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Impact of Generative AI on Developer Productivity: An Empirical Analysis of Tools, Workflows, and Outcomes

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Abstract

The proliferation of Generative Artificial Intelligence (GenAI) tools—particularly Large Language Model (LLM)-based code assistants—has introduced a paradigm shift in how software developers conceptualize, write, test, and maintain code. This paper presents a comprehensive empirical investigation into the productivity implications of integrating GenAI tools into professional software development workflows. Employing a mixed-methods research design, we conducted a controlled experiment involving 128 software developers across four experience brackets and administered structured productivity surveys over a 16-week period. Participants were assigned to either a treatment group (utilizing GitHub Copilot and ChatGPT-4) or a control group (working without AI assistance). Productivity was measured across five dimensions: lines of code committed per day, task completion time, defect density, cognitive load (via NASA-TLX), and developer satisfaction. Results indicate that GenAI-assisted developers demonstrated a mean 34.7% reduction in task completion time and a 28.3% improvement in code output volume, though defect density showed a non-linear relationship with experience level. Critically, junior developers exhibited greater gains in raw throughput, while senior developers leveraged GenAI for architectural ideation and documentation quality. The paper also identifies key challenges, including over-reliance, contextual misunderstanding by models, and intellectual property concerns, and proposes a structured framework for responsible AI-augmented development. These findings have direct implications for software engineering education, enterprise tooling strategy, and the evolution of human-AI collaboration in technical domains.

Keywords—Generative AI, Developer Productivity, Large Language Models, GitHub Copilot, Code Generation, Software Engineering, Human-AI Collaboration, Cognitive Load, Empirical Software Engineering

I. Introduction

The act of writing software has never been purely mechanical. It is a cognitive endeavour that interleaves problem decomposition, pattern recognition, syntax recall, and systems thinking. Yet for decades, tools supporting this process—IDEs, linters, version control systems—have primarily served as scaffolding rather than active collaborators. The emergence of Generative AI, anchored by transformer-based Large Language Models (LLMs), represents a qualitative departure from this paradigm. Tools such as GitHub Copilot [1], OpenAI's ChatGPT [2], Amazon CodeWhisperer [3], and Google Gemini Code Assist [4] now generate syntactically correct, contextually aware code completions that previously required either human expertise or extensive template libraries.

This transformation has arrived at scale. GitHub reported in late 2023 that Copilot was responsible for generating over 46% of code in repositories where it was enabled [5]. Meanwhile, Stack Overflow's 2024 Developer Survey found that approximately 76% of professional developers either actively use or plan to adopt AI-powered coding tools [6]. These statistics signal not merely a trend but a structural change in how software is produced. Consequently, the academic community faces an urgent need to move beyond anecdotal reporting toward rigorous empirical assessment of how these tools affect developer output, work quality, cognitive burden, and professional satisfaction.

Prior investigations have begun to address this gap. Peng et al. [7] conducted a seminal randomized controlled trial demonstrating that GitHub Copilot users completed tasks approximately 55% faster in controlled settings. However, this study was limited to short, isolated coding tasks and excluded long-term productivity effects, collaboration dynamics, and experience-level differentiation. Subsequent studies [8], [9] have raised important qualifications, noting that AI-generated code often carries subtle logical errors, requires careful review, and may inhibit the deep skill acquisition that characterizes expert-level development.

This paper addresses the following research questions:

RQ1: To what extent do GenAI coding tools improve measurable developer productivity metrics over a sustained period?

RQ2: How does the productivity impact of GenAI assistance vary by developer experience level?

RQ3: What qualitative dimensions of developer work are most and least benefited by current GenAI tools?

RQ4: What risks and limitations emerge under sustained real-world deployment conditions?

To answer these questions, we designed a 16-week mixed-methods study combining controlled experimentation with longitudinal survey instruments. Our contributions include a validated multi-dimensional productivity measurement framework, experience-stratified productivity data, a cognitive load analysis conducted via NASA Task Load Index (NASA-TLX), and a discussion of systemic risks derived from thematic analysis of developer journals. The paper proceeds as follows: Section II reviews the relevant literature, Section III describes methodology, Section IV presents results, Section V provides critical discussion, and Sections VI through IX cover challenges, future scope, and conclusions.

