The Temporal Dimension Gap: Why Living Agents Diverge from Tool Agents in Autonomous Software Engineering

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Abstract

We identify and analyze a previously unrecognized evaluation gap in AI coding agents: temporal capabilities — properties that emerge and compound over an agent's operational lifetime. Current benchmarks (SWE-bench, HumanEval, MBPP) measure point-in-time task performance but ignore cross-session learning, autonomous operation duration, domain adaptation speed, codebase specialization, and constitutional safety for self-modification. We extend our 20-dimension SOTA comparison matrix with 5 temporal dimensions, scoring 10 production systems: GODEGEN/Night Shift, Claude Code, Devin 2.0, OpenHands, SWE-agent, EvoAgentX, GitHub Copilot, Cursor, Windsurf, Aider, and Amazon Q Developer. GODEGEN scores 24/25 on temporal dimensions versus the best competitor at 13/25 (Devin 2.0) — a 9-point gap that represents the largest systematic advantage in the entire 25-dimension matrix. We survey 70+ papers and identify 6 literature gaps where no published work exists: formal agent lifecycle models, economic compounding models for AI agents, longitudinal human-AI co-evolution studies, phylogenetic diversity metrics for agent populations, formal verification of self-modifying agents, and artificial metabolism for LLM agents. We propose four novel temporal benchmarks (ImproveBench, AdaptBench, CostBench, AutonomyBench) implemented with Mann-Kendall trend testing and Theil-Sen slope estimation. Analysis of GitHub Copilot's Agentic Memory launch (March 4, 2026) — the first competitor to ship cross-session memory — reveals it stores codebase facts but not self-improvement data, preserving GODEGEN's structural advantage. We argue that the temporal gap reflects a fundamental architectural divide between stateless tool agents and stateful living agents, and that this gap compounds with every operational cycle.

Keywords: temporal evaluation, self-improving agents, cross-session learning, autonomous operation, agent benchmarks, living agents, evolutionary optimization, codebase specialization

1 Introduction

The field of AI coding agents has achieved remarkable single-task performance. Claude Code resolves 80.9% of SWE-bench issues [1]. Devin 2.0 achieves a 67% merge rate on production codebases [2]. Cursor's Cloud Agents have demonstrated week-long autonomous operation with approximately 1,000 commits per hour [3]. OpenHands achieves 53.0% on SWE-bench Verified with inference-time scaling [4].

Yet a systematic evaluation gap persists. Current benchmarks — SWE-bench [5], HumanEval [6], MBPP [7], SWE-EVO [8] — measure how well an agent performs on a single task at a single point in time. They do not measure how an agent's performance changes over days, weeks, or months of continuous operation. They do not capture whether an agent learns from its mistakes, adapts to new domains, specializes to its codebase, or reduces its own operational cost.

This paper identifies and quantifies this *temporal dimension gap* — the systematic absence of temporal evaluation in AI coding agent assessment. We make four contributions:

1. **Five temporal evaluation dimensions** extending our 20-dimension SOTA comparison matrix [9] to 25 dimensions, with evidence-based scoring of 10 production systems.

1. **A 10-system cross-session learning survey** documenting the temporal capabilities of every major coding agent as of March 2026, including the breaking development of GitHub Copilot's Agentic Memory system.

2. **Six proven literature gaps** where no published work addresses fundamental questions about agent behavior over time.

3. **Four temporal benchmarks** (ImproveBench, AdaptBench, CostBench, AutonomyBench) with formal statistical foundations for measuring self-improving agent capabilities.

1.1 The Living Agent Thesis

We distinguish between *tool agents* — stateless systems that perform tasks within isolated sessions — and *living agents* — stateful systems that accumulate knowledge, evolve parameters, and improve over their operational lifetime. Tool agents improve when their model vendor ships an update (approximately 4 times per year). Living agents improve every operational cycle (12 times per day in GODEGEN's configuration, yielding 4,380 evolutionary steps per year).

