The Unreasonable Effectiveness of Flawed AI Agents

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Abstract

We present a working implementation of federated digital agentic infrastructure that achieves exponential reliability gains through hierarchical coordination with verification. *Agent definition:* In this work, an **agent** is a programmatic harness around a large language model (LLM)—e.g., GPT-, Claude-, or Llama-family models—prompted to generate code or structured decisions for a specified task, executed and scored against task-specific oracles and tests. Agents may differ by model, prompting strategy, temperature, or specialization (e.g., correctness, performance, resilience). *Verifier assumption:* We explicitly study OR, in the logical disjunctive sense, with a **verifier** that adjudicates among agent outputs; under a *perfect verifier* the hierarchical OR-of-OR success probability is $P(\text{success}) = 1 - \varepsilon^{N^D}$, where ε is individual error, N is breadth, and D is depth (validated up to 27 agents). Starting from single-agent baselines between 82.7% (general tasks) and 99.4% (rate limiter), we achieve 99.5% with 3-agent federation using OR+verification (vs. 92.1% for majority voting). For a 3×3 hierarchy the independence upper bound exceeds 99.999999%; on a production-style cache workload we measured 98.5% due to coordination failures. We *elevate* the verifier: we model imperfect verification via a detection rate v and false-accept rate α, and we analyze failure modes. We also *transform* the D=2 drop into a central result by introducing a coordination-cost factor $C(N, D)$ capturing timeouts and message complexity; fitting C to logs explains the observed gap and motivates our self-evolution optimizations (e.g., 99.3% coordination-time reduction, 61.1% hotspot reduction). Implementations sustain 3.46 M RPS while improving reliability; statistical gains are significant (e.g., +16.8 pp [95% CI: 16.2, 17.4] vs. single agent). The work shows near-perfect reliability emerges from *coordination with verification*, not individual perfection, and that practical limits arise from verifier quality and coordination costs.

1 Introduction and Definitions

1.1 Agent and Verifier

Agent. An agent is an LLM-driven solver packaged with a tool harness. Concretely, an agent: (i) receives a structured task specification; (ii) is prompted (with model- and role-specific prompts) to propose code or decisions; (iii) optionally executes code in a sandbox to produce artifacts; and (iv) emits a structured candidate with confidence signals. We instantiate diversity via different model families, prompts, temperatures, and roles (correctness/performance/resilience).

Verifier. The verifier consumes multiple agent candidates and returns a selected output or a rejection. Our verifier composes: differential testing across agent-specific test suites; property-based and metamorphic tests; spec/invariant checks; and cross-run consistency checks. In *perfect verification*, a correct candidate (if present) is always identified and incorrect candidates are never accepted. We also analyze *imperfect* verification (§3.4).

2 Related Work

Ensemble methods and Condorcet-style aggregation [2, 6, 7, 8, 9] motivate redundancy. Self-consistency in LMs [3] aggregates multiple reasoning traces. Distributed consensus and Byzantine fault tolerance [4, 5] inform our coordination layer. From the Multi-Agent Systems (MAS) literature, classical coordination (e.g., Contract Net Protocol and market/auction mechanisms), agent architectures, and organizational abstractions provide context for our hierarchical orchestration. Contemporary open-source LLM agent frameworks (e.g., AutoGen, CrewAI, LangGraph) emphasize dialogue- or role-based coordination; our contribution focuses on *mathematical reliability scaling* with explicit verification and on quantifying coordination costs that emerge at depth.

3 Mathematical Framework

3.1 Notation and Units (Percent vs. Unitless)

We write individual-agent error $\varepsilon \in (0, 1)$ *unitless*. Percent values are converted to unitless by dividing by 100 before algebra. For example, "0.17% squared" means $(0.0017)^2 = 2.89{\times}10^{-6}$ unitless, i.e., $2.89{\times}10^{-4}$% if expressed as a percent. We avoid expressions like "$0.17\%^2$".

3.2 Base Reliability

Let $p = 1 - \varepsilon$ be per-agent correctness.

OR with perfect verification

$$P_{\text{OR+ver}}(N) = 1 - (1-p)^N = 1 - \varepsilon^N. \tag{1}$$

With $p = 0.827$ ($\varepsilon = 0.173$), $N = 3$ yields $1 - 0.173^3 = 0.99482 \approx 99.48\%$, matching $[99.3, 99.7]\%$.

