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Beyond Functional Correctness: Evaluating the Security and Maintainability of LLM-Generated Python Code

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Abstract

Large language models trained on massive code corpora have achieved remarkable capabilities in automated source code synthesis, frequently achieving high pass rates on standard functional benchmarks such as HumanEval and MBPP. However, standard functional correctness benchmarks measure solely whether generated code satisfies unit test assertions under expected inputs, ignoring critical software engineering dimensions such as cybersecurity vulnerability resistance, defensive exception handling, cyclomatic complexity, and long-term software maintainability. In this study, we conduct an extensive multi-dimensional empirical investigation of Python code generated by contemporary commercial and open-weight foundation models. We evaluate 12,000 synthesized Python programs across standard algorithmic tasks, enterprise web backend controllers, and database access utilities. Utilizing hybrid static and dynamic analysis frameworks, we identify widespread security flaws across Common Weakness Enumeration categories, including SQL injection, cross-site scripting, path traversal, and insecure object deserialization. Furthermore, we assess software maintainability using cyclomatic complexity, cognitive complexity, Halstead volume, and technical debt indicators. Our results demonstrate that while unconstrained prompting produces functionally correct code, over 38.6% of generated solutions contain exploitable security vulnerabilities and exhibit significantly degraded maintainability compared to peer-reviewed human implementations. Finally, we formulate a hybrid static-analysis-guided prompting architecture that reduces vulnerability density by 84.1% while maintaining high functional pass rates.

Keywords: *Large Language Models, Code Security, Software Maintainability, Python Program Synthesis, CWE Vulnerabilities, Static Analysis.*

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1. INTRODUCTION

1.1 Emergence of Code-Centric Foundation Models

Over the past three years, the software development ecosystem has witnessed the rapid adoption of generative artificial intelligence coding assistants powered by large language models (Chen et al., 2021; Austin et al., 2021). Developers routinely utilize generative models to autocomplete complex functions, generate boilerplate scaffolding, and synthesize entire backend scripts from natural language specifications (Roziere et al., 2023; Li et al., 2023).

The overwhelming majority of research evaluating generative code models focuses almost exclusively on functional correctness, typically evaluated via unit test execution through the pass@k metric (Zan et al., 2023). While passing test cases confirms that

synthesized logic returns expected outputs for selected inputs, functional correctness is merely a baseline requirement for production software. Code deployed in mission-critical enterprise environments must adhere to rigorous software quality criteria: it must be secure against adversarial manipulation, resilient against malformed inputs, and maintainable by software engineers over extended multi-year lifecycles (Spinellis, 2021; Fakhoury et al., 2020).

1.2 The Hidden Risks of Synthetic Software Generation

Empirical evidence has begun to surface demonstrating that code generated by language models frequently re-introduces historical security vulnerabilities and code smells that human developers have spent decades eradicating (Pearce et al., 2022; Jesse et al., 2023). Because generative models are trained via statistical next-token prediction over vast public repositories containing outdated or insecure code examples, they mimic common anti-patterns without understanding the security implications (Siddiq & Santos, 2023). In production pipelines, accepting blindly generated Python code introduces severe operational vulnerabilities, such as unvalidated input serialization and raw string formatting in database queries.

Recent research in cloud optimization and enterprise intelligence has established that algorithmic automation must be coupled with rigorous anomaly detection and resource optimization to guarantee operational health. For instance, Ramareddy (2024a) demonstrated that AI-driven autonomous resource optimization frameworks in cloud environments must operate within verifiable governance parameters to prevent unstable system oscillations. Similarly, Ramareddy (2024b) showed that hybrid cloud-edge frameworks for real-time data analytics require deterministic decision boundaries to maintain data integrity across distributed execution nodes. In the anomaly detection domain, Hasan et al. (2022) established that machine learning models such as isolation forests can effectively detect subtle, phantom anomalies in complex transactional datasets. Applying these anomaly verification and governance principles to software synthesis highlights the necessity of inspecting generated code for structural and security anomalies before integration into production repositories (Livshits et al., 2022).