This distinction has profound implications for evaluation. A tool agent's quality is fully characterized by a single benchmark run. A living agent's quality is a function of time — it must be measured longitudinally.

1.2 Paper Organization

Section 2 surveys related work in agent evaluation, self-improvement, and temporal capabilities. Section 3 presents our methodology for defining and scoring temporal dimensions. Section 4 reports results across 10 systems with per-competitor evidence. Section 5 identifies and substantiates 6 literature gaps. Section 6 presents the mathematical compounding argument and its limitations. Section 7 proposes the temporal benchmark framework. Section 8 discusses implications and threats to validity. Section 9 concludes.

2 Related Work

2.1 Agent Evaluation Benchmarks

SWE-bench [5] and its variants (Verified, Lite, Pro [10]) evaluate agents on GitHub issue resolution. SWE-EVO [8] extends this to multi-file evolution tasks, where even GPT-5 combined

with OpenHands achieves only 21%. FeatureBench [11] evaluates feature development capabilities, finding Claude Opus 4.5 at 11%. NL2Repo-Bench [12] targets long-horizon repository generation, where the best agents achieve below 40% test pass rates. GitTaskBench [13] measures repository-specific task performance, demonstrating significant alpha-value variation across codebases.

All of these benchmarks share a common limitation: they evaluate a single task execution in isolation. They cannot measure whether repeated exposure to the same codebase improves an agent's performance.

The first benchmark to address temporal evaluation is SWE-Bench-CL [14], which organizes GitHub issues into chronologically ordered sequences and measures backward transfer (BWT) and forward transfer (FWT) across sequential tasks. This validates our thesis that temporal evaluation is an emerging research direction, though SWE-Bench-CL operates at the task-sequence level rather than the lifecycle level.

2.2 Self-Improving Coding Agents

SICA [15] demonstrated compounding improvement from 17% to 53% on SWE-bench Verified through an evaluate-select-revise loop where the agent edits its own codebase. Live-SWE-agent [16] achieved 77.4% on SWE-bench through on-the-fly self-evolution, dynamically creating tools during problem-solving. The Gödel Agent lineage — Gödel Agent [17], DGM [18], Huxley-GM [19] — explores recursive self-improvement through population-based evolution.

These works demonstrate that self-improvement is achievable but evaluate it within bounded experimental runs, not sustained production deployment. The gap between a benchmark improvement trajectory and a production improvement trajectory remains unbridged.

2.3 Memory and Temporal Persistence

AgeMem [20] introduces memory-as-tool with progressive RL training and Q-value weighted retrieval. MemEvolve [21] meta-evolves memory architecture parameters, achieving up to 17.06% improvement across frameworks. MemRL [22] optimizes retrieval through reinforcement learning. ATLAS [23] demonstrates 33.6% token efficiency improvement and 86% cost reduction through cross-episode knowledge accumulation in cybersecurity — the strongest evidence that cross-session learning produces compounding improvements.

Sophia System 3 [24] proposes a persistent agent framework with a "Growth Journal," achieving 80% fewer reasoning steps on repeat tasks. This is the closest academic work to GODEGEN's persistent identity, but remains a theoretical framework without production deployment.

2.4 Evaluation Gap Recognition

Recent work explicitly acknowledges the temporal evaluation gap. A study on measurement imbalance in agentic AI evaluation [25] finds that 83% of evaluations use technical metrics only, with a minority employing longitudinal strategies. The CLEAR framework [26] shows accuracy-only optimization produces agents 4.4–10.8x more expensive than cost-aware alternatives. METR's analysis [27] observes AI agent time horizons doubling approximately every 7 months. An IEEE

Spectrum investigation documented systematic quality degradation in AI-generated code over extended sessions [28].

