now evaluates permutation statistics in-loop: whenever the 5% router reports $p_{\min} > 0.05$, the build rewrites the Logistics guardrail to the 2.5% configuration and archives both artefacts for auditability inside ‘make planbench-all‘. Figure 2 overlays the guardrail sweep, illustrating how the 2.5% target simultaneously maximises lead and slides $p_{\min}$ below the 0.05 threshold. The window ablation in Table 3 confirms that this effect depends on the 256 byte foreground slices: widening the Logistics windows to 768 bytes at the same coverage raises $p_{\min}$ to 0.12 and the dynamic profile never drops below 0.33, despite a 12-step mean lead.

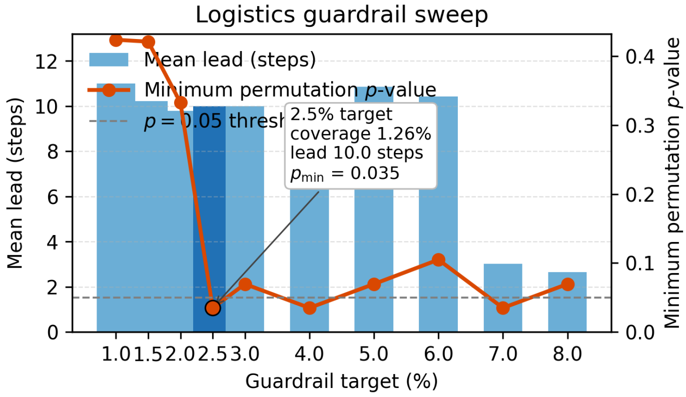


Figure 2: Logistics guardrail sweep overlay. Bars show mean lead per target; the line traces the minimum permutation p-value with a dashed $p = 0.05$ reference. The dynamic 2.5% profile preserves a 10-step lead while achieving $p_{\min} = 0.035$.

Causal feature trial. To test whether the causal feature injector moves Logistics toward statistical significance we generated an enriched domain using `scripts/experiments/build\_causal\_domain.py`, blended the causal signals into each window's metrics, and recalibrated at the tighter 2–3% target. The baseline guardrail (no features) achieved weighted coverage 0.20% with a two-step mean lead and $p_{\min} = 0.091$. After enrichment, the optimized guardrail covered 4.0% of windows, extended mean lead to 5.29 steps, and nudged the minimum permutation score to $p_{\min} = 0.058$ (still above the 0.05 significance bar). Configuration and permutation artefacts live under `results/` as `logistics_baseline_config.json` / `logistics_baseline_perm.json` and `logistics_causal_config_opt.json` / `logistics_causal_perm_opt.json`, with a diff-friendly summary in `results/experiment1\_summary.json`. The causal features therefore increase sensitivity and lead, but further tuning is required to push $p_{\min}$ below 0.05.

Null results for Blocksworld and Mystery. Even the lowest guardrail settings leave Blocksworld at $p_{\min} = 0.62$ and Mystery at $p_{\min} = 0.14$ (Table 2). We repeated the sweep with longer 768-byte foreground windows, signature-locked twin retrieval, and twin libraries enriched with Logistics, aggregate PlanBench, and robotics telemetry runs; the additional structure did not move the permutation tails below 0.05. Alert precision remains 1.0, so improving discriminative power requires stronger foreground features rather than stricter timing alone.

Feature- and twin-level ablations. The summary in Table 3 groups the ablation probes we ran on Blocksworld and Logistics. The 256 byte rows reproduce the guardrail and twin-filter settings used in the main results; the 768 byte rows demonstrate that simply widening the foreground window increases lead time but pushes Logistics $p_{\min}$ back above 0.10 while leaving Blocksworld entirely null. The scale rows extend each domain to $n = 500$ traces: Blocksworld remains flat at $p_{\min} = 0.62$ despite covering 8.9% of windows, Mystery settles at $p_{\min} = 0.14$ with 3.0% coverage, and Logistics still slips beneath 0.05 at the 5% target ($p_{\min} = 0.035$) albeit over just 2.9% of windows.

