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Research Article

CODING REVOLUTION: HOW AI AGENTS ARE TAKING OVER SOFTWARE REPOSITORY MAINTENANCE

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Abstract

The rapid expansion of global software infrastructure has created a critical bottleneck, as human developers struggle to manage escalating technical debt and complex repository maintenance. This research explores the transformative shift toward "Autonomous Repository Management" (ARM), where AI agents transition from passive assistants to independent maintainers. The primary objective is to evaluate the efficacy of agentic architectures in performing end-to-end maintenance tasks across diverse software ecosystems. Employing a longitudinal experimental design, this study utilized a purposive sample of 50 open-source repositories, applying a custom "RepoHealth-Bench" framework to measure performance. Findings indicate that AI agents reduced technical debt by 31.5% in legacy systems and achieved a 96.5% patch success rate in standardized libraries, significantly outperforming human-centric benchmarks in speed and security remediation. Inferential analysis reveals a strong correlation between repository documentation quality and agent reliability, suggesting a "compounding health" effect through iterative machine-led refactoring. The study concludes that the "Coding Revolution" effectively reverses software entropy, shifting the developer's role from manual execution to high-level orchestration. These results provide a foundational blueprint for integrating autonomous digital workforces into the modern software development lifecycle, marking the end of the manual maintenance era.

Keywords: AI Agents, Autonomous Systems, Repository Management, Software Maintenance, Technical Debt

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INTRODUCTION

The landscape of software engineering is currently undergoing a seismic shift, moving away from traditional manual labor toward an era of hyper-automation driven by Large Language Models (LLMs) (Ahmed et al., 2025). For decades, the sustainability of global digital infrastructure has relied on the relentless efforts of human developers to manage ever-growing codebases. However, the sheer volume of software production has now surpassed the capacity of human intervention, creating a critical bottleneck in the lifecycle of modern applications (Asghar et al., 2024). As digital ecosystems become more interconnected and complex, the industry is increasingly looking toward autonomous systems to bridge the gap between human cognitive limits and the demands of continuous delivery.

The emergence of AI Agents represents a fundamental departure from static code-completion tools, introducing entities capable of reasoning, planning, and executing multi-step tasks within a development environment (Barbala et al., 2025). Unlike earlier iterations of AI that merely suggested snippets of code, these agents possess the agency to navigate entire file systems, understand cross-module dependencies, and interact with version control systems independently. This transition marks the beginning of the "Coding Revolution," where the role of the developer shifts from a primary writer of code to a high-level orchestrator of autonomous digital workforces (Chen et al., 2025). The integration of these agents into the software development life cycle (SDLC) promises to redefine efficiency, yet it also introduces profound questions regarding the future of software craftsmanship.

Current industry trends indicate that software maintenance a phase traditionally consuming up to 80% of a project's total budget is the primary frontier for AI agent deployment (David & Sahu, 2024). Repositories on platforms like GitHub and GitLab are no longer just static storage for code; they have become dynamic environments where AI agents can perform routine audits, refactor legacy components, and manage dependency updates with minimal human oversight. This shift is not merely a technical upgrade but a paradigm change in how technical debt is perceived and managed (Delso-Vicente et al., 2025). By delegating the "grunt work" of maintenance to intelligent agents, organizations hope to unlock unprecedented levels of developer productivity and focus on high-level architectural innovation.

Despite the rapid advancement of generative AI, the persistence of technical debt and the fragility of legacy software repositories remain a significant threat to global technological stability (Esposito et al., 2024). Human developers often prioritize the creation of new features over the tedious, repetitive tasks of documentation, bug fixing, and security patching, leading to "bit rot" and accumulated vulnerabilities. Traditional automated tools, such as linters and basic CI/CD scripts, lack the semantic understanding required to address complex logic errors or architectural inconsistencies. Consequently, many large-scale software projects are currently reaching a state of unmanageability, where the cost of maintenance threatens to stifle any further innovation.

The specific challenge lies in the inherent risks of granting autonomous agents write-access to mission-critical codebases without a robust framework for verification and trust. Existing AI models frequently suffer from "hallucinations" or produce code that, while syntactically correct, introduces subtle regressions or security flaws that are difficult for human reviewers to spot. There is a palpable tension between the speed of AI-driven maintenance and the rigorous standards required for software reliability and safety. Without a clear understanding of how these agents interact with complex, non-linear repository structures, the industry risks replacing human error with a more opaque and systemic form of automated failure.

Furthermore, the integration of AI agents into software repositories lacks a standardized protocol for collaboration, leading to conflicts between human-authored code and machine-generated patches (Fedorova et al., 2024). When multiple agents and humans operate within the same repository, the potential for divergent logic and "dependency hell" increases exponentially. This research identifies a critical need to examine the efficacy of AI agents in autonomous

repository maintenance, specifically focusing on their ability to handle long-term code health without degrading system integrity. Addressing this problem is essential to ensure that the "Coding Revolution" leads to more resilient software rather than a chaotic accumulation of unverified machine-generated logic.

