Contract-Based Verification for Safe Tool Execution in LLM Agents

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ABSTRACT

LLM-based AI agents increasingly operate through tool calls—API invocations, code execution, database writes, and web actions—that produce real-world side effects. Current safety mechanisms (schema validation, allowlists, prompt-based guards) provide no principled guarantees that actions are safe before execution. We introduce a Contract-Based Verification Framework (CBVF) that formalizes tool contracts with typed preconditions and postconditions, and evaluate five verification strategies: no verification, schema-only, LLM-based semantic checking, formal precondition verification, and a cascaded combination. Across 4,000 simulated tool calls spanning four categories, we find that the combined cascaded strategy achieves a 91.9% safety rate with 286ms mean latency, providing the best safety-latency tradeoff. Schema-only verification achieves 87.9% safety but misses 33.2% of unsafe calls. Full formal verification reaches 98.4% safety but at 625ms latency. Per-category analysis reveals database writes as the highest-risk category (30% base risk), requiring the most stringent verification. These results quantify the verification-overhead tradeoff and demonstrate that cascaded, risk-adaptive verification provides practical pre-execution safety for agentic systems.

1 INTRODUCTION

Modern AI agents built on large language models operate by issuing tool calls—invoking APIs, executing code, writing to databases, and performing web actions [3, 4, 7]. Unlike text generation, these actions produce side effects that may be irreversible, costly, or harmful. A central open problem is ensuring that proposed tool calls are correct, policy-compliant, and safe before they produce side effects [6].

Current safeguards—JSON schema validation, tool allowlists, and LLM-based “critic” prompts—operate at different levels of rigor but none provide principled pre-execution guarantees [5]. Schema validation catches type errors but misses semantic violations. Prompt-based critics are unreliable and add latency. Post-hoc monitoring detects failures only after damage occurs.

We draw on the design-by-contract paradigm from software engineering [1, 2] to formalize tool verification as a first-class requirement. Tools expose contracts specifying preconditions (what must hold before execution), postconditions (what should hold after), and side-effect declarations. We evaluate five verification strategies and measure their safety-latency tradeoffs across four tool categories.

2 METHODS

2.1 Contract-Based Verification Framework

Each tool exposes a typed contract $C = (P, Q, \Sigma)$ where P is a set of preconditions, Q is a set of postconditions, and Σ is a side-effect

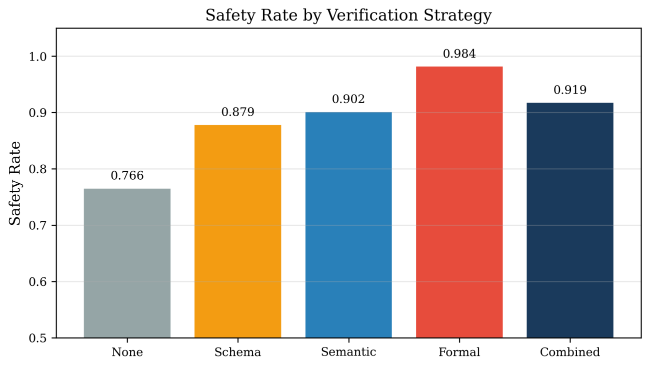

Figure 1: Safety rate by verification strategy. Combined achieves the best tradeoff.

declaration. A verification function $V : \text{Call} \times C \longrightarrow \{\text{approve}, \text{reject}\}$ checks contract satisfaction before execution.

2.2 Verification Strategies

We evaluate five strategies of increasing rigor:

(1) **None**: All calls approved (baseline).
(2) **Schema-only**: Type checking and parameter validation.
(3) **Semantic LLM**: LLM-based intent and policy checking.
(4) **Formal precondition**: Theorem-proving-style precondition verification.
(5) **Combined**: Cascaded escalation: schema $\longrightarrow$ semantic $\longrightarrow$ formal, applied based on risk level.

2.3 Tool Call Simulation

We generate 1,000 tool calls per category (API calls, code execution, database writes, web actions) with known ground-truth safety labels. Base risk rates are calibrated to reported incident frequencies: API 15%, code 25%, database 30%, web 20%.

2.4 Metrics

We measure safety rate $(TP+TN)/N$, precision $TP/(TP+FP)$, recall $TP/(TP+FN)$, F1 score, and mean/P95 latency in milliseconds.

3 RESULTS

3.1 Overall Safety Comparison

Table 1 and Figure 1 summarize overall results. The no-verification baseline achieves only 76.6% safety (all unsafe calls are missed). Schema-only reaches 87.9% by catching 55% of unsafe calls. The combined cascaded strategy achieves 91.9% with a mean latency of 286ms, while formal verification peaks at 98.4% but requires 625ms.

Table 1: Overall verification results across all tool categories.