II. Literature Review

A. Foundations of AI-Assisted Software Development

Early interest in automated programming dates to Dijkstra's pioneering work on structured programming and formal verification [10]. However, practical AI assistance in coding workflows became tangible only with the advent of statistical code completion models. Intelli Code [11] by Microsoft, released in 2018, represented one of the first commercially deployed ML-driven suggestions within an IDE, leveraging usage patterns from public GitHub repositories. Its effectiveness in reducing boilerplate and surfacing contextually appropriate API calls established a foundation upon which subsequent LLM-based systems would build.

The transformer architecture, introduced by Vaswani et al. [12] in 2017, fundamentally altered what was achievable in natural language and code generation. When applied to programming, transformers enabled models to capture long-range syntactic and semantic dependencies within code, making them far more capable than n-gram or LSTM-based predecessors at understanding intent expressed in both natural language comments and surrounding code context. OpenAI Codex [13], trained on approximately 159 GB of Python code scraped from public repositories, became the engine behind GitHub Copilot and demonstrated that at scale, LLMs could generate functionally correct code for a broad range of standard tasks.

B. Empirical Studies on Developer Productivity

The most cited empirical benchmark in this domain remains the Peng et al. [7] randomized controlled trial, in which 95 developers were tasked with implementing an HTTP server in JavaScript. The Copilot-assisted group completed the task in a mean of 1.2 hours versus 2.7 hours for the control group—a 55.8% reduction. While methodologically sound for its

scope, critics have noted that this experiment isolated a single task type and controlled away many sources of real-world friction, such as codebase complexity, team dependencies, and ambiguous requirements.

A broader investigation by Ziegler et al. [14] introduced the concept of "code acceptance rate" as a proxy for AI utility, finding that developers accepted approximately 26–30% of Copilot suggestions, with acceptance rates correlating positively with perceived productivity. Notably, their survey data revealed significant variance across programming languages and task types, with boilerplate-heavy languages such as Java exhibiting higher acceptance rates than dynamically typed languages like Python, where expressive brevity may reduce the marginal value of generated code.

Sobania et al. [8] examined the quality of ChatGPT-generated solutions for competitive programming problems, finding that while the model solved a significant fraction of LeetCode Easy problems, it struggled with medium and hard variants requiring algorithmic novelty. This suggests that current GenAI tools function most effectively as amplifiers of existing developer knowledge rather than replacements for fundamental problem-solving skill—a distinction with significant implications for workforce development.

More recently, Microsoft Research's study by Bird et al. [15] surveyed 2,631 GitHub users and found that 88% reported being more productive with Copilot, though 72% also reported spending additional time reviewing and debugging AI-generated code. This paradox—perceived productivity gains alongside increased verification overhead—suggests that raw output metrics alone provide an incomplete picture, a gap the present study directly addresses.

C. Cognitive Load and Developer Experience

Cognitive load theory, originating with Sweller [16], posits that human working memory has a finite capacity, and that effective learning and task performance require managing intrinsic, extraneous, and germane load. In software development, studies by Siegmund et al. [17] have employed fMRI imaging and electroencephalography to demonstrate that program comprehension activates areas associated with working memory and attention. GenAI tools may reduce extraneous load by offloading syntax recall and boilerplate generation, potentially freeing cognitive resources for higher-order architectural reasoning.

However, Vaithilingam et al. [18] conducted usability studies revealing that developers unfamiliar with a library domain found Copilot suggestions cognitively disruptive when suggestions were plausible but incorrect. Resolving incorrect suggestions consumed disproportionate attention, particularly among junior developers who lacked the contextual knowledge to quickly identify errors. This observation motivates our experience-stratified analysis and highlights that productivity gains from GenAI tools are not uniformly distributed.

D. Code Quality and Security Concerns

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Quality represents perhaps the most contentious dimension of AI-assisted development. Pearce et al. [19] analyzed 1,689 GitHub Copilot-generated code completions across security-relevant contexts and found that approximately 40% contained at least one Common Weakness Enumeration (CWE) vulnerability, including SQL injection susceptibility, buffer overflows, and improper error handling. While these vulnerabilities were largely well-known and detectable by static analysis, their prevalence suggests that organizations adopting GenAI coding tools without complementary security review processes face meaningful risk.

Contrariwise, Imai [20] found that Copilot-assisted developers produced code with fewer defects in unit-testable functions than control developers when tasks were well-specified, attributing this to the tool's tendency to generate self-contained, idiomatically correct implementations for common patterns. This tension between security vulnerability introduction and idiomatic correctness underscores the need for context-sensitive quality assessment, which our study incorporates through defect density tracking across complexity tiers.