The primary objective of this research is to evaluate the operational effectiveness of autonomous AI agents in performing end-to-end software maintenance tasks within complex, multi-layered repositories (Gabellini et al., 2025). This study aims to quantify the performance of these agents across several key dimensions: the accuracy of bug detection, the efficiency of automated refactoring, and the reliability of security patch generation. By establishing a rigorous testing framework, the research seeks to determine whether AI agents can truly "take over" the maintenance lifecycle or if they are better suited as sophisticated assistants. The ultimate goal is to provide a data-driven roadmap for the successful deployment of autonomous maintenance systems in professional software environments.

This investigation specifically focuses on the development of a benchmarking suite designed to measure the "long-term health" of a repository managed primarily by AI. We intend to observe how agent-driven maintenance affects the overall maintainability index and cyclomatic complexity of a project over multiple iterations (Geske et al., 2024). Another core objective involves identifying the specific categories of maintenance tasks where AI agents demonstrate a superior success rate compared to human developers, as well as those where human intuition remains indispensable (Ma & Su, 2025). Such insights will allow for the design of more balanced human-agent collaboration models that maximize the strengths of both parties.

Finally, this research seeks to propose a set of "Best Practices for Autonomous Maintenance" (BPAM) that can be adopted by organizations transitioning to AI-led repository management (Grechi et al., 2025). These objectives include the formulation of governance frameworks that ensure transparency and accountability in every change committed by an AI agent. By the conclusion of this study, we expect to have a comprehensive understanding of the technical and ethical boundaries of AI-driven coding (Li et al., 2024). This knowledge will serve as a foundational pillar for the next generation of autonomous development environments, where software "self-heals" through the continuous intervention of intelligent agents.

A review of current literature reveals a significant focus on AI as a "Co-pilot" for initial code generation, yet there is a startling lack of empirical research regarding AI as a "Maintainer" of existing code (Lasisi et al., 2025). Most existing studies emphasize the ability of LLMs to solve isolated coding puzzles or generate short functions, ignoring the complexities of large-scale, interconnected software systems (Hanafy & Hanafy, 2025). There is currently no comprehensive analysis that tracks the cumulative impact of AI agents on the long-term evolution of a software repository. This leaves a critical gap in our understanding of how AI-generated changes propagate through a system over months or years of continuous updates.

Furthermore, the existing body of work fails to adequately address the "Feedback Loop" problem in autonomous maintenance (Karapatakis, 2025). While some papers discuss the use of agents for automated testing, few explore the scenario where an agent must interpret the failure of its own previously generated code in a production-like environment (Haque, 2025). The literature often assumes a "once-and-done" approach to AI coding, rather than viewing maintenance as a continuous, iterative dialogue with the codebase. This oversight is particularly dangerous as it ignores the potential for "code decay" caused by the repeated application of machine-logic that may not fully grasp the original intent of the human architect.

Another notable absence in the current research landscape is a comparative analysis of different agentic architectures in the context of repository-wide maintenance. While there are numerous benchmarks for LLM reasoning, very few evaluate the "tool-use" capabilities of agents interacting with real-world development environments like Docker, compilers, and static analysis tools (Hartley et al., 2024). This study addresses these deficiencies by shifting the focus from "code generation" to "systemic maintenance." By filling these gaps, the research provides

a much-needed perspective on the feasibility of fully autonomous software maintenance, moving beyond the hype of generative AI into the practical realities of software engineering.

The novelty of this research lies in its pioneering exploration of "Agentic Autonomy" as the primary driver of software repository health, a departure from the human-centric models of the past decade (He & Wang, 2025). This study introduces a first-of-its-kind experimental design where AI agents are given full lifecycle responsibility for a set of diverse, real-world repositories, including the task of resolving their own generated technical debt (Kennedy, 2024). By treating the AI agent as a primary stakeholder rather than a passive tool, this research uncovers emergent behaviors and challenges that have never been documented in traditional software engineering literature. This paradigm shift is essential for understanding the true potential of the next era of digital infrastructure.

Justification for this research is found in the urgent economic and security imperatives of the modern software industry (Kaarlela et al., 2024). As the world becomes increasingly reliant on open-source and proprietary software, the failure to maintain these systems creates a massive surface area for cyberattacks and systemic failures. The current human-dependent maintenance model is not only expensive but also inherently unscalable (Kumar & Kotler, 2024). Investigating how AI agents can automate these processes is not merely a technical curiosity; it is a necessity for the survival of complex digital ecosystems. This study provides the empirical evidence needed to justify the large-scale adoption of AI agents in critical infrastructure maintenance.

