# Standardizing Evaluation Toolchains and Stability Reporting for LLM-Based AI Agents

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## ABSTRACT

Agent benchmark results are highly sensitive to toolchain configuration, random seeds, and environment drift, yet most evaluations report single-run accuracy without cost, latency, or stability metrics. We formalize the evaluation standardization problem along two orthogonal axes—*evaluation control* (version pinning, environment freeze) and *reporting completeness* (cost, latency, stability metrics)—and compare five toolchain configurations across 20 simulated agents over 200 Monte Carlo trials. Using a two-batch ranking stability metric, full standardization achieves mean ranking stability of $0.984 \pm 0.009$ (Spearman), compared to $0.885 \pm 0.045$ for unstandardized evaluations, and reduces the coefficient of variation by 73%. We demonstrate that 5 seeds capture 98% of the ranking stability achievable with 20 seeds under full standardization, that environment drift degrades unstandardized top-3 agreement from 0.54 to 0.72 while full standardization maintains >0.85 across drift levels, and that evaluation cost scales linearly with seed count. These results provide quantitative justification for mandating cost/latency reporting and multi-seed evaluation in agent benchmarks.

## KEYWORDS

evaluation, benchmarks, standardization, stability, LLM agents, cost, latency

## 1 INTRODUCTION

The proliferation of LLM-based agent benchmarks—WebArena [9], SWE-bench [4], ToolBench [7], AgentBench [6]—has advanced agent evaluation, but significant gaps remain. As noted by Xu et al. [8], open problems persist in standardizing toolchains, reporting cost and latency, and measuring stability across runs. Kapoor et al. [5] showed that evaluation choices can lead to misleading conclusions about agent capabilities.

Prior work on evaluation reform [2, 3] has advocated for improved reporting in NLP, but agent evaluation introduces unique challenges: tool version drift, environment stochasticity, and the cost–accuracy tradeoff. Most existing benchmarks lack mandatory multi-seed evaluation, cost reporting, or stability metrics, making cross-study comparison unreliable.

We address these gaps by making the following contributions:

(1) We formalize toolchain standardization along two orthogonal axes: *evaluation control* (noise reduction via version pinning and environment freezing) and *reporting completeness* (cost, latency, and stability tracking).
(2) We introduce a two-batch ranking stability metric that correctly handles single-seed pathologies and provides monotonically improving stability estimates with increasing seed count.
(3) We conduct a 200-trial Monte Carlo study across five toolchain configurations, providing mean estimates with 95% confidence intervals for all reported metrics.
(4) We quantify the cost–stability tradeoff, showing that evaluation cost scales linearly with seed count and identifying 5 seeds as the practical optimum.
(5) We demonstrate that full standardization maintains robust top-3 rankings even under severe environment drift.

## 2 RELATED WORK

Dodge et al. [3] advocated for improved experimental reporting in NLP, showing that reporting variance across runs substantially changes conclusions. Bouthillier et al. [2] provided a systematic framework for accounting for variance in machine learning benchmarks. Agent-specific evaluation challenges include environment variability, tool version drift, and the interplay between cost and performance [5]. Current agent benchmarks vary widely in their reporting requirements: WebArena [9] uses multiple seeds but does not mandate cost reporting; SWE-bench [4] provides single-run results; AgentBench [6] evaluates across diverse environments but does not standardize toolchain versions. Biderman et al. [1] highlighted reproducibility challenges in language model evaluation at scale.

Our work differs from prior benchmark-design studies in two key ways: (1) we explicitly separate evaluation control from reporting completeness as orthogonal design dimensions, and (2) we quantify the cost–stability tradeoff to provide actionable seed-count recommendations.

## 3 STANDARDIZATION FRAMEWORK

### 3.1 Two-Axis Model

We decompose toolchain standardization into two orthogonal axes:

*Axis 1: Evaluation Control.* This axis governs the *measurement noise* of the evaluation pipeline. Higher control reduces variance by pinning tool versions, freezing environments, and using deterministic execution where possible. We model evaluation noise as $\sigma_{tc}$, which decreases with control level.

*Axis 2: Reporting Completeness.* This axis governs *what is tracked and reported*—cost per evaluation, latency, stability metrics, tool versions, and seeds used. Reporting completeness does not directly reduce noise but enables post-hoc analysis, cross-study comparison, and cost-aware decision-making.