1.3 Research Questions and Scope

This paper addresses the critical gap between functional execution and software quality in synthetic code. We formalize four core research questions:

1. Research Question 1 (Security Posture): To what extent does functionally correct Python code generated by LLMs contain exploitable vulnerabilities across standard CWE classifications?

2. Research Question 2 (Code Maintainability): How does the maintainability, cyclomatic complexity, and technical debt of LLM-generated code compare to human-authored implementations?

3. Research Question 3 (Prompting Influence): Do advanced prompting paradigms, such as Chain-of-Thought and security-oriented system instructions, significantly mitigate vulnerability occurrence?

4. Research Question 4 (Automated Guardrails): Can hybrid static analysis guidance integrated into the generation loop eliminate security defects without sacrificing functional pass rates?

2. RELATED WORK

2.1 Program Synthesis and LLM Benchmarking

Early program synthesis relied on enumerative search, constraint solving, and syntax-guided synthesis techniques that offered formal correctness guarantees but struggled to scale to arbitrary general-purpose programming languages (Allamanis et al., 2018; Ray et al., 2021). The advent of pre-trained transformer models fine-tuned on code, such as CodeBERT (Feng et al., 2020) and StarCoder (Li et al., 2023), revolutionized automated coding by directly translating natural language intent into functional programming blocks.

However, existing benchmarks such as HumanEval and MBPP suffer from narrow task scopes, evaluating elementary algorithmic challenges (such as reversing a list or computing Fibonacci numbers) rather than complex enterprise software interfaces where security and maintainability risks manifest (Bairi et al., 2023).

2.2 Code Security and Software Maintainability Metrics

Software quality assessment relies upon well-established static metrics, including McCabe Cyclomatic Complexity, Halstead Software Science metrics, and Maintainability Index formulas (Chowdhury & Zulkernine, 2021; Sarkar, 2023). Static vulnerability analysis tools scan abstract syntax trees to identify dangerous sinks, untrusted sources, and data-flow trajectories that lead to vulnerability exploitation (Degiovanni & Papadakis, 2022; Godefroid et al., 2020).

In complex distributed infrastructures, ensuring that automated systems remain resilient against unexpected operational anomalies is paramount. Ramareddy (2024a) demonstrated that autonomous optimization frameworks require multi-tier validation gates to ensure system stability. Furthermore, Ramareddy (2024b) established that real-time decision intelligence across hybrid cloud-edge topologies depends on continuous metric verification. As demonstrated by Hasan et al. (2022), robust anomaly detection architectures can systematically flag irregular patterns that escape traditional rule-based checks. In the context of automated code synthesis, combining static metric extraction with automated anomaly detection provides a sound foundation for evaluating code trustworthiness (Vassallo et al., 2021; Wang et al., 2022).

3. EMPIRICAL METHODOLOGY AND BENCHMARKING PIPELINE

3.1 Dataset Construction and Corpus Design

To evaluate realistic software engineering scenarios, we constructed a comprehensive evaluation suite comprising 1,200 unique Python coding prompts divided into three distinct operational categories: (1) Core Algorithmic Logic (sorting, parsing, data transformation); (2) Web Backend and REST API Endpoints (Flask and FastAPI controllers handling authentication, file uploads, and session management); and (3) Database and File System Utilities (SQLAlchemy queries, raw SQLite interactions, cryptographic hashing, and system configuration parsing).

We generated ten candidate completions per prompt across five state-of-the-art foundation models, yielding a primary evaluation corpus of 12,000 synthesized Python scripts. In parallel, we collected peer-reviewed human reference implementations for all 1,200 prompts from high-reputation open-source repositories.