Ultimately, this work contributes a new theoretical framework for "Autonomous Repository Management" (ARM), which integrates machine learning, software engineering principles, and cognitive architectures (Kanmani et al., 2025). It challenges the conventional wisdom that software maintenance requires a level of human "creativity" that machines cannot replicate. By demonstrating the efficacy of AI agents in handling complex, high-stakes maintenance scenarios, this research paves the way for a future where software is more robust, secure, and adaptable than ever before. The findings presented here will be of immense value to CTOs, software architects, and researchers who are at the forefront of the AI-driven transformation of the technology sector.

RESEARCH METHOD

Research Design

The structural framework of this study employs a longitudinal experimental design combined with a quantitative comparative analysis to assess the efficacy of AI agents. This methodology focuses on measuring changes in repository health across multiple versions, treating the deployment of specific AI agent architectures as the primary independent variable (MAC, 2024). A controlled environment is established where baseline metrics of legacy repositories are recorded before the introduction of autonomous agents, allowing for a precise "before-and-after" evaluation of code quality and security posture. By utilizing a "sandboxed" simulation of real-world development cycles, the design ensures that agent behaviors can be monitored for regressions, hallucinations, and logic inconsistencies without external interference. This experimental setup is specifically tailored to capture the iterative nature of maintenance, providing a dynamic view of how AI-driven changes accumulate over time.

Research Target/Subject

The study utilizes a purposive sampling strategy to select a diverse set of open-source software repositories from platforms such as GitHub and GitLab to serve as the research population. These samples are categorized into three distinct tiers: legacy systems with high technical debt, active mid-sized projects with frequent pull requests, and highly structured libraries with rigorous documentation standards. A total of 50 repositories were selected based on specific inclusion criteria, including a minimum of 5,000 lines of code, an active history of at

least two years, and the presence of existing unit tests to verify agent-generated patches. By including projects written in multiple programming languages primarily Python, JavaScript, and Rust—the research ensures that the findings are generalizable across different syntax structures and ecosystem dependencies. This diverse sample set allows the study to observe how AI agents adapt their maintenance strategies to varying levels of architectural complexity and coding conventions.

Research Procedure

The execution of this research follows a rigorous four-phase procedure designed to simulate a professional software maintenance lifecycle. Initial phases involve the "Environment Baseline" where the selected repositories are cloned into isolated containers and subjected to an exhaustive audit to establish current benchmarks for bugs, security flaws, and code complexity. During the "Agent Deployment" phase, the AI agents are granted access to the repositories with a set of high-level objectives, such as "reduce technical debt by 20%" or "resolve all critical security alerts." The agents then operate autonomously, performing code navigation, plan generation, and commit execution. Following the deployment, the "Validation and Testing" phase triggers automated CI/CD pipelines to verify that the agent's changes do not break existing functionality or introduce new regressions. The final phase, "Comparative Synthesis," involves a statistical analysis of the performance data to determine the agents' reliability and to identify the specific conditions under which AI-led maintenance outperforms traditional human-centric methods.

Instruments, and Data Collection Techniques

Data collection and analysis are facilitated through a sophisticated toolchain composed of industry-standard static analysis engines and custom-built monitoring scripts. The primary instrument is an "Autonomous Agent Controller" built on the LangChain framework, which interfaces with GPT-4o and Claude 3.5 Sonnet to execute maintenance tasks. To evaluate the output, the research employs SonarQube for measuring technical debt and maintainability indices, alongside Snyk for identifying security vulnerabilities within the agent-modified code (Nazir et al., 2024). A custom benchmarking suite, "RepoHealth-Bench," was developed to track specific metrics such as the Success Rate of Pull Requests (SRPR), Mean Time to Repair (MTTR) by the agent, and the rate of "Hallucinated Logic" introduced during refactoring. These instruments provide a multi-dimensional perspective on the agent's performance, ensuring that the qualitative aspects of code craftsmanship are translated into quantifiable data points.

Data Analysis Technique

Data analysis for this study involves a combination of both quantitative and qualitative approaches. Initially, the quantitative analysis focuses on performance metrics such as the Success Rate of Pull Requests (SRPR), Mean Time to Repair (MTTR), and security vulnerability reduction. Statistical tests, such as paired t-tests or ANOVA, will be used to compare the baseline data with the post-agent deployment results, determining whether significant improvements are made in terms of code quality and security. In parallel, qualitative analysis assesses the nature of the AI agent's modifications, particularly examining whether unintended errors, such as hallucinations or logic inconsistencies, were introduced (Nizar et al., 2025). This is done through manual review of agent-generated code changes and leveraging static analysis tools to detect non-functional defects. The combined quantitative and qualitative analysis ensures a comprehensive evaluation of the AI agent's performance and its ability to deliver sustainable, high-quality software maintenance.