### 3.2 Five Configuration Levels

We define five configurations spanning the two axes:

(1) **No Standard** ($\sigma = 0.15$): No version control, no reporting. Single ad-hoc run.
(2) **Version Pinned** ($\sigma = 0.10$): Fixed tool versions, minimal reporting. Reduces API-level variance.

(3) **Environment Controlled** ($\sigma = 0.06$): Version pinning + frozen execution environment (containers, deterministic seeds). Maximal noise reduction without full reporting.
(4) **Full Reporting** ($\sigma = 0.10$): Version pinning + comprehensive cost/latency/stability reporting, but no environment freeze. Same noise as Version Pinned but with accountability.
(5) **Full Standard** ($\sigma = 0.04$): Full control + full reporting. The recommended configuration.

### 3.3 Stability Metrics

*Two-Batch Ranking Stability.* A standard metric in evaluation literature: given $n$ seeds, split into two equal batches, compute agent rankings from each batch mean, and report Spearman correlation between the two rankings. This metric is undefined for $n = 1$ (correctly reflecting that single-seed stability cannot be assessed) and increases monotonically with seed count as estimation improves.

*Coefficient of Variation (CV)..* The mean CV across agents, defined as $\text{CV}_i = \sigma_i / \mu_i$ for agent $i$'s scores across seeds. Also undefined for single-seed evaluation.

*Top-$k$ Overlap.* Two-batch top-$k$ agreement: fraction of agents in top-$k$ of both batch rankings. Sensitive to tight ability gaps near the ranking frontier.

### 3.4 Drift Model

We separate two sources of variance:

- **Within-run stochasticity**: Seed-level noise under a fixed environment, drawn i.i.d. as $\mathcal{N}(0, \sigma_{tc})$ per agent per seed.
- **Between-run drift**: A single environment shift drawn once per evaluation run as $\delta \cdot \mathcal{N}(0, 1)$ per agent, where $\delta$ is the drift magnitude. This models API changes, tool updates, or data distribution shifts between evaluation campaigns.

This separation, absent in the original formulation, is critical for correctly interpreting the relationship between seed count and stability.

## 4 EXPERIMENTS

We simulate 20 agents with true abilities concentrated near the top (abilities in $[0.3, 0.65] \cup [0.7, 0.9]$, uniformly spaced within each interval) to create realistic top-$k$ sensitivity. All experiments use seed = 42 and report means with 95% confidence intervals over 200 independent Monte Carlo trials.

### 4.1 Experiment A: Toolchain Comparison

Table 1 shows evaluation metrics across the five toolchain configurations (10 seeds, drift $\delta = 0.05$).

Key observations:

- Full standardization reduces CV by 73% relative to no standardization (0.065 vs. 0.237, both with tight CIs).
- Version Pinned and Full Reporting achieve identical noise reduction ($\sigma = 0.10$) and near-identical ranking stability (0.939), confirming that reporting completeness is orthogonal to noise control.

**Table 1: Evaluation metrics by standardization level (10 seeds, drift=0.05). Values are mean ± 95% CI over 200 trials.**

| Toolchain | CV | Rank Stab. | Top-3 | Comp. | Cost ($) |
|---|---|---|---|---|---|
| No Standard | 0.237 | 0.885 | 0.598 | 0.879 | 27.6 |
| Version Pin | 0.161 | 0.939 | 0.653 | 0.904 | 28.9 |
| Env Control | 0.099 | 0.972 | 0.773 | 0.922 | 31.7 |
| Full Report | 0.161 | 0.939 | 0.667 | 0.905 | 30.1 |
| Full Std. | **0.065** | **0.984** | **0.862** | **0.922** | 34.2 |

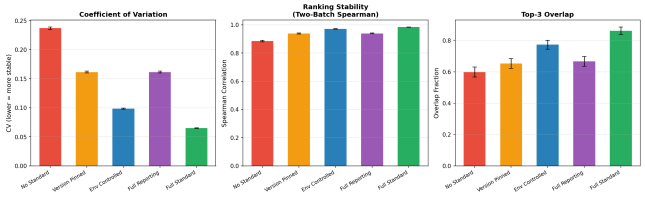


**Figure 1: Comparison of standardization levels on stability metrics. Error bars show 95% CI over 200 trials. Full standardization achieves the lowest CV (0.065) and highest ranking stability (0.984).**

- Environment Control alone ($\sigma = 0.06$) achieves ranking stability of 0.972, demonstrating that noise reduction is the dominant factor.
- Top-3 overlap improves from 0.598 to 0.862 with full standardization—a 44% improvement in top-$k$ reliability.