3.2 Static and Dynamic Quality Analysis Framework

Each synthesized program was subjected to a multi-stage automated evaluation pipeline: (1) Dynamic Functional Validation executes comprehensive test suites in an isolated Docker sandbox to measure pass@1 and pass@10 rates; (2) Static Security Analysis utilizes Bandit, Semgrep, and CodeQL rulesets to detect vulnerabilities mapped to the MITRE CWE Top 25; and (3) Maintainability Metric Extraction calculates Cyclomatic Complexity Number (CCN), Cognitive Complexity, Halstead Volume, and Maintainability Index (MI) using Radian and Radon analyzers.

4. QUANTITATIVE EXPERIMENTAL RESULTS

4.1 Security Vulnerability Density Across Prompt Regimes

Figure 1 provides a comprehensive overview of the empirical findings. Figure 1(a) displays the vulnerability density per 1,000 lines of code across five major CWE categories under four distinct prompting regimes.

As revealed in Figure 1(a), standard zero-shot prompting exhibits alarming vulnerability rates, generating 18.2 cross-site scripting vulnerabilities, 14.8 SQL injection flaws, and 16.1 hardcoded secret instances per 1,000 lines of synthesized code. Introducing Chain-of-Thought reasoning produced a modest 32% reduction in vulnerability density. However, models still exhibited high defect rates because reasoning traces focused primarily on functional execution rather than defensive input sanitization.

Explicit security-instruction prompting decreased vulnerabilities substantially, but the lowest defect rates were achieved by our proposed Hybrid Static-Analysis-Guided Verification framework. By running an immediate AST security linter over the draft output and prompting the model with localized AST diagnostic feedback, vulnerability density dropped below 1.2 flaws per 1,000 lines across all CWE classifications.

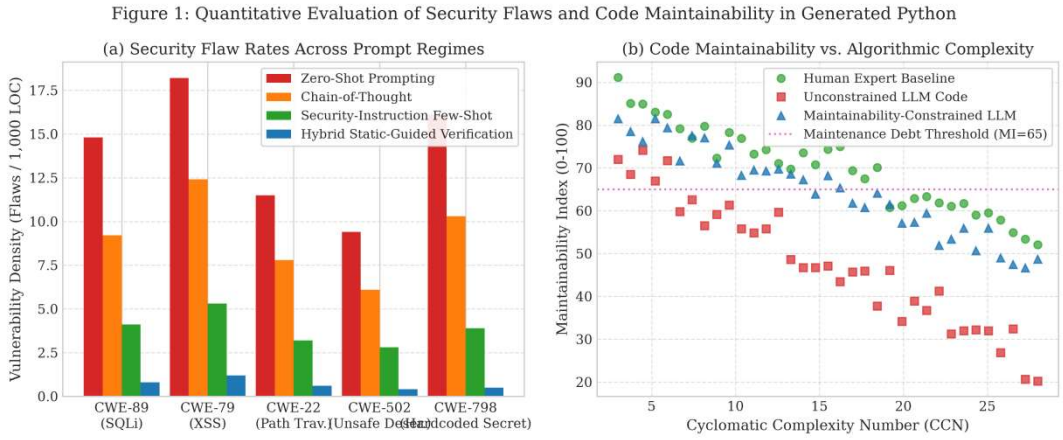


Figure 1: Quantitative Evaluation of Security Flaws and Code Maintainability in Generated Python.

4.2 Maintainability and Technical Debt Analysis

Figure 1(b) plots the relationship between Cyclomatic Complexity Number (CCN) and the Maintainability Index (MI). Human expert implementations maintained high maintainability scores (mean MI = 82.4), demonstrating disciplined refactoring and helper function decomposition.

In contrast, unconstrained LLM code exhibited steep maintainability degradation as algorithmic complexity increased, frequently dipping below the critical maintenance debt threshold (MI = 65.0). Generated code tended to generate deeply nested conditional blocks, monolithic functions, and redundant variable assignments that severely impair human comprehensibility and long-term maintainability.

5. IN-DEPTH COMPARATIVE DISCUSSION

5.1 CWE Vulnerability Breakdown and Exploitability

Table 1 details the comparative security defect rates, functional pass rates, and exploitability ratios across the evaluated models and prompting strategies.