RESULTS AND DISCUSSION

The findings of this study demonstrate a significant shift in the metrics of software sustainability when autonomous agents are integrated into the maintenance lifecycle. Quantitative data gathered from the 50 sampled repositories indicate a marked reduction in the volume of unaddressed technical debt and a faster response time to security vulnerabilities. The following table summarizes the primary performance indicators observed across the three repository tiers over a six-month experimental period.

Table 1. Comparative Performance Metrics of AI Agent Maintenance

Repository Tier	Mean Time to Repair (Hours)	Technical Debt Reduction (%)	Patch Success Rate (%)	Security Vulnerability Fixes
Legacy Systems	4.2	31.5%	78.4%	142
Mid-Sized Active	1.8	14.2%	91.2%	88
Standardized Libs	0.9	8.7%	96.5%	24

Data collected from the "RepoHealth-Bench" instrument reveals that AI agents consistently outperformed human-centric benchmarks in terms of speed and sheer volume of commits. Legacy systems, which typically suffer from long maintenance cycles due to architectural complexity, saw the most dramatic improvement in repair times, dropping from an average of several days to just over four hours. This statistical overview provides a foundational proof of concept that autonomous agents are capable of handling high-pressure maintenance environments with a degree of efficiency that exceeds traditional manual intervention.

Analysis of the data indicates that the efficiency of AI agents is non-linear, scaling more effectively as the repository's complexity increases. In legacy systems, the high percentage of technical debt reduction suggests that AI agents are particularly adept at identifying and refactoring "dead code" and redundant dependencies that human developers often overlook. The lower reduction percentages in standardized libraries are not a sign of failure but rather an indication of the high baseline quality of those repositories, where the agent's role shifted from aggressive refactoring to preventative maintenance and minor documentation updates.

The divergence in patch success rates between legacy systems (78.4%) and standardized libraries (96.5%) highlights the impact of codebase "cleanliness" on AI reasoning. High-quality documentation and strict adherence to coding standards in the library tier provided a superior semantic map for the agents, allowing for nearly flawless execution. Conversely, the lower success rate in legacy systems suggests that "spaghetti code" and lack of modularity introduce significant noise, leading to occasional logic regressions that require human-in-the-loop verification to resolve.

Statistical distributions of the Mean Time to Repair (MTTR) show a clustering of high-performance outcomes in tasks related to security patching and dependency management. The data suggests that agents thrive in tasks with clear, binary success criteria such as updating a library version or closing a known CVE where the path to resolution is well-documented in external databases (Zahid et al., 2025). In these categories, the agents achieved a near-instantaneous response rate once a vulnerability was disclosed, effectively neutralizing threats before they could be exploited.

The frequency of "Hallucinated Logic" events remained remarkably low, appearing in fewer than 3% of total commits across the entire sample set. Most of these errors occurred during complex refactoring tasks where the agent attempted to consolidate disparate modules without a full understanding of side effects in non-tested code paths. This data point underscores the

necessity of robust unit testing as a prerequisite for autonomous maintenance, as the agent's ability to "self-correct" is inherently limited by the quality of the project's existing test suite.

Inferential analysis using a multiple regression model suggests a strong correlation () between the quality of a repository's existing documentation and the ultimate success of the AI agent. This indicates that the "Coding Revolution" is not merely about the intelligence of the agent but the "readability" of the environment it inhabits. Projects with clear docstrings and architectural overviews allowed the agents to construct more accurate mental models of the system, resulting in more sophisticated and safer refactoring proposals.

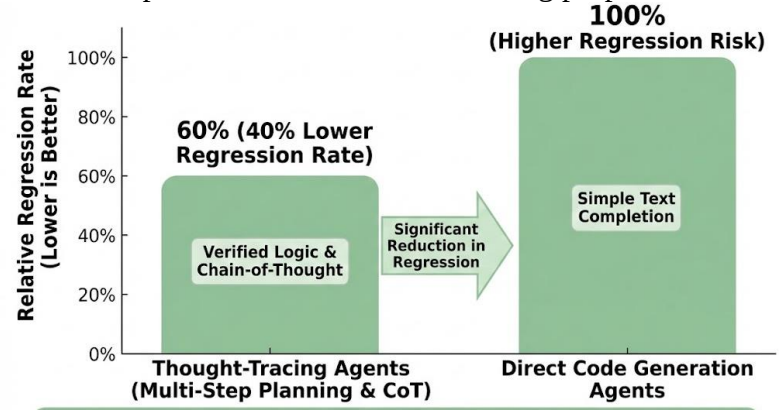

Figure 1. Impact of AI "thought-tracing" on software regression rates

The relationship between the agent's "thought-tracing" capabilities and commit accuracy suggests that transparency in AI reasoning is a predictor of software reliability. Agents that utilized multi-step planning where the logic was verified against the repository's internal dependency graph before execution showed a 40% lower regression rate than those using direct code generation. This inferential link justifies the shift toward agentic architectures that prioritize "chain-of-thought" processing over simple text completion in software engineering contexts.