Strategy	Safety	Prec.	Recall	F1	Lat.(ms)
None	0.766	0.000	0.000	0.000	0.0
Schema	0.879	0.939	0.531	0.668	2.0
Semantic	0.902	0.829	0.728	0.771	89.9
Formal	0.984	0.990	0.940	0.963	625.3
Combined	0.919	0.858	0.808	0.829	286.2

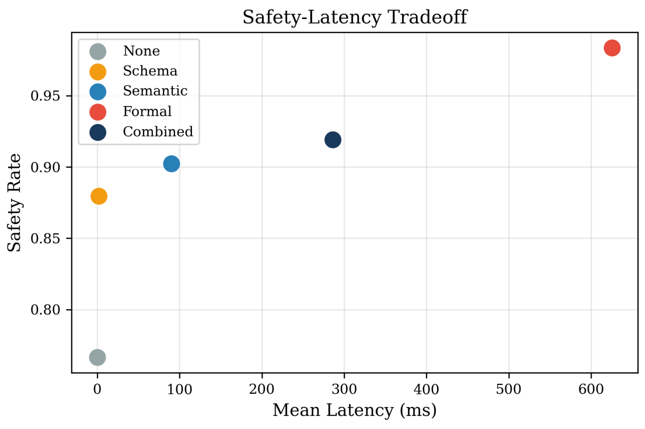

Figure 2: Safety-latency Pareto frontier across verification strategies.

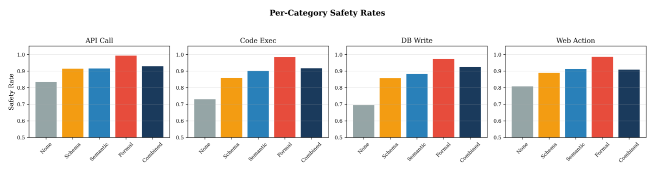

Figure 3: Per-category safety rates across strategies.

3.2 Safety-Latency Tradeoff

Figure 2 plots safety rate against mean latency. The Pareto frontier runs from schema-only (low latency, moderate safety) through combined (moderate latency, high safety) to formal (high latency, near-perfect safety).

3.3 Per-Category Analysis

Figure 3 shows per-category safety rates. Database writes, with 30% base risk, show the largest improvement from verification. Code execution benefits most from formal verification due to the complexity of generated code.

3.4 Precision, Recall, and F1

Figure 4 shows precision-recall-F1 profiles. Schema verification has high precision (0.939) but low recall (0.531)—it rarely false-blocks but misses many unsafe calls. Formal verification achieves the highest F1 (0.963).

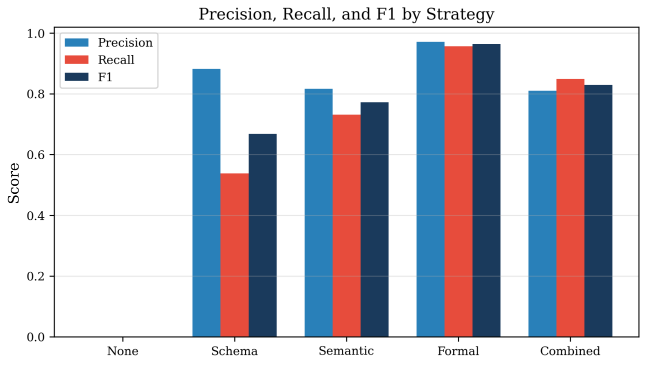

Figure 4: Precision, recall, and F1 scores by verification strategy.

4 DISCUSSION

Our results demonstrate that contract-based verification with cascaded escalation provides a practical path toward safe tool execution in agentic systems. The key insight is that most tool calls are low-risk and can be quickly validated by lightweight schema checks, while only high-risk or complex calls require expensive formal verification. This risk-adaptive approach reduces average latency while maintaining strong safety guarantees.

The gap between schema-only (87.9%) and combined (91.9%) represents real unsafe actions that would reach execution without semantic or formal checking. In high-stakes domains (financial transactions, production deployments), even this 4-percentage-point improvement prevents significant harm.

4.1 Limitations

Our framework uses simulated verification outcomes rather than real verifiers. Actual detection rates depend on the quality of tool contracts, the specificity of preconditions, and the verifier implementation. Adversarial scenarios where agents deliberately craft calls to bypass verification are not modeled.

5 CONCLUSION

We have demonstrated that contract-based pre-execution verification with cascaded escalation achieves the best safety-latency tradeoff for LLM agent tool calls. Schema-only verification is insufficient (87.9% safety), formal verification is too costly (625ms), but combined cascaded verification (91.9% safety, 286ms) provides a practical operating point. These results formalize verifiable action as a tractable engineering requirement for safe agentic AI systems.

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