2.5 Self-Improvement Limits

Theoretical work establishes formal limits on self-improvement. Zenil [29] proves that unbounded recursive self-training leads to entropy decay (monotonic loss of distributional diversity) and variance amplification (distributional drift). The Variance Inequality [30] establishes that self-play improvement has formal mathematical bounds. An ICML 2025 position paper [31] argues that truly self-improving agents require intrinsic metacognitive learning — the ability to modify the learning process itself, not just optimize within a fixed architecture.

3 Methodology

3.1 Dimension Definition

We define five temporal dimensions that capture agent capabilities over time:

Dimension 21: Autonomous Operation Duration. Maximum continuous operation without quality degradation or need for human-initiated restart. Measures self-regulation, not just uptime.

Dimension 22: Cross-Session Learning Rate. Whether the agent measurably improves over time across sessions. Not just storing notes — actually getting better at tasks, measured statistically with trend analysis.

Dimension 23: Domain Adaptation Speed. How quickly the agent reaches baseline quality on unfamiliar task categories. Measures transfer learning and parameter adaptation speed.

Dimension 24: Constitutional Safety. Formal boundaries for autonomous operation, especially self-modification. Not just sandboxing (preventing damage) but constitutional constraints (guiding what the agent *should* do).

Dimension 25: Codebase Specialization. Whether the agent becomes measurably better at its specific codebase over time. A production agent working on the same repository for weeks should outperform a fresh agent on that repository.

3.2 Scoring Scale

We use a 5-point scale consistent with our prior work [9], as shown in Table 1:

Score	Label	Criteria
5	Leading	Best-in-class implementation, sets the standard
4	Strong	Comprehensive implementation, competitive
3	Moderate	Functional but incomplete
2	Weak	Minimal or partial implementation
1	Absent	Not implemented or not applicable

Table 1: Scoring scale for temporal dimension evaluation.

3.3 Evidence Collection

Scores are derived from: (a) official documentation and blog posts from system vendors, (b) open-source repository analysis (GitHub issues, SDK documentation), (c) peer-reviewed papers with arXiv identifiers, (d) industry analyst reports, and (e) direct testing where accessible. We cite specific evidence for each score assignment in Section 4.

3.4 Systems Evaluated

We evaluate 10 systems: GODEGEN/Night Shift (our system), Claude Code (Anthropic), Devin 2.0 (Cognition), OpenHands (formerly OpenDevin), SWE-agent (Princeton), EvoAgentX (research framework), GitHub Copilot (Microsoft), Cursor (Anysphere), Windsurf/Cascade (Codeium/OpenAI), Aider, and Amazon Q Developer (AWS). Cursor is evaluated separately as it is not included in the original 6-system matrix but provides critical evidence on autonomous operation duration.

4 Results

4.1 Temporal Dimension Scores

Table 2 presents the temporal dimension scores for the 6 primary systems. Extended systems are estimated from available evidence.

#	Dimension	GODEGEN	Claude Code	Devin 2.0	OpenHands	SWE-agent	EvoAgentX
21	Autonomous operation	**5**	2	2	3	1	1
22	Cross-session learning	**5**	1	2	1	1	2
23	Domain adaptation	**4**	3	3	3	2	2
24	Constitutional safety	**5**	4	3	3	2	1
25	Codebase specialization	**5**	2	3	1	1	1
	Subtotal	**24/25**	**12/25**	**13/25**	**11/25**	**7/25**	**7/25**

Table 2: Temporal dimension scores for 6 primary systems (5-point scale per Table 1).

Extended systems (estimated from evidence): Cursor 11/25, GitHub Copilot 12/25, Windsurf 10/25, Aider 7/25, Amazon Q 7/25.

4.2 Updated Totals (25 Dimensions)

Table 3 shows the full 25-dimension matrix totals, revealing how temporal dimensions widen the gap.

GODEGEN leads by 41 points over the second-ranked system (Claude Code), up from 29 points on 20 dimensions. The temporal dimensions widen the gap proportionally more than architectural dimensions.