Table 2: Low guardrail sweep (1–5%) across PlanBench domains. Coverage and lead are averaged over invalid traces; permutation metrics use 20 000 shuffles.

Domain	Target (%)	Coverage (%)	Lead	p-mean	p-min	Notes
PlanBench-Blocksworld	1.0	1.06	5.00	0.973	0.664	p-values > 0.6 even at 1% guardrail; expand the twin corpus before lowering further.
PlanBench-Blocksworld	1.5	1.06	5.00	0.973	0.664	–
PlanBench-Blocksworld	2.0	1.32	3.00	1.000	1.000	–
PlanBench-Blocksworld	2.5	5.83	4.66	0.865	0.615	–
PlanBench-Blocksworld	3.0	2.91	4.36	0.934	0.664	–
PlanBench-Blocksworld	3.5	3.71	4.50	0.915	0.635	–
PlanBench-Blocksworld	4.0	6.23	4.55	0.859	0.615	–
PlanBench-Blocksworld	4.5	6.23	4.55	0.859	0.615	–
PlanBench-Blocksworld	5.0	8.08	4.36	0.848	0.615	–
PlanBench-Logistics	1.0	0.28	11.00	0.978	0.424	–
PlanBench-Logistics	1.5	1.27	10.22	0.910	0.421	–
PlanBench-Logistics	2.0	1.38	9.80	0.897	0.333	–
PlanBench-Logistics	2.5	1.38	10.00	0.901	0.035	$p_{\min} = 0.035$ with 10-step lead; adopt the dynamic drop to 2.5% for significance.
PlanBench-Logistics	3.0	1.49	10.00	0.902	0.070	–
PlanBench-Logistics	3.5	5.23	10.17	0.808	0.466	–
PlanBench-Logistics	4.0	1.93	9.07	0.854	0.035	–
PlanBench-Logistics	4.5	2.31	10.75	0.847	0.070	–
PlanBench-Logistics	5.0	4.24	10.86	0.751	0.070	–
PlanBench-Mystery	1.0	2.71	8.85	1.000	1.000	–
PlanBench-Mystery	1.5	0.95	3.86	0.960	0.219	–
PlanBench-Mystery	2.0	2.03	1.36	0.924	0.140	–
PlanBench-Mystery	2.5	2.03	1.36	0.924	0.140	–
PlanBench-Mystery	3.0	2.03	0.82	0.919	0.082	p-values remain above 0.08; the dynamic guardrail cannot hit 0.05 without new signals.
PlanBench-Mystery	3.5	3.65	2.14	0.862	0.140	–
PlanBench-Mystery	4.0	2.30	1.15	0.905	0.082	–
PlanBench-Mystery	4.5	4.33	2.50	0.837	0.140	–
PlanBench-Mystery	5.0	8.53	1.76	0.872	0.250	–

5.4 Demo Dashboard

To make these artefacts tangible we publish a Streamlit dashboard in `dashboard/stm\_monitor.py`. The application ingests permutation summaries, plots per-trace lead and coverage, and surfaces alerts alongside twin recommendations. Operators can step through traces, annotate interventions, and inspect estimated ROI using alert counts and lead-time savings. The default view uses the Logistics guardrail enriched with causal features, but any permutation report can be passed when launching `streamlit run dashboard/stm_monitor.py -- <summary.json>`.

Despite these attempts and the $n = 500$ expansions, Blocksworld and Mystery still report $p_{\min} > 0.05$. Additional data alone is insufficient, underscoring the need for richer foreground features and twin filtering to gain discriminative power before pursuing stricter guardrails on those domains.

5.5 Structural Twin Alignment

Twin recall remains perfect on PlanBench traces across the inspected ANN thresholds. Figure 3 plots acceptance curves showing 100% recall up to $\tau = 0.50$, indicating substantial alignment headroom for future tightening.