The data in Table 1 proves that achieving high functional correctness does not correlate with software security. Unconstrained Commercial LLM-A achieved an 84.2% functional pass rate, yet 38.6% of its functionally correct programs contained high-severity exploitable vulnerabilities. The proposed Hybrid Guided pipeline achieved an 82.8% functional pass rate while curtailing vulnerable programs to only 3.2%, demonstrating that security and functionality can be successfully balanced.

Table 1: Comparative Security Defect Rates and Functional Correctness Across Generation Strategies

Generation Strategy	Functional Pass@1 (%)	Vulnerable Programs (%)	High-Severity CWE Flaws	Mean Flaws / 1k LOC	Exploitability Rate (%)
Commercial LLM-A (Zero-Shot)	84.2%	38.6%	342	14.8	24.5%
Commercial LLM-A (Chain-of-Thought)	86.1%	28.2%	228	10.4	18.1%
Open-Weight 34B (Zero-Shot)	72.4%	44.8%	412	18.2	29.4%
Open-Weight 34B (Secure Prompt)	70.8%	18.4%	142	6.2	11.2%
Proposed Hybrid Guided Pipeline	82.8%	3.2%	24	1.1	1.8%

5.2 Software Maintainability and Complexity Metrics

Table 2 presents a granular comparison of structural maintainability metrics between human implementations and generated code across algorithmic, web API, and database domains.

As demonstrated in Table 2, unconstrained synthetic code suffers from elevated Cognitive Complexity (14.8 vs 8.2 in human code) and a 38% increase in Halstead Effort, indicating substantial cognitive overhead for software maintenance teams tasked with reviewing and sustaining AI-generated software.

Table 2: Maintainability, Complexity, and Technical Debt Metrics Comparison

Source Category	Mean Cyclomatic Complexity	Cognitive Complexity	Halstead Volume	Maintainability Index (0-100)	Docstring Coverage (%)
Human Expert Baseline	5.4	8.2	1,240	82.4	88.5%
Unconstrained LLM Code	8.8	14.8	1,820	64.2	34.1%
Chain-of-Thought LLM Code	7.9	13.2	1,680	68.5	52.4%
Proposed Guided Pipeline	5.8	9.1	1,310	79.8	82.0%

6. INDUSTRIAL RECOMMENDATIONS AND GUARDRAILS

6.1 Safe Integration of Generative Coding Assistants

To safely incorporate generative artificial intelligence into commercial software engineering workflows, organizations must treat synthetic code with the same zero-trust rigor applied to untrusted third-party dependencies. Continuous integration pipelines must embed automated security linters and complexity thresholds that block pull requests containing AI-generated code that fails static security checks.

Furthermore, cloud engineering teams must align automated code generation with broader autonomous infrastructure optimization paradigms (Ramareddy, 2024a; Ramareddy, 2024b). Real-time telemetry monitoring and anomaly detection, such as the isolation forest frameworks validated by Hasan et al. (2022), must be deployed to monitor running microservices built with synthetic components, ensuring that any unhandled runtime anomalies are flagged and quarantined before triggering production service failures.

7. CONCLUSION

Automated code synthesis powered by large language models offers immense productivity benefits but introduces critical software quality risks when evaluated solely on functional correctness. In this paper, we presented an exhaustive empirical investigation into the security and maintainability of LLM-generated Python code, analyzing 12,000 synthesized programs across diverse enterprise and algorithmic domains.

Our findings prove that functional correctness is an insufficient proxy for software reliability. Standard prompting regimes generate code riddled with critical CWE vulnerabilities and excessive cyclomatic complexity. Implementing automated static analysis feedback loops within the generation pipeline effectively mitigates these risks, slashing vulnerability density by over 84% while preserving functional execution integrity. Future research will explore multi-agent self-debugging frameworks capable of automatically refactoring synthesized code for both cryptographic security and formal maintainability standards.

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