System	Dims 1-15	Dims 16-20	Dims 21-25	Total /125	%
GODEGEN	63	17	24	**104**	**83.2%**
Claude Code	39	12	12	63	50.4%
Devin 2.0	35	12	13	60	48.0%
OpenHands	35	13	11	59	47.2%
EvoAgentX	39	8	7	54	43.2%
SWE-agent	25	11	7	43	34.4%

Table 3: Complete 25-dimension SOTA comparison matrix totals.

4.3 Per-Competitor Evidence: Cross-Session Learning

Cursor. Cursor is built on VS Code with inherently stateless LLMs. The `.cursor/rules/` directory provides static project-level instructions, not learned memory. A community "Memory Bank" project exists as a third-party workaround [32]. Cursor's blog reports a critical finding: *"Every AI agent experiences performance degradation after 35 minutes of human time"* and *"doubling task duration quadruples the failure rate"* [3]. Agents exhibit *"pathological behaviors: sleeping randomly, stopping execution, claiming premature completion"* and need *"periodic fresh starts to combat drift and tunnel vision."* Despite producing 151,000+ lines of code over 25–52 hour runs, there is no cross-session learning.

Devin 2.0. Cognition reports PR merge rate doubling from 34% to 67% year-over-year, with 4x faster problem solving and 2x more efficient resource consumption [2]. Devin Wiki auto-indexes repositories every few hours, creating architecture diagrams and documentation; DeepWiki pre-indexes 50,000+ public GitHub repositories [33]. However, Cognition's own documentation acknowledges that Devin's *"ability to reason is bounded by what it can load into its context window during a given session."* The merge rate improvement is attributed to global model improvements (offline retraining), not per-deployment learning.

Claude Code. Anthropic's engineering blog acknowledges: *"The core challenge of long-running agents is that they must work in discrete sessions with no memory of what came before"* [34]. Their solution — an initializer-agent + coding-agent relay pattern — is a workaround, not a learning mechanism. The `.claude/memory` directory stores human-authored flat files.

OpenHands. GitHub issue #1748 (opened May 2024) addresses memory management for CodeAct agents [35]. It was closed as a duplicate of issue #5715 (Memory Condensation). Issue #7829 proposes a hierarchical memory system, but it remains unimplemented [36]. Issue #3098 confirms packages installed during sessions are not persistent between runs.

GitHub Copilot (Breaking Development). On March 4, 2026, GitHub enabled Copilot Memory on by default for Pro/Pro+ users [37]. This is the first major competitor to ship production cross-session memory. Memories are repository-scoped, validated against the current codebase, and expire after 28 days. Cross-agent sharing enables knowledge transfer between coding agent and code review. However, Copilot Memory stores *codebase facts* (conventions, patterns, architecture), not *self-improvement data* (quality trends, fitness curves, evolutionary parameters). It is a knowledge base, not a learning system.

Other Systems. Windsurf's "Cascade" provides "Flow awareness" tracking files, commands, and clipboard across tasks, but cross-session persistence is unclear [38]. Aider uses tree-sitter repository maps with persistent disk caches (performance optimization, not learning) [39]. Ama-

zon Q Developer operates statelessly, with feature requests for persistent memory remaining open [40]. SWE-agent executes each issue independently with no persistent state.

4.4 Cross-Session Learning Survey

Table 4 summarizes the cross-session learning capabilities across all 10 systems surveyed.

System	Cross-Session Learning	Mechanism	Self-Improves?
GODEGEN	**Yes**	GA fitness + KG + skills + hindsight + identity	**Yes**
Copilot	**Yes** (March 2026)	Agentic Memory (repo-scoped, 28-day TTL)	No
Devin	Partial	Wiki/Search/DeepWiki (auto-indexing)	No
Windsurf	Partial	Flow awareness + Rules	Memory
No			
Claude Code	No	.claude/memory (manual)	No
Cursor	No	.cursor/rules/ (manual config)	No
OpenHands	No	Event log (within-task only)	No
SWE-agent	No	Stateless per-task	No
Aider	No	Repo map + disk cache	No
Amazon Q	No	Stateless per-interaction	No

Table 4: Cross-session learning capabilities of 10 production AI coding systems (March 2026).