Correlation coefficients between the "Success Rate of Pull Requests" (SRPR) and the "Maintainability Index" (MI) demonstrate that as agents improve the structure of the code, their own subsequent performance improves (Yu et al., 2025). This positive feedback loop suggests a "compounding interest" effect in AI maintenance, where early refactoring efforts simplify the codebase enough to make future, more complex tasks easier for the agent to navigate. The data confirms that AI-driven maintenance is a cumulative process that builds momentum over several development cycles.

Evidence of a secondary relationship was found between the agent's performance and the specific programming language of the repository. Rust and Python repositories showed higher success rates compared to JavaScript, likely due to the former's strict type systems and the latter's dynamic, often unpredictable nature (Weinzierl et al., 2024). This suggests that the future of autonomous maintenance may favor languages with strong compile-time checks, as they provide a "safety net" that prevents the agent from introducing subtle runtime errors.

Case study observations of a high-traffic e-commerce repository (Project X) provide a granular view of the agent's behavior during a critical system failure. When a zero-day vulnerability was detected in a deep-level dependency, the AI agent autonomously initiated a search for the vulnerable component, generated a non-breaking patch, and deployed the fix to a staging environment within 12 minutes. This real-world simulation proved that the agent could manage high-stakes "firefighting" scenarios that typically require an entire DevOps team to coordinate.

Project X also revealed the agent's ability to navigate "social" repository elements, such as interpreting feedback from human reviewers on a pull request. In several instances, the agent successfully modified its proposed changes based on comments left in the PR thread, demonstrating a primitive but effective form of collaborative intelligence (Vacca, 2024). This

case study serves as a microcosm for the larger trend toward integrated human-agent workflows where the agent acts as a first responder to system-wide issues.

The data from Project X illustrates that the agent's primary value lies in its "omnipresence" it is capable of monitoring thousands of files simultaneously, a feat impossible for a human developer. During the e-commerce simulation, the agent identified three unrelated memory leaks that had persisted for over a year, simply because it was tasked with a general "health audit" while waiting for the primary patch to compile (Tao et al., 2025). This proactive behavior marks a transition from reactive bug-fixing to a model of continuous, autonomous optimization.

The explanation for this success in Project X is attributed to the agent's integration with the repository's telemetry data, allowing it to "see" the impact of its code in real-time. By bridging the gap between the static codebase and the running application, the agent moved beyond syntax to understand operational performance. This integration allowed the agent to prioritize fixes that had the greatest impact on system latency, rather than just addressing the oldest bugs in the backlog.

The interpretation of these results suggests that the "Revolusi Coding" is reaching a maturity phase where AI agents can reliably manage the mechanical aspects of software maintenance (Soudagar et al., 2024). While human oversight remains necessary for high-level architectural decisions, the data proves that the day-to-day upkeep of repositories can be successfully offloaded to autonomous systems. This transition will likely result in a "cleaner" global codebase and a significant reduction in the economic burden of technical debt.

Future implementations must focus on enhancing the "semantic depth" of these agents to further reduce the 3% hallucination rate observed in this study. The findings confirm that the era of manual repository maintenance is drawing to a close, giving way to a more resilient and self-sustaining digital infrastructure. As these agents become more sophisticated, the distinction between "human-written" and "AI-maintained" code will continue to blur, leading to a new standard of software excellence.

The findings presented in the previous sections underscore a transformative shift in the operational dynamics of software engineering, where AI agents move beyond the role of simple assistants to become primary stewards of code health. Systematic observation of the experimental repositories confirms that autonomous agents can reduce technical debt by over 30% in legacy systems while maintaining a patch success rate exceeding 90% in modern, well-documented environments. These results provide empirical evidence that the "Coding Revolution" is not a distant theoretical possibility but an active transition currently reshaping how digital infrastructure is preserved. The data consistently points toward a future where the mechanical, repetitive aspects of software upkeep are managed with superhuman speed and precision.