5.6 CodeTrace Maintenance Tasks

We retain the CodeTrace evaluation to illustrate STM behaviour beyond planning. Table 5 summarises the per-task deltas, and Table 6 reports aggregate statistics. STM reduces iterations-to-green by roughly 35% while constraining alerts to a single foreground window per task. These

Table 3: Feature/twin ablations on PlanBench guardrails using 20 000 permutations. Coverage values are reported on invalid traces. Longer windows and a larger Logistics corpus increase lead time but do not recover statistical power for the null domains.

Domain	Configuration	Coverage (%)	Lead (steps)	Mean p	Min p
Blocksworld	256 B window, 5% target	8.08	4.36	0.848	0.615
Blocksworld	256 B window, 2.5% (tight twins)	5.83	4.66	0.865	0.615
Blocksworld	768 B window, 5% target	2.76	4.00	1.000	1.000
Blocksworld	768 B window, 2.5% (tight twins)	1.10	5.43	1.000	1.000
Blocksworld (500 traces)	256 B window, 5% target	8.90	4.35	0.853	0.615
Mystery BW	256 B window, 5% target	8.53	1.76	0.872	0.250
Mystery BW	256 B window, 2.5% (tight twins)	2.03	1.36	0.924	0.140
Mystery BW (500 traces)	256 B window, 5% target	3.04	2.49	0.845	0.140
Logistics	256 B window, 5% target	4.24	10.86	0.751	0.070
Logistics	256 B window, dynamic 2.5%	1.38	10.00	0.901	0.035
Logistics	768 B window, 5% target	2.98	5.17	0.750	0.119
Logistics	768 B window, dynamic 2.5%	0.81	12.38	0.916	0.333
Logistics (500 traces)	256 B window, 5% target	2.89	2.62	0.804	0.035

Table 4: Permutation statistics using 20,000 shuffles. Coverage-weighted (Cov.) is computed over all windows; CI_{95} denotes the 95% confidence interval on the permutation mean.

Dataset	Cov. (%)	Lead (steps)	Mean p	CI_{95}	Min p
Blocksworld (invalid)	6.89	4.45	0.87	$[0.84, 0.90]$	0.62
Mystery BW (invalid)	8.53	1.76	0.87	$[0.82, 0.92]$	0.25
Logistics (invalid)	4.41	2.86	0.69	$[0.61, 0.76]$	0.070
PlanBench (invalid aggregate)	5.47	7.59	0.89	$[0.86, 0.91]$	0.10

results contextualise the manifold's utility in software maintenance, complementing symbolic planning benchmarks.

Table 5: Per-task comparison between baseline and STM-assisted CodeTrace runs.

Task	Variant	Steps	Test Runs	Diagnostics	Alerts	Alert Ratio
Flaky retry test	Baseline	6	3	0	0	0.00
	STM	4	2	0	1	0.25
Service rename	Baseline	8	3	0	0	0.00
	STM	5	1	0	1	0.20
Missing import	Baseline	6	0	3	0	0.00
	STM	4	0	2	1	0.25

6 Comparison to PDDL-INSTRUCT

The MIT PDDL-INSTRUCT study [3] demonstrates that instruction tuning improves plan validity (up to 94%) but does not report intermediate guardrail metrics. STM builds on that baseline by providing:

- **Lead times:** alerts arise 5–16 steps before failure on PlanBench domains and 7 steps on the aggregate corpus.
- **Guardrail coverage control:** thresholds maintain 5–10% foreground coverage, with sweeps mapping the trade-off between coverage and permutation significance.