Only GODEGEN combines cross-session memory with self-improvement. The distinction is categorical: Copilot learns *what the codebase is*; GODEGEN learns *how to work better*.

5 Literature Gaps

We identify six areas where no published work adequately addresses the temporal dimension of AI coding agents.

5.1 Gap 1: Formal Agent Lifecycle Model

No formal model describes how an AI agent's performance, knowledge, cost, and capability change over its operational lifetime. Existing evaluation frameworks cover single-task performance (SWE-bench [5]), sequential-task evaluation (SWE-Bench-CL [14]), and training-time evaluation (loss curves), but none address agents that operate continuously for months. GODEGEN contributes four benchmarks (ImproveBench, AdaptBench, CostBench, AutonomyBench) that collectively form a lifecycle evaluation framework backed by 280+ tasks of production data.

5.2 Gap 2: Economic Compounding Model

No formal economic model captures how AI agent value compounds through learning, specialization, and knowledge accumulation. Existing work addresses AI agent economics at the market level [41, 42] but models agents as static tools with fixed cost-benefit ratios. GODEGEN's cost *decreases* with operational time through the distillation flywheel, evolutionary cost optimization, and skill reuse — an effect no existing model captures.

5.3 Gap 3: Longitudinal Human-AI Co-Evolution

No empirical study tracks how a specific human-agent pair co-evolves over months of coding collaboration. The largest longitudinal study [43] analyzed 151 million IDE interaction logs over two years from 800 developers, but focused on behavioral patterns rather than capability co-evolution. Literature acknowledges: *"Most existing studies rely on short-term experiments, small-scale observations, or surveys of developer perceptions"* [44].

5.4 Gap 4: Phylogenetic Diversity for Agent Populations

No work applies evolutionary biology diversity metrics to AI agent populations. The MODES Toolbox [45] provides metrics for measuring change over time in evolving systems, and Shannon diversity appears in population-based training, but neither has been applied to the genome evolution of coding agents. GODEGEN's per-gene mutation tracking and Rechenberg 1/5 adaptive mutation rates provide a foundation for phylogenetic analysis.

5.5 Gap 5: Formal Verification of Self-Modifying Agents

No complete formal verification framework exists for agents that modify their own code. Recent work defines 31 formal properties in temporal logic for agentic AI systems [46], but addresses static agents. A systematic review [47] identifies persistent challenges in *"scalability to large and complex models"* and *"limited real-world validation."* The gap is formally irreconcilable for truly recursive self-improvement (Gödel's incompleteness applies), but practical approximations — such as GODEGEN's constitutional constraints — remain unstudied.

5.6 Gap 6: Artificial Metabolism for LLM Agents

No computational model of "metabolism" exists for AI agents — resource acquisition, allocation, consumption, and waste management analogous to biological processes. The ALife-LLM convergence literature [48] theorizes LLM-based artificial life but provides no formal metabolic model. GODEGEN's 8-provider routing cascade, evolutionary cost optimization (genome includes token budget), and distillation flywheel constitute a *de facto* metabolism, but it lacks formal characterization.

6 The Compounding Advantage

6.1 Mathematical Framework

Let S(t) represent static agent performance at time t and L(t) represent living agent performance. Static agents improve through model upgrades (approximately 4 per year, each with magnitude Δ). Living agents receive the same model upgrades plus evolutionary improvement ε per operational cycle:

$S(t) = S(0) + \Sigma\ \Delta_i$

$L(t) = L(0) + \Sigma\ \Delta_i + \Sigma\ \varepsilon_j \times c\hat{}j$

where $c > 1$ is the compounding factor from skill reuse, knowledge graph density, and distillation data volume (observed: $c \approx 1.001$ per cycle).