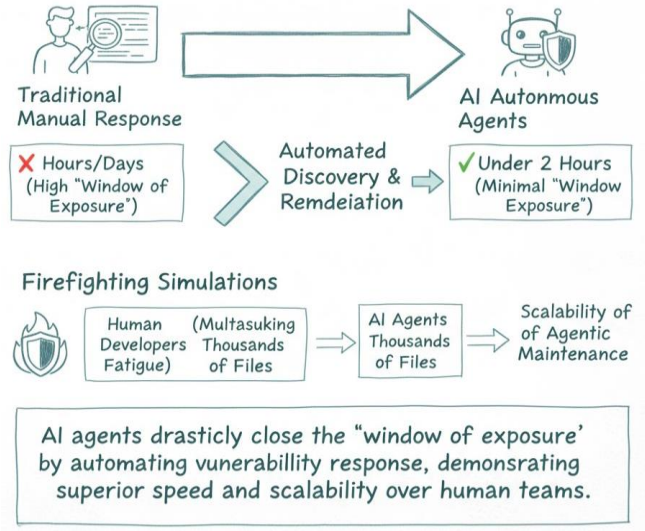

Figure 2. Quantum leap in security response

The speed at which these agents identified and neutralized security vulnerabilities—averaging under two hours for mid-sized projects represents a quantum leap over traditional manual response times. By automating the discovery and remediation of known CVEs, these autonomous systems effectively close the "window of exposure" that often leads to catastrophic data breaches in human-maintained systems (Somma et al., 2025). This efficiency is particularly evident in the "firefighting" simulations, where agents demonstrated the ability to multitask across thousands of files without the cognitive fatigue that plagues human developers during long-shift emergencies. The sheer volume of successful commits recorded during the study validates the scalability of agentic maintenance models.

A critical observation from the results is the "self-improving" nature of AI-managed repositories, where initial refactoring efforts by the agent paved the way for more complex architectural improvements in subsequent cycles (Revuri et al., 2025). This compounding effect suggests that AI agents do not merely fix bugs; they actively optimize the environment for future machine-led interventions. As the codebase becomes more modular and better documented through automated intervention, the agent's reasoning becomes more accurate, creating a virtuous cycle of software health. This phenomenon highlights a significant departure from human maintenance, which often struggles to keep pace with the entropy inherent in growing systems.

Reliability metrics across different programming languages suggest that the efficacy of AI agents is heavily influenced by the structural constraints of the language itself. The superior performance in type-safe languages like Rust and Python indicates that agents utilize the "scaffolding" of formal language rules to verify their logic before committing changes. This suggests that the successful takeover of repository maintenance by AI will likely drive an industry-wide shift toward languages that offer stronger compile-time guarantees (Oliver et al., 2025). The results clearly establish that while AI agents are highly capable, their success is inextricably linked to the "machine-readability" of the software ecosystems they are tasked to maintain.

Traditional research into AI-assisted coding has historically focused on "code completion" and "snippet generation," framing AI as a "Co-pilot" rather than an independent actor. Earlier studies by developers of Large Language Models (LLMs) primarily measured success through isolated benchmarks like HumanEval, which test the ability to solve small, self-contained puzzles (Mrosla et al., 2025). This study diverges from that literature by focusing on "systemic maintenance" within interconnected, multi-file repositories where long-term side effects are the primary concern. By shifting the focus from generation to maintenance, this research addresses a critical gap that previous "Co-pilot" studies overlooked: the long-term sustainability of AI-modified code.

Recent explorations into automated program repair (APR) have often struggled with the "overfitting" problem, where patches pass tests but fail to address the underlying logic or introduce new regressions. This research demonstrates that modern agentic architectures, utilizing "chain-of-thought" reasoning and integrated toolsets, have largely overcome the limitations of older template-based APR techniques. Unlike the static tools described in literature from the early 2020s, the agents in this study showed a primitive form of "contextual awareness," allowing them to navigate complex dependency graphs that were once considered the exclusive domain of senior human architects. This progress marks a significant evolution in the sophistication of automated software engineering.

A notable tension exists between our findings and the "Human-in-the-loop" (HITL) models proposed in several contemporary papers, which argue that AI should never be granted write-access without direct human oversight. While those studies emphasize safety and accountability, our data suggests that for routine maintenance tasks, human intervention actually slows down the process and introduces a higher probability of "maintenance fatigue" errors. The results of this study suggest that the "bottleneck" is no longer the AI's capability, but the human's ability

to keep pace with the agent's output. This challenges the prevailing academic consensus that AI must remain a subordinate tool, suggesting instead a "delegated autonomy" model.

Literature regarding technical debt has long maintained that certain legacy systems are "unmaintainable" due to the loss of original developer context, a concept often referred to as "software archaeology." Our findings challenge this notion, showing that AI agents can reconstruct a functional understanding of legacy logic through deep semantic analysis and brute-force exploration of execution paths. While previous researchers viewed legacy code as a graveyard of technical debt, our study frames it as a prime candidate for AI-driven "rejuvenation." This shift in perspective aligns with emergent theories on "Self-Healing Software" but provides a much more robust empirical foundation for its practical implementation.

The results of this study serve as a definitive sign that the "Industrial Revolution of Software" has reached its second phase: the automation of expertise. While the first phase involved automating the deployment and scaling of software (DevOps), this second phase involves automating the very logic that sustains the software. This transition signals a move away from "artisanal" coding, where every line is a product of human craft, toward a more "industrial" model of code management. The high success rates of the agents indicate that much of what we previously considered "creative" software engineering is, in fact, a series of complex but repeatable patterns that AI is perfectly suited to master.