III. Methodology

A. Research Design

This study employed a convergent parallel mixed-methods design [21], combining a 16-week randomized controlled experiment with longitudinal survey instruments and developer journal analysis. The dual-method approach was selected

to capture both objective, quantifiable productivity shifts and the qualitative experiential dimensions that numerical metrics cannot adequately represent. All participants provided informed consent in accordance with the ethics protocol approved by the Institutional Review Board (IRB Ref: IIT-AHD-2024-CS-041).

B. Participant Recruitment and Stratification

We recruited 128 professional software developers from three channels: industry partnerships (n=74), freelance platform outreach (n=32), and academic research collaborator networks (n=22). Participants were stratified into four experience brackets based on years of professional coding experience: Junior (0–2 years, n=32), Mid-Level (3–5 years, n=36), Senior (6–10 years, n=34), and Principal/Architect (10+ years, n=26). Within each stratum, participants were randomly assigned to a Treatment Group (GenAI tools enabled, n=64) or a Control Group (standard tooling, no AI assistance, n=64) using a blocked randomization scheme to ensure experience-level balance across conditions.

The treatment group was provided with standardized access to GitHub Copilot (Enterprise license) integrated within VS Code, and explicitly instructed in the use of GPT-4 via the OpenAI API for documentation generation, debugging assistance, and code explanation. Control group participants used VS Code with all AI-based extension features disabled, but retained access to conventional tooling including debuggers, linters, and Stack Overflow. Both groups worked on a standardized task backlog drawn from a curated repository of realistic microservice development challenges.

C. Productivity Metrics Framework

Productivity in software development resists reduction to a single metric. To address this, we operationalized productivity across five dimensions derived from established frameworks in empirical software engineering [22]:

1. Code Volume: Daily Lines of Code (LOC) committed to version control (normalized for blank lines and comments).

2. Task Completion Time (TCT): Wall-clock time from task assignment to accepted pull request, averaged across the week.

3. Defect Density (DD): Number of defects per 1,000 lines of code identified within 72 hours of merge, via automated test suite and peer review.

4. Cognitive Load: Assessed biweekly using the NASA Task Load Index (NASA-TLX), a validated six-dimension instrument covering mental demand, physical demand, temporal demand, performance, effort, and frustration [23].

5. Developer Satisfaction: Measured on a 7-point Likert scale across five facets—autonomy, competence, interest, perceived output quality, and tool satisfaction—adapted from the SPACE framework [24].

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All quantitative data were collected automatically via instrumented CI/CD pipelines and anonymized before analysis. Qualitative data were gathered through biweekly semi-structured journals in which participants described workflow patterns, frustrations, and notable interactions with tools.

D. Task Design and Validity Controls

The task backlog consisted of 48 individual developer stories spanning four complexity tiers—Trivial, Standard, Complex, and Architectural—classified using a modified McCabe Cyclomatic Complexity rubric and expert panel review. Tasks included REST API endpoint implementation, database schema migration scripts, unit test suite development, bug investigation and resolution, and module-level documentation. To control for domain familiarity effects, all tasks were embedded within a purpose-built fictitious e-commerce application domain introduced to all participants via a standardized onboarding session at the study's outset.

To mitigate the Hawthorne effect, participants were informed only that the study examined developer tooling satisfaction; the specific focus on productivity differential was disclosed in the debrief. Weekly check-ins were conducted to maintain engagement and resolve environmental setup issues, but researchers remained blind to individual performance data until the study conclusion.

E. Statistical Analysis

Between-group differences in quantitative metrics were assessed using independent-samples t-tests for normally distributed variables (verified via Shapiro-Wilk) and Mann-Whitney U tests for non-normal distributions. Effect sizes were reported using Cohen's d. Experience-level interaction effects were analyzed via two-way ANOVA with Bonferroni post-hoc correction. Qualitative journal data were subjected to thematic analysis following Braun and Clarke's framework [25], with two independent coders achieving an inter-rater reliability of Cohen's $\kappa = 0.81$.

IV. Results

A. Overview of Quantitative Findings

Across the 16-week study period, the treatment group demonstrated statistically significant improvements in four of the five productivity dimensions. Table I presents the aggregate between-group comparison. All figures represent group means with standard deviation in parentheses. Statistical significance was assessed at $\alpha = 0.05$.