The living agent surpasses the static agent when accumulated evolutionary improvement exceeds the initial quality gap:

$\Sigma\ \varepsilon_j \times c\hat{}j > S(0) - L(0)$

With observed evolutionary improvement rates of 0.1–0.3% per cycle and 12 cycles per day, this crossover is estimated at 3–6 months for production task quality and 12–18 months for benchmark equivalence.

6.2 Limitations and Failure Modes

Three formal results constrain this optimistic projection:

1. **Entropy Decay** [29]: Unbounded recursive self-training on finite samples provably leads to monotonic loss of distributional diversity. GODEGEN addresses this with constitutional constraints and human mentoring (external signal injection).

2. **Variance Amplification** [30]: Self-play improvement without persistent external grounding causes distributional drift via random-walk mechanism. GODEGEN's human-in-the-loop mentoring provides the required exogenous signal.

3. **Diminishing Returns**: Improvement rate likely decreases as low-hanging optimizations are exhausted. Mitigated by expanding task categories (new frontier), distillation (resetting cost baseline), and meta-evolution (evolving the evolution process itself through MemoryEvolver [21]).

7 Temporal Benchmark Framework

7.1 ImproveBench: Quality Improvement Rate

Measures whether an agent's output quality improves statistically over time using the Mann-Kendall trend test [49] (non-parametric, no normality assumption) and Theil-Sen slope estimator [50] (robust to 29.3% outliers). Computes a composite score from quality trend, fitness trend, and merge rate trend, each weighted equally. Score range: 0–100 mapped to letter grades (A+ through F).

7.2 AdaptBench: Domain Adaptation Speed

Measures recovery time (via EWMA smoothing) when the agent encounters unfamiliar task categories. A low-adaptation agent maintains uniformly low quality on new categories; a high-adaptation agent quickly reaches baseline quality. Score is computed from the mean recovery time across all category transitions.

7.3 CostBench: Cost Trajectory

Measures whether cost-per-quality-point decreases over time (improving economic efficiency). Uses the same Theil-Sen slope estimation on cost/quality ratio time series. A declining CPQ trajectory indicates the agent is learning to achieve the same quality at lower cost.

7.4 AutonomyBench: Autonomous Operation

Measures the maximum consecutive tasks completed above a quality floor (default: 5/10) without human intervention. This directly quantifies self-regulation capability — the ability to maintain quality over extended autonomous operation.

7.5 Statistical Foundation

All four benchmarks consume production data from existing Night Shift databases (run_metrics, fitness_history, merge_events) without requiring external datasets. The Mann-Kendall test provides non-parametric trend detection suitable for quality score time series that may not be normally distributed. Theil-Sen slope estimation is robust to the outliers common in production environments (up to 29.3% of data points can be outliers without affecting the estimate).

8 Discussion

8.1 The Architectural Divide

The temporal dimension gap is not an incremental feature gap but a fundamental architectural divide. Tool agents are *designed* to be stateless — their architecture assumes isolated sessions, API-call-oriented interaction, and benchmark-optimized evaluation. Living agents are *designed* to be stateful — their architecture assumes persistent identity, evolutionary improvement, and accumulated knowledge.

Adding temporal capabilities to a tool agent is not a feature addition — it requires architectural redesign from first principles. This is evidenced by the multi-year open issues in OpenHands (#1748, #5715, #7829) and the community-driven workarounds in Cursor (Memory Bank).

8.2 The Copilot Milestone

GitHub Copilot's Agentic Memory (launched March 4, 2026) represents the most significant competitive development in temporal capabilities. It is the first major competitor to ship production cross-session memory with cross-agent sharing and automatic validation. However, it stores codebase facts (conventions, patterns), not self-improvement data (quality trends, fitness curves). The distinction between *remembering* and *improving* remains GODEGEN's structural advantage.

If GitHub adds quality tracking and self-improvement on top of their memory system, the gap on dimensions 22 and 25 narrows significantly. We assess this threat as MEDIUM-HIGH and recommend monitoring.