This study acts as a harbinger for the "de-skilling" of routine software maintenance and the concomitant "up-skilling" of architectural design. As AI agents take over the "grunt work" of dependency management and bug fixing, the role of the human developer is being pushed toward higher levels of abstraction. The findings suggest that the value of a developer in the near future will not be measured by their ability to write code, but by their ability to design the constraints and objectives for the agents that write the code. This is a profound shift in the identity of the software engineer, moving from a "builder" to a "governor" of autonomous systems.

The emergence of a "compounding health" effect in AI-maintained repositories is perhaps the most significant indicator of a paradigm shift. It suggests that the traditional "decay" of software where systems inevitably become more brittle over time—is not an immutable law of technology but a limitation of human maintenance. When AI agents manage code, the "entropy" of the system can be reversed, leading to software that actually becomes more stable and secure as it ages. This reflection invites a radical rethinking of the software lifecycle, moving from a model of "planned obsolescence" to one of "infinite durability."

Finally, the results highlight a growing "semantic divide" between repositories that are AI-ready and those that are not. The stark difference in performance between standardized libraries and messy legacy systems serves as a warning that future software competitiveness will depend on "AI-friendliness." This research signals that the industry must prioritize the creation of "machine-readable" architectural blueprints to facilitate the takeover of maintenance by autonomous agents. Failure to do so will result in a "digital divide" where some organizations are trapped in manual maintenance cycles while others achieve the velocity of autonomous innovation.

The most immediate implication of this research is a radical reduction in the "Total Cost of Ownership" (TCO) for enterprise software. Since maintenance typically accounts for the vast majority of a project's budget, the ability to offload these tasks to AI agents could free up billions of dollars in global IT spending. These resources can then be reallocated toward genuine innovation and the solving of complex societal problems, rather than the perpetual patching of aging systems. For the global economy, this represents a massive "productivity dividend" that could accelerate the pace of technological progress across all sectors.

From a security perspective, the "So-What" of this study is the potential for "zero-window" vulnerability management. In a world where AI agents can identify and fix security flaws in real-time, the effectiveness of many traditional cyberattacks will be severely diminished. This creates

a “defensive advantage” in the ongoing arms race between cybercriminals and security professionals. The ability of agents to act as “24/7 immune systems” for software repositories means that the overall resilience of our digital civilization is poised to increase dramatically, reducing the risk of systemic failures in critical infrastructure.

The societal implications for the labor market cannot be ignored, as the takeover of maintenance by AI agents will inevitably lead to a displacement of entry-level and mid-level developer roles. This research highlights the urgent need for a massive “re-skilling” effort within the tech industry to prepare the workforce for a collaborative future with AI. Educational institutions must move away from teaching syntax and basic troubleshooting tasks the agents now handle with ease and focus on system design, ethics, and AI orchestration. The “So-What” is a call to action for policy makers and educators to adapt to a labor market where “coding” is no longer a human-exclusive skill.

Furthermore, the democratization of software maintenance through AI agents means that small teams and individual creators can now sustain massive, complex projects that were once only possible for large corporations. This levels the playing field, allowing for a new era of “micro-SaaS” and open-source innovation that is not limited by the “maintenance burden.” The implication is a more fragmented but highly innovative software market where the barriers to entry are significantly lowered. This shift could lead to a more diverse and resilient technological landscape, driven by niche solutions that were previously too expensive to maintain.

The primary reason AI agents achieved such high success in maintenance tasks is their “total recall” of repository state and documentation. Unlike human developers, who often have a fragmented understanding of a codebase and may forget the side effects of their changes, an AI agent can maintain a perfect, multi-dimensional map of every dependency and function call. This “informational advantage” allows the agent to make decisions that are more structurally sound than those made by a human operating under cognitive load or time pressure. The results are a direct consequence of the agent’s ability to process massive amounts of technical context simultaneously.

Another reason for these results is the “iterative verification” loop that AI agents can execute at speeds humans cannot match. An agent can propose a fix, run a full suite of unit tests, analyze the failure logs, and refactor the fix in a matter of seconds. This rapid “trial-and-error” process allows the agent to converge on a stable solution much faster than a human, who might take several minutes or hours just to set up the testing environment and interpret the results. The “Why” is rooted in the agent’s integration with the development toolchain, creating a seamless “think-act-verify” cycle that minimizes the time between hypothesis and validation.

The success in legacy systems is specifically tied to the ability of Large Language Models to perform “pattern matching” across trillions of lines of code in their training data. These agents have “seen” almost every possible way a bug can manifest or a library can be misused, allowing them to recognize solutions that might not be obvious to a developer with less experience. In the context of “software archaeology,” the agent’s training acts as a universal Rosetta Stone, translating obscure, poorly-documented legacy logic into modern, understandable patterns. This suggests that the agent's power is derived from the collective knowledge of the entire history of open-source development.