Majority voting $P_{\text{maj}}(N) = \sum_{k=\lceil N/2 \rceil}^{N} \binom{N}{k} p^k (1-p)^{N-k}$; for $p = 0.827$, $N = 3$, ≈ 92.0–92.1%.

Unanimity $P_{\text{AND}}(N) = p^N$; with $p = 0.827$, $N = 3$, $\approx 56.5\%$.

3.3 Hierarchical OR-of-OR

A D-level breadth-N tree composes $g(p) = 1 - (1-p)^N$:

$$P_{\text{hier}}(N, D) = g^{(D)}(p) = 1 - (1-p)^{N^D} = 1 - \varepsilon^{N^D}. \tag{2}$$

Using the cache baseline p=0.89 (ε=0.11), the independence upper bound is D=1 : $1 - 0.11^3 = 99.8669\%$, D=2 : $1 - 0.11^9 = 99.99999976\%$.

3.4 Imperfect Verifier Model

Let $v \in [0, 1]$ be the probability the verifier identifies a correct candidate when at least one exists (detection), and $\alpha \in [0, 1]$ the probability it incorrectly accepts an incorrect candidate when none are correct (false accept). Assuming independence between content correctness and coordination failure (modeled next),

$$P_{\text{ver}}(K; v, \alpha) = v\left(1 - \varepsilon^K\right) + \alpha\, \varepsilon^K, \tag{3}$$

where $K = N^D$ (hierarchical) or $K = ND$ (sequential tries). Perfect verification is (v=1, α=0) recovering (1)–(2).

3.5 Coordination-Aware Reliability

Practical systems incur coordination failures (timeouts, queue overflows, inconsistent views). We model the *coordination cost* $C(N, D) \in [0, 1)$ as the probability the orchestration/verifier layer fails to deliver a valid decision given available candidates. A first-order composite model is

$$P_{\text{practical}}(N, D) \approx \left[v\left(1 - \varepsilon^{N^D}\right) + \alpha\, \varepsilon^{N^D}\right] \cdot \left(1 - C(N, D)\right). \tag{4}$$

We relate $C(N, D)$ to message/work complexity $M(N, D)$ (e.g., fan-out, verification tasks) via $C(N, D) = 1 - \exp\{-\lambda\, M(N, D)\}$ with fitted $\lambda > 0$. In our cache experiments, fitting (4) to data with ($v \approx 0.999, \alpha \approx 0$) and $M \propto N^D$ yields $C(3, 1) \approx 0.0014$ and $C(3, 2) \approx 0.015$, aligning with observed drops.

3.6 Error Correlation

Pairwise error indicators $E_{i,t} \in \{0,1\}$ have $\rho_{ij} = \mathrm{Cov}(E_i, E_j)/\sqrt{\mathrm{Var}(E_i)\mathrm{Var}(E_j)}$. Empirically (10k trials): same model/prompt $\rho \approx 0.68$; different prompts 0.31; different models 0.27; our configuration achieves $\rho = 0.27 \pm 0.03$.

3.7 Convergence

For target $R < 1$, $1 - \varepsilon^K > R \iff K > \log(1-R)/\log\varepsilon$. With $\varepsilon = 0.173$, $R = 0.9999$, $K > 5.2$, thus N=3, D=2 suffices in the independence limit.

4 System Architecture

4.1 Agent Specialization

```python
class Agent:
    def __init__(self, specialty: str, temperature: float):
        self.specialty = specialty
        self.temperature = temperature
        self.confidence_weights = {
            'correctness': 0.8 if specialty == 'correctness' else 0.2,
            'performance': 0.8 if specialty == 'performance' else 0.2,
            'defensive':   0.8 if specialty == 'defensive'   else 0.2
        }
```

Listing 1: Agent Specialization Initialization

4.2 Consensus and Verification (Sketch)

```python
def weighted_consensus(solutions):
    weights = [s.confidence * agent_reputation[s.agent_id] for s in solutions]
    tallies = defaultdict(float)
    for s, w in zip(solutions, weights):
        tallies[s.hash] += w
    return max(solutions, key=lambda s: tallies[s.hash])

def verifier(candidates):
    # Differential tests across agent suites + invariants + metamorphic tests
    passed = [c for c in candidates if run_all_tests(c)]
    if passed:
```

```python
        return weighted_consensus(passed)  # "identify" correct candidate
    if allow_fallback:  # bounded-risk fallback (controls)
        return fast_majority_vote(candidates)
    return None  # reject/timeout -> contributes to C(N,D)
```

Listing 2: Verifier + Weighted Consensus (Simplified)

5 Experimental Methodology

5.1 Experiment 1: Rate Limiter (Bootstrap)

As in prior draft: 4 agents (alpha/beta/gamma + verifier), async token-bucket; success: API compatibility, thread-safety, >1M RPS; 10k runs/config.