TABLE I. Aggregate Productivity Metrics: Treatment vs. Control Group (N=128, 16 Weeks)

Metric	Treatment (GenAI)	Control (No AI)	% Change	p-value
LOC/Day	187.4 (41.2)	143.6 (38.9)	+30.5%	<0.001
Task Compl. Time (hrs)	4.82 (1.14)	7.38 (1.67)	−34.7%	<0.001
Defect Density (/KLOC)	14.3 (5.8)	11.7 (4.9)	+22.2%*	0.012
NASA-TLX Score (0–100)	41.2 (9.3)	54.8 (11.4)	−24.8%	<0.001
Developer Satisfaction (1–7)	5.61 (0.87)	4.23 (1.02)	+32.6%	<0.001

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** Defect density increase in the treatment group is discussed in Section V. Asterisk denotes direction counterintuitive to initial hypothesis.*

B. Experience-Stratified Analysis

The aggregate figures presented in Table I mask meaningful variation across experience tiers. Figure 1 (represented in Table II) shows that the productivity gains from GenAI tools are not uniformly distributed: junior developers show the greatest improvement in code volume and task completion time, while principal/architect-level developers demonstrate negligible improvement in throughput but exhibit the most pronounced reduction in cognitive load and highest satisfaction gains.

TABLE II. Task Completion Time Reduction (%) by Experience Level

Experience Level	LOC/Day Gain (%)	TCT Reduction (%)	Defect Density Change (%)	NASA-TLX Reduction (%)
Junior (0–2 yrs)	+41.3%	−47.2%	+38.1%*	−18.4%
Mid-Level (3–5 yrs)	+33.8%	−39.6%	+19.4%*	−24.7%
Senior (6–10 yrs)	+22.1%	−25.3%	+8.2%	−28.9%
Principal (10+ yrs)	+9.4%	−13.8%	−3.1%	−31.2%

** Defect density increase among junior developers correlates with reduced code review time and over-reliance on generated outputs without adequate testing.*

The interaction between GenAI tool usage and experience level was statistically significant ($F(3, 120) = 14.73$, $p < 0.001$, partial $\eta^2 = 0.27$), confirming that experience moderates the productivity effect. Junior developers benefited most in throughput dimensions, consistent with the hypothesis that GenAI tools partially compensate for gaps in pattern knowledge and API familiarity. However, their defect density increased markedly (+38.1%), revealing a quality-throughput trade-off that raises significant pedagogical concerns explored in Section V.

C. Cognitive Load Findings

NASA-TLX composite scores declined significantly in the treatment group ($M=41.2$, $SD=9.3$) compared to the control group ($M=54.8$, $SD=11.4$), a difference of 13.6 points (Cohen's $d = 1.29$, large effect). Sub-scale analysis revealed that the largest reductions were observed in Mental Demand (−18.3%), Effort (−21.6%), and Frustration (−24.1%). Physical Demand and Temporal Demand showed negligible differences, consistent with the cognitive rather than physical nature of the work. Notably, senior and principal developers showed the highest frustration reductions, attributing this in qualitative journals to the elimination of context-switching to documentation lookup.

D. Qualitative Themes

Thematic analysis of developer journals yielded five primary themes: (1) Accelerated Onboarding—junior developers reported faster adaptation to unfamiliar codebases through AI-assisted code explanation; (2) Reduced Boilerplate Fatigue—mid-level developers described reduced frustration with repetitive scaffolding tasks; (3) Architectural Ideation Support—senior and principal developers used ChatGPT-4 as a sounding board for design pattern selection; (4) Verification Overhead—all experience levels reported spending additional time reviewing AI output before committing; and (5) Skill Atrophy Concern—junior developers expressed uncertainty about whether AI assistance was helping or impeding their long-term skill development.

V. Discussion

A. Interpreting the Productivity Gains

The 34.7% mean reduction in task completion time observed in our study aligns directionally with prior work by Peng et al. [7], though our figure is more conservative. This discrepancy is likely methodological: our tasks were more complex, spanned longer durations, and were embedded in a shared codebase with inter-module dependencies—conditions closer to real-world software development than isolated algorithmic exercises. Moreover, Peng et al.'s study was conducted over a single session, whereas our 16-week longitudinal design captured productivity adaptation curves, including an initial learning period (Weeks 1–3) during which treatment group performance was lower due to tool familiarization overhead.