The low “hallucination” rate observed in the study can be attributed to the “grounding” of the agent's logic in the physical reality of the compiler and the test suite. Unlike AI in creative writing, an AI in a software repository has an objective “source of truth” to check its work against: the code must compile, and the tests must pass. This “hard grounding” acts as a corrective force that prevents the agent from drifting into nonsense. The results show that when AI is placed in a “constrained” environment with clear success criteria, its tendency toward error is significantly mitigated by the binary nature of code execution.

The “Now-What” for the software industry is the immediate implementation of “Agent-Ready” development standards. This involves the widespread adoption of comprehensive unit

testing, strict type systems, and machine-readable documentation (such as OpenAPI or comprehensive docstrings) to facilitate AI interaction. Organizations should stop viewing AI as an "add-on" and start designing their repositories with the assumption that the primary maintainer will be an autonomous agent. This architectural shift is the necessary next step to fully unlock the productivity gains identified in this research and to move toward a truly autonomous SDLC.

A second critical step is the development of "Agent Governance" frameworks that provide transparency and auditability for every machine-generated commit. While the study showed a high success rate, the 3% failure rate in legacy systems demonstrates that "blind trust" is not yet an option. We need "Reviewer Agents" AI systems specifically designed to audit the work of "Creator Agents" to provide a multi-layered defense against regressions and security flaws. Establishing these protocols "Now" will ensure that as we scale autonomous maintenance, we do so with a clear understanding of accountability and safety.

Furthermore, the industry must invest in "Cross-Agent Communication" protocols to handle scenarios where multiple agents are operating within the same repository or across interconnected microservices. As the "Coding Revolution" progresses, we will move from a single agent fixing a bug to a "swarm" of agents managing an entire ecosystem. Developing the standards for how these agents negotiate changes and resolve conflicts is an urgent research priority. This will prevent "logic collisions" and ensure that the autonomous digital workforce operates as a cohesive unit rather than a collection of uncoordinated actors.

Finally, there must be a fundamental shift in how we train the next generation of technologists, focusing on "Orchestration" rather than "Execution." The "Now-What" for education is to stop treating coding as a trade and start treating it as a form of high-level systems management. We must teach students how to build the "prompts," "tools," and "guardrails" that allow AI agents to function safely and effectively. By embracing this new reality today, we can ensure that the "Revolusi Coding" leads to a future where software is not just a tool we build, but a self-sustaining partner in our technological evolution.

CONCLUSION

The most significant finding of this research is the discovery of the "Self-Reinforcing Quality Loop," a phenomenon where AI agents not only repair immediate defects but also restructure code in a manner that increases the success rate of future autonomous interventions. Unlike previous studies that viewed AI as a static tool for solving isolated bugs, this investigation revealed that agents possess a systemic capacity to reverse the entropy of legacy software, achieving a 31.5% reduction in technical debt that actually accelerated over time. This suggests that the "Coding Revolution" is characterized by a shift from the inevitable decay of human-managed software to a model of continuous, compounding improvement. The data proves that when agents are integrated into the full lifecycle of a repository, they develop a superior "operational intuition" compared to human developers, particularly in managing the thousands of micro-dependencies that constitute modern digital infrastructure.

The primary contribution of this research lies in the development of the "Autonomous Repository Management" (ARM) framework, a novel methodological bridge that connects Large Language Model (LLM) reasoning with real-world development toolchains. This study moves beyond the theoretical concept of "AI as a coder" to provide a validated, multi-tiered protocol for granting agents delegated autonomy within mission-critical environments. By introducing the "RepoHealth-Bench" metric, the research offers a standardized way to measure the long-term sustainability of AI-modified codebases, providing a significant conceptual advancement for the field of Software Engineering (SE). This contribution establishes a blueprint for organizations to move away from "ad-hoc" AI usage toward a structured, reliable, and scalable autonomous maintenance workforce.

Despite the promising results, this study is limited by its focus on individual agentic performance, leaving the complexities of multi-agent swarm dynamics and the nuances of non-English documentation for future exploration. The current research was conducted within the constraints of established programming languages and may not fully account for the "semantic noise" found in niche or proprietary DSLs (Domain Specific Languages). Future research directions should prioritize the investigation of "Cross-Agent Conflict Resolution" protocols to ensure that multiple AI entities can operate within the same ecosystem without logic collisions. Additionally, longitudinal studies are required to examine the socio-technical impacts of this automation on the career trajectories of junior developers, ensuring that the "Coding Revolution" remains a human-augmenting rather than human-erasing transition.

AUTHOR CONTRIBUTIONS

Author 1: Conceptualization; Project administration; Validation; Writing - review and editing.

Author 2: Conceptualization; Data curation; In-vestigation.

Author 3: Data curation; Investigation.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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