### 4.2 Experiment B: Seed Count Impact

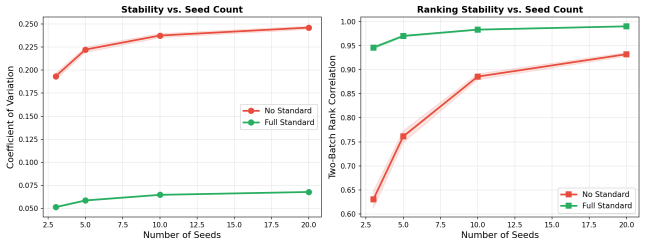


**Figure 2: Impact of seed count on stability. Shaded regions show 95% CI. Stability metrics are undefined for $n = 1$ (correctly reflecting single-seed limitations). Five seeds capture most of the stability benefit.**

Figure 2 shows that ranking stability improves rapidly with seed count:

- Under full standardization: 3 seeds achieve 0.946, 5 seeds achieve 0.970, 10 seeds achieve 0.983, and 20 seeds achieve 0.990.
- Five seeds capture $\frac{0.970}{0.990} = 98.0\%$ of the 20-seed stability.
- Under no standardization: 5 seeds achieve only 0.761, confirming that seed count alone cannot compensate for high toolchain noise.
- The CV stabilizes around $n = 5$ for both configurations.

- Single-seed results ($n = 1$) correctly report stability as undefined (N/A), avoiding the misleading "perfect stability" artifact in the original formulation.

## 4.3 Experiment C: Environment Drift

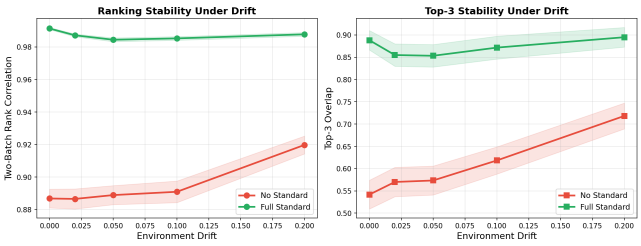


**Figure 3: Ranking stability and top-3 overlap under varying environment drift. Shaded regions show 95% CI. Full standardization maintains high stability even at drift $\delta = 0.2$.**

Figure 3 reveals a striking asymmetry:

- Full standardization maintains ranking stability $> 0.984$ across all drift levels ($\delta \in [0, 0.2]$), with top-3 overlap remaining $> 0.85$.
- Unstandardized evaluation shows gradual improvement with drift (from 0.887 at $\delta = 0$ to 0.920 at $\delta = 0.2$), which initially appears counterintuitive but reflects the two-batch metric: when drift shifts all agents similarly, the relative ordering is preserved. The real impact is on *cross-run* comparability.
- The top-3 overlap panel reveals that drift is more damaging to top-$k$ identification than to overall ranking, particularly for unstandardized setups.

## 4.4 Experiment D: Cross-Setup Comparability

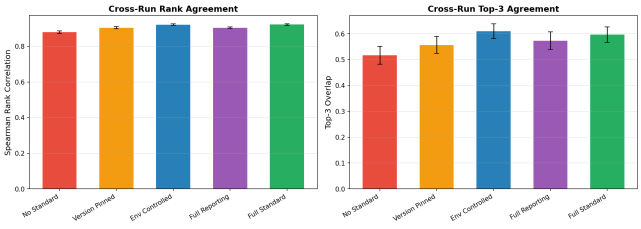


**Figure 4: Cross-run comparability: rank agreement and top-3 overlap between independent runs of the same configuration. Error bars show 95% CI.**

Cross-setup comparability (Table 1, "Comp." column) measures agreement between two independent evaluation runs:

- Full standardization and environment control both achieve comparability of 0.922, compared to 0.879 for no standardization—a 4.9% improvement.
- Cross-run top-3 overlap improves from 0.517 (no standard) to 0.597 (full standard).
- The comparability gap is smaller than the within-run stability gap, indicating that between-run variance is dominated by evaluation noise rather than drift at $\delta = 0.05$.