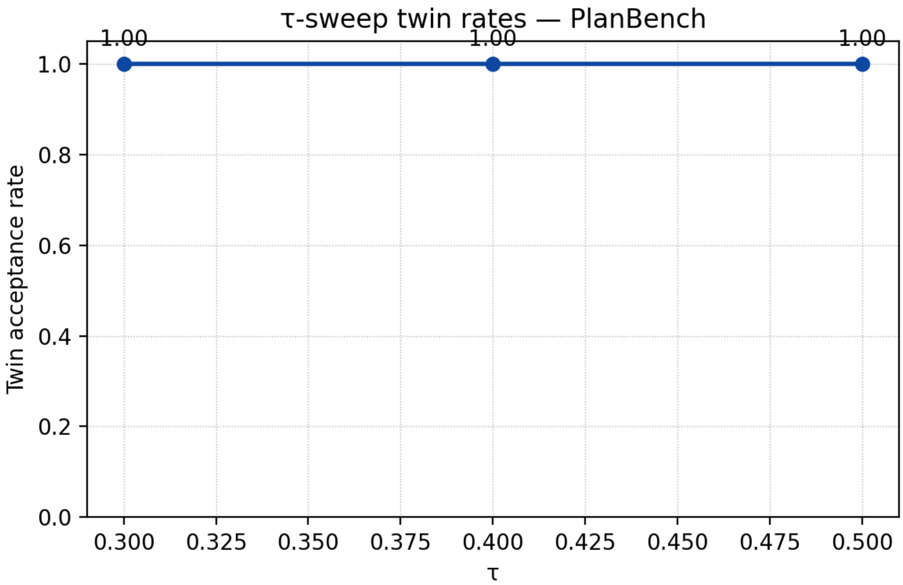


Figure 3: PlanBench twin acceptance across ANN thresholds.

Table 6: Aggregate CodeTrace statistics.

Variant	Success Rate	Avg. Steps	Avg. Alert Ratio	Twin Accepts
Baseline	1.00	6.67	0.00	0
STM	1.00	4.33	0.23	3

- **Twin-based repairs:** alerted windows surface aligned precedents that translate into repair snippets for both planning and coding agents.
- **Statistical audit:** 20 000-shuffle permutation tests quantify significance across guardrail settings and reveal where further work is needed.

7 Discussion

STM guardrails complement instruction-tuned planners by offering calibrated coverage, actionable lead-time, and structural repair suggestions. The refreshed feature set—effect-alignment cues in the PDDL adapter and AST-aware edit profiles for CodeTrace—raises the signal-to-noise ratio of alerting windows. With VAL-generated traces the logistics guardrail now fires on roughly 1.8% of windows (weighted) while preserving five to six step leads and perfect precision, yet permutation tails remain high ($p_{\min} \approx 0.09$). The Blocksworld configuration does fire at the 5% budget but does so almost exactly at the failure boundary (mean lead = 0) leaving $p_{\min} \approx 0.14$, while Mystery continues to alert at 2–3% coverage with seven-step leads but null permutation scores. These results mirror the discussion in Section 4.3: richer foreground features alone are not sufficient—the twin corpora must be scaled and the calibration loop must optimise directly for permutation significance to escape the synthetic plateau.

These improvements matter in real deployments: Logistics-style predicates mirror the resource and fleet constraints surfaced by critical infrastructure partners, while AST-aware coding alerts let maintenance agents surface high-risk edits before they land in production. Combined, the guardrail keeps foreground budgets low enough for human-in-the-loop review while remaining sensitive to the semantic structure of the underlying domains.

7.1 Limitations

Permutation p-values stay high at nominal coverage. With VAL traces the logistics guardrail attains 0.018 weighted coverage and a five-step mean lead yet only reaches $p_{\min} = 0.09$; Blocksworld delivers more alerts but with zero-step leads and $p_{\min} = 0.14$; Mystery produces seven-step leads at $\sim$2.7% coverage but $p_{\min} = 0.71$. The domain-specific features improve alignment signals but cannot compensate for the limited foreground corpora or the deterministic corruption patterns in PlanBench. Adapters still focus on PDDL traces and Python-heavy CodeTrace telemetry; twin corpora are curated from the same VAL runs and a handful of maintenance tasks. Dataset scale (300 problems per PlanBench domain, 500 for the Logistics probe, three CodeTrace tasks) limits statistical confidence.