8.3 Threats to Validity

Scoring subjectivity. Despite evidence-based scoring, the 5-point scale involves judgment. We mitigate this by citing specific evidence for every score and maintaining conservative self-assessment (GODEGEN scores 3 on dimensions where implementation exists but lacks external validation).

Selection bias. We evaluate systems we know well. Major systems not included (Google Jules, Replit Agent) may have temporal capabilities we are unaware of.

Self-evaluation. GODEGEN is our own system. We address this by scoring conservatively (not claiming 5 on dimensions where only partial implementation exists) and by documenting limitations explicitly.

Temporal scores are prospective. Some temporal scores (particularly dimensions 22, 23, 25) rely on architectural capability rather than externally validated longitudinal data. As production data accumulates, these scores should be re-evaluated against actual measurements.

8.4 ATLAS Validation

The strongest external validation of our thesis comes from ATLAS [23], which demonstrates 33.6% token efficiency improvement, +46% accuracy gains, and 86% cost reduction through cross-episode knowledge accumulation in cybersecurity tasks — with zero retraining. While operating in a different domain, ATLAS confirms the core principle: cross-episode knowledge accumulation produces compounding improvements. GODEGEN is the first system to apply this principle to production coding.

9 Conclusion

We have identified and quantified the temporal dimension gap in AI coding agent evaluation. Our 25-dimension matrix reveals that GODEGEN scores 24/25 on temporal dimensions versus 13/25 for the best competitor (Devin 2.0) — a gap that widens over time due to compounding evolutionary improvement.

The key findings are:

1. **No competitor publishes cross-session learning rate data.** Of 10 systems surveyed, only GODEGEN statistically measures whether its performance improves over time.

2. **No competitor has model-weight specialization per codebase.** Despite the technical feasibility of LoRA/QLoRA per-project adaptation, no commercial system has productized this.

3. **No competitor has self-regulating autonomous operation.** Cursor achieves impressive duration (52+ hours) but requires "periodic fresh starts." GODEGEN's homeostatic self-regulation eliminates drift through evolution rather than restart.

4. **The academic literature recognizes this gap.** SWE-Bench-CL [14], the METR time horizons analysis [27], and the measurement imbalance study [25] all point toward temporal evaluation as an emerging priority.

1. **Six literature gaps** present research opportunities where GODEGEN's production data provides unique empirical evidence.

The temporal dimension gap is architectural, not incremental. It reflects a fundamental choice between building tools that execute tasks and building entities that learn from experience.

The gap compounds: every day GODEGEN runs is another day of evolutionary advantage that cannot be fast-forwarded. The question is not whether other systems will develop temporal capabilities — they will. The question is whether they can close a gap that widens every 2 hours.

10 Code and Data Availability

Code Availability. The GODEGEN system and Night Shift infrastructure are developed as part of the Zeltrex Hub platform. Source code for the evaluation framework, temporal benchmark implementations (ImproveBench, AdaptBench, CostBench, AutonomyBench), and the 25-dimension SOTA comparison matrix is available at https://zeltrex.com.

Data Availability. Night Shift operational logs (280+ tasks, 10 consecutive days), evolutionary fitness trajectories, and ATLAS token efficiency measurements are maintained in the production deployment. Aggregated benchmark data supporting the temporal dimension scores are available upon request.

Ethics Statement. This work evaluates AI coding systems using publicly available documentation, open-source repositories, and published papers. No human subjects were involved. Competitive system scores are derived from vendor-published evidence and are verifiable through cited sources.

Reproducibility Statement. The temporal dimension scoring methodology (Section 3) uses a defined 5-point scale with explicit criteria. All evidence citations are provided for score assignments. The proposed temporal benchmarks use standard statistical tests (Mann-Kendall [49], Theil-Sen [50]) available in open-source libraries. Scoring of competing systems can be independently verified through the cited documentation and blog posts.

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