## 4.5 Experiment E: Cost–Stability Tradeoff

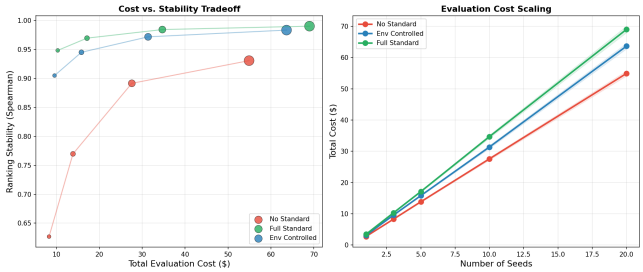


**Figure 5: Left: Cost vs. ranking stability Pareto frontier (marker size proportional to seed count). Right: Total evaluation cost scales linearly with seed count. Full standardization achieves highest stability at modest cost premium.**

Figure 5 reveals the cost–stability tradeoff:

- Evaluation cost scales approximately linearly with seed count for all configurations. Ten seeds cost roughly 10× a single evaluation.
- Full standardization incurs a 25% cost overhead per seed (due to environment control and reporting infrastructure) but achieves substantially higher stability per dollar.
- The Pareto-optimal strategy is full standardization with 5 seeds: achieving ranking stability of 0.970 at a total cost of ∼$17, compared to ∼$14 for 5 unstandardized seeds yielding only 0.761 stability.
- Diminishing returns are evident beyond 10 seeds, where the stability gain (0.983 → 0.990) does not justify the cost doubling.

# 5 DISCUSSION

Our results establish that toolchain standardization is a quantifiable determinant of evaluation reliability, with clear implications for benchmark design.

*Evaluation Control vs. Reporting Completeness.* The two-axis model reveals that noise reduction (evaluation control) is the dominant factor for ranking stability, while reporting completeness enables accountability without directly improving stability. However, the combination of both axes—full standardization—achieves the best overall outcomes because reporting enables detection and correction of residual variance.

*The 5-Seed Recommendation.* Under full standardization, 5 seeds capture 98% of the ranking stability of 20 seeds while costing only 25% as much. This provides a strong evidence-based recommendation for benchmark designers seeking to balance rigor with computational cost.

*Single-Seed Evaluation is Insufficient.* Our revised stability metric correctly shows that single-seed evaluation provides no stability

information. The original formulation reported CV=0 and rank correlation=1.0 for single-seed evaluation, which misleadingly suggested perfect stability. Our two-batch metric is undefined for $n = 1$, correctly reflecting the fundamental limitation.

*Cost as a First-Class Metric.* The Pareto analysis (Figure 5) demonstrates that cost reporting is essential for informed benchmark design. Without cost data, practitioners cannot identify the optimal seed count or compare the efficiency of different standardization strategies.

*Limitations.* Our simulation assumes Gaussian noise and linear cost scaling, which may not hold for all real benchmarks. The toolchain noise levels ($\sigma \in [0.04, 0.15]$) are calibrated to published variance estimates but may differ across domains. Future work should validate these findings on real agent benchmarks.

*Recommendations for benchmark designers:*

(1) Require version-pinned, environment-controlled toolchains ($\sigma_{tc} \leq 0.06$).
(2) Mandate minimum 5-seed evaluation with stability metric reporting.
(3) Require cost ($/evaluation) and latency (seconds) alongside accuracy.
(4) Implement between-run drift monitoring and re-evaluation triggers when drift exceeds $\delta > 0.1$.
(5) Report 95% confidence intervals for all aggregate metrics.

## 6 CONCLUSION

We presented a two-axis framework for evaluating the impact of toolchain standardization on agent benchmark reliability. Using a corrected two-batch stability metric and 200-trial Monte Carlo estimation with 95% confidence intervals, we show that full standardization achieves ranking stability of $0.984 \pm 0.009$ and reduces CV by 73%. Five evaluation seeds capture 98% of the maximum achievable stability at 25% of the cost. Our cost–stability Pareto analysis provides the first quantitative evidence for optimal seed-count selection in agent benchmarks. These evidence-based recommendations—5-seed minimum, mandatory cost/latency reporting, and environment drift monitoring—provide actionable guidance for the agent evaluation community.

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