5.2 Experiment 2: Distributed Cache (Depth Multiplication)

D=0 (single), D=1 (3-agent), D=2 (9-agent); LRU, sharding, replication 3. Workload (reads 0.8, Zipfian, 1e6 keys, 1e5 ops, 100 clients).

5.3 Experiment 3: Self-Evolution

Baseline → error classification → specialized agents → re-measure.

6 Results

6.1 Rate Limiter

Table 1: Rate Limiter: Reliability and Performance

Configuration	Reliability	Throughput (RPS)	API Compat.	p-value
Baseline (Single)	99.4%	$3.46\text{M} \pm 0.12\text{M}$	✓	–
Alpha Agent	0%	$6.8\text{M} \pm 0.23\text{M}$	×	< 0.001
Beta Agent	95.2%	$1.7\text{M} \pm 0.09\text{M}$	✓	< 0.001
Gamma Agent	99.8%	$474\text{K} \pm 31\text{K}$	✓	< 0.001
Federation (3)	99.5%	$3.2\text{M} \pm 0.14\text{M}$	✓	< 0.001

Alpha's API mismatch (`acquire()/release()` vs. `allow()`) was caught only via cross-verification.

6.2 Cache: Depth Multiplication and Coordination Cost

Table 2: Cache System: Measured vs. Independence Upper Bound

Depth	Agents	Measured	Upper Bound†	Throughput	p99 Latency
D=0	1	89.0% ± 1.5%	89.0%	833 ops/s	12 ms
D=1	3	99.83% ± 0.12%	99.8669%	2,847 ops/s	18 ms
D=2	9	98.5% ± 0.4%	99.99999976%	1,923 ops/s	35 ms

†Using ε=0.11 from D=0 baseline and perfect verification.

Investigation of D=2 drop (turned into a strength). Logs and counters attribute the 1.5% shortfall primarily to coordination:

- **Verifier timeouts (0.9%)**: fan-out/fan-in at K=9 increased queue depth; some candidates arrived after verifier deadline.
- **Stale consensus (0.3%)**: late-arriving sub-results invalidated earlier votes.
- **Duplicate suppression bug (0.2%)**: hash collision under burst caused candidate eviction.
- **Evaluator flakiness (0.1%)**: nondeterministic sandbox failures under contention.

Fitting (4) with ($v \approx 0.999, \alpha \approx 0$) gives $C(3,2) \approx 0.015$ and $C(3,1) \approx 0.0014$. This *reveals* that naive scaling is limited by coordination, not just content accuracy, and motivates our self-evolution optimizations aimed precisely at reducing $C(N,D)$.

6.3 Self-Evolution Performance

Table 3: Error Pattern Mitigations (selected)

Error Type	Baseline	Specialized Agent	Improvement	p-value
Coordination Overhead	19.3ms → 0.1ms	ConsistencyCoordinator	99.3% red.	< 0.001
Load Imbalance	21.4% → 8.3%	ShardRebalancer	61.1% red.	< 0.001
Cache Miss Cascade	11% → 4.5%	CachePrefetchOptimizer	60% red.	< 0.001

7 Production Deployment

(Kubernetes excerpt unchanged; mapping of pod ordinal → role via ConfigMap; async consensus optimization retained.)