The LOC/day improvement of 30.5% warrants careful interpretation. Lines of code is an acknowledged imperfect metric [26]; it conflates verbose implementations with productive output and can be gamed. However, in our study, LOC was normalized and cross-validated against task completion records and pull request metrics. When triangulated with TCT

and satisfaction data, the convergent picture supports a genuine improvement in developer throughput, not merely a stylistic change in verbosity. The fact that LOC gains were concentrated among junior developers (41.3%) while senior developer gains were modest (9.4%) suggests that GenAI tools primarily provide value at the execution layer—translating known intent into code—rather than at the design layer where senior developers invest most of their cognitive effort.

B. The Defect Density Paradox

The counterintuitive increase in defect density within the treatment group (22.2% more defects per KLOC) is the most provocative finding of this study and demands nuanced interpretation. Three mechanisms appear to be operating simultaneously. First, junior developers exhibited a trust calibration deficit: they accepted AI suggestions with insufficient scrutiny, particularly in edge cases and error handling paths. This aligns with Pearce et al.'s [19] security analysis, which found that AI-generated code disproportionately fails in security-sensitive contexts that require domain-specific judgment rather than pattern matching. Second, the treatment group's increased code velocity meant more code was written in less time, leaving proportionally less time for review. Third, AI-generated code, while often syntactically correct, can introduce subtle semantic errors that require deep domain knowledge to identify—precisely the knowledge that junior developers lack.

Importantly, senior and principal developers in the treatment group showed either no change or a modest decrease in defect density, suggesting that experience mediates the risk. This finding has direct practical implications: organizations deploying GenAI coding tools should implement tiered review policies in which AI-generated code from less experienced developers receives additional scrutiny, and junior developers should be provided with explicit training on the failure modes of LLM-generated code.

C. Comparison with Existing Literature

Our findings both confirm and complicate the prevailing narrative in the literature. The productivity gains we observe are consistent with Bird et al. [15] and Ziegler et al. [14], both of which reported strong perceived productivity benefits. However, our objective defect density data introduces a qualification absent from survey-based studies: the risk that AI assistance creates a productivity illusion by front-loading code generation while deferring quality debt to later review and debugging cycles. This observation resonates with Begel and Simon's [27] earlier work on developer productivity, which cautioned against conflating output speed with sustainable, high-quality software production.

Furthermore, our cognitive load results extend the work of Vaithilingam et al. [18], who found that Copilot could increase cognitive load when suggestions were inappropriate. In contrast, our sustained-use study found net cognitive load reduction, suggesting that as developers calibrate their mental model of when to trust AI suggestions, the disruption effect diminishes. This learning-curve dynamic was visible in our week-by-week NASA-TLX data, where treatment group scores were higher than the control group in Week 2 before declining below them from Week 5 onward.

D. Architectural and Documentation Implications

A finding that has received insufficient attention in prior literature is the value senior developers derive from GenAI tools not for code generation but for documentation, architectural ideation, and code explanation. In our journals, 83% of senior and principal-level treatment group participants described using ChatGPT-4 for activities unrelated to direct code generation: writing technical specifications, explaining complex legacy code to teammates, exploring design pattern tradeoffs, and drafting automated test strategies. This suggests that the productivity value of GenAI is architecturally broader than the code completion framing that dominates discourse, and that future research should measure documentation quality and architectural decision quality as first-class productivity dimensions.

VI. Challenges and Limitations

A. Study Limitations

Several limitations constrain the generalizability of our findings. First, despite our efforts to approximate real-world conditions, the task backlog was purpose-built for the study and may not fully capture the complexity and ambiguity of

production software engineering. Tasks were time-boxed and well-specified, whereas real-world development often involves open-ended discovery and extended system evolution.

Second, our participant pool, while diverse, skewed toward developers comfortable with the English language and Western development conventions. The effectiveness of GenAI tools trained predominantly on English-language code and documentation may differ for developers working primarily in other natural languages, a dimension not examined in this study.

Third, self-reported Likert satisfaction data is susceptible to social desirability bias. Participants assigned to the treatment group may have inflated their satisfaction ratings due to the novelty effect associated with new technology adoption—an effect that typically attenuates over six to twelve months of sustained use.

B. Technical and Ethical Challenges

Beyond methodological concerns, our study surfaced several challenges that developers and organizations face in practice. Intellectual property ambiguity remains unresolved: when AI-generated code closely resembles licensed open-source code from the model's training corpus, the copyright status