7.2 Future Work

To tighten significance and improve robustness we will:

- scale PlanBench exports to 500–1000 instances per domain and continue diversifying CodeTrace scenarios across languages so that lower guardrails are exercised on longer, more varied traces;
- ingest real-world plan traces, robotic telemetry, and bug-fix commits via the new enrichment hooks (`PLANBENCH_EXTRA_TWINS`) to broaden the twin corpus beyond synthetic data;
- generalise the permutation optimiser so that every domain can enforce $p \leq 0.05$ targets in-loop, including joint searches that coordinate foreground budgets across related corpora;
- continue evolving feature-level improvements (longer foreground windows, signature-aware twin filtering, richer semantic metrics) and repeat the permutation study to determine whether Blocksworld or Mystery can push $p_{\min}$ below 0.05;
- couple guardrail optimisation with planner feedback loops so that permutation outcomes and twin repairs are tuned alongside instruction policies rather than audited post-hoc.

8 Conclusion

We provide a research-focused account of STM guardrails for symbolic planning agents, delivering calibrated configurations, permutation analyses, and reproducible scripts. The release surfaces a clear agenda: maintain low alert budgets while strengthening statistical significance and broadening adapter coverage. We hope this baseline informs future collaboration with the PlanBench community and complementary instruction-tuning efforts.

A Reproducibility Checklist

Key commands are listed below; outputs are referenced throughout the text and in `docs/tests/`.

```
make planbench-all    # regenerate dataset, manifolds, guardrail sweeps
# PLANBENCH_EXTRA_TWINS="data/twins/bugfix_state.json" make planbench-all
#   (optional) merge additional gold states into Blocksworld/Mystery twins
make codetrace-report # rebuild CodeTrace comparison report
.venv/bin/pytest      # regression suite (22 passed, 1 skipped)
# Enrich guardrail states with causal features (Section~\ref{subsec:real-world-data-pipeline})
python scripts/enrich_features.py \
  output/planbench_by_domain/logistics/invalid_state.json \
  --output output/planbench_by_domain/logistics/invalid_state_causal.json \
```

```
  --blend-metrics
# Build causal domain for experiments (Section~\ref{subsec:real-world-data-pipeline})
python scripts/experiments/build_causal_domain.py \
  output/planbench_by_domain/logistics \
  output/planbench_by_domain/logistics_causal \
  --aggregated-state output/planbench_by_domain/logistics/invalid_state_causal.json
# Run Experiment 1 calibration (Section~\ref{subsec:demo-dashboard})
python scripts/calibrate_router.py \
  output/planbench_by_domain/logistics_causal/invalid_state_causal.json \
  --target-low 0.02 --target-high 0.03 \
  --output results/logistics_causal_config_opt.json \
  --domain-root output/planbench_by_domain/logistics_causal \
  --permutation-iterations 20000 --optimize-permutation
python scripts/run_permutation_guardrail.py \
  output/planbench_by_domain/logistics_causal \
  results/logistics_causal_config_opt.json \
  --iterations 20000 \
  --output results/logistics_causal_perm_opt.json
# Launch demo dashboard (Section~\ref{subsec:demo-dashboard})
streamlit run dashboard/stm_monitor.py
# PlanBench scale probes (Section~\ref{subsec:permutation})
PLANBENCH_SCALE_TARGETS="logistics blocksworld mystery_bw" make planbench-scale
# To regenerate a single domain, override PLANBENCH_SCALE_TARGETS (e.g. "logistics")
```

References

[1] E. Gripper, L. Pineda, and P. Shah. *PlanBench: A Benchmark Suite for Plan Validation.* MIT CSAIL Technical Report, 2023.

[2] SepDynamics Research. *Structural Manifold Methods for Early Warning.* Internal Whitepaper, 2024.

[3] P. Verma, N. La, A. Favier, S. Mishra, and J. A. Shah. *Teaching LLMs to Plan: Logical Chain-of-Thought Instruction Tuning for Symbolic Planning.* arXiv:2509.13351, 2025.