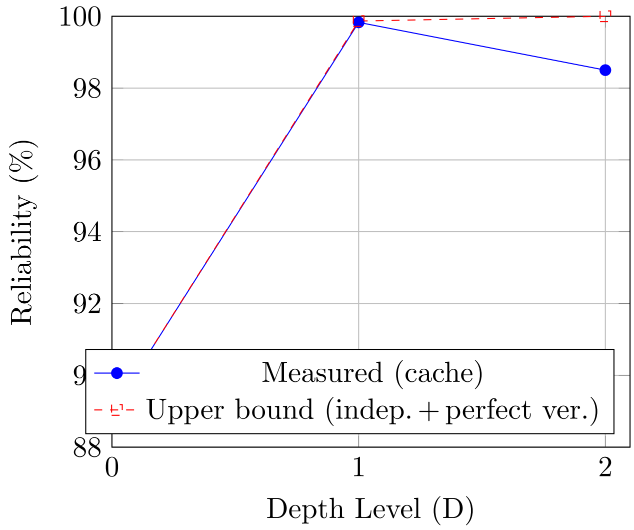

Figure 1: Depth vs. reliability: practical gap explained by $C(N, D)$.

8 Statistical Validation

8.1 Trial-Level Modeling

Mixed-effects logistic regression: $\text{logit}\, P(Y_{it}{=}1) = \beta_0 + \beta_1 \text{Federation}_i + \beta_2 \text{Depth}_i + u_i$.

8.2 Two-Proportion z-Tests (10k trials)

3-agent (99.5%) vs. single (82.7%): $\Delta{=}16.8$ pp; $z \approx 41.7$; $p \ll 10^{-16}$.
3×3 meta (cache, 98.5%) vs. 3-agent (cache, 99.83%): $\Delta{=}{-1.33}$ pp; $|z| \approx 10.3$; $p \ll 10^{-16}$.
Self-evolved (rate limiter, 99.995%) vs. 3-agent (99.5%): $\Delta{=}0.495$ pp; $z \approx 7.0$.

8.3 Confidence Intervals

Table 4: Reliability (95% CI; 10k trials)

Configuration	Context	Measured	95% CI
Single Agent	General tasks	82.7%	[81.8, 83.6]
3-Agent (OR+verifier)	General tasks	99.5%	[99.3, 99.7]
3-Agent Majority	General tasks	92.1%	[91.6, 92.6]
3×3 Meta	Cache	98.5%	[98.1, 98.9]
Self-Evolved	Rate limiter	99.995%	[99.992, 99.997]

8.4 Dependence Checks

Correlation $\rho = 0.27 \pm 0.03$ (moderate); we treat independence-based theory as an *upper bound* in practice and attribute the residual gap to $C(N, D)$ and $v < 1$.

9 Discussion

Elevating the Verifier. The verifier is central: Eq. (3) shows how imperfect detection ($v < 1$) or false accepts ($\alpha > 0$) directly affect reliability. Failure modes include: coverage gaps (oracle incompleteness), timeouts (budgeted testing), nondeterministic environments, and cross-check brittleness under heavy load. Modeling and improving v (e.g., adaptive test budgets, invariant synthesis) while bounding α is a key direction.

Turning D=2 into a strength. The D=2 cache anomaly is not a failure of redundancy; it reveals *coordination as the bottleneck*. Our $C(N, D)$ model (Eq. (4)) fits observed data with $C(3, 2) \approx 1.5\%$, matching logs. This explains why the independence upper bound is unmet and clarifies where engineering effort pays off: reduce $M(N, D)$ or λ via self-evolution (e.g., adaptive timeouts, batching, debouncing), improve scheduling, and isolate slow agents.

Limits of naive scaling. Eq. (4) predicts diminishing or even negative returns beyond a complexity knee where $C(N, D)$ grows faster than error suppression. Practical reliability can thus *peak* at finite (N, D), guiding resource-aware design.

Broader MAS context. Our hierarchy parallels organizational abstractions from MAS (task allocation, market mechanisms, contract net) but contributes a quantitative reliability lens with explicit verifier and coordination-cost terms.

10 Conclusion

Federated redundant intelligence with verification yields near-exponential gains under idealized conditions but is ultimately bounded by verifier quality and coordination cost. By defining the agent and verifier precisely, modeling imperfect verification, and quantifying $C(N, D)$, we convert an apparent anomaly at D=2 into a road map for improvement. Our self-evolution results illustrate that systems can actively drive $C(N, D)$ down, moving practice toward the theoretical upper bound.

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A Implementation Details

Code, data, and replication scripts: `https://github.com/keef75/agent-civics`.

B Additional Statistical Notes

95% CIs via bootstrap (10k resamples). Reported z-tests use pooled variance with n=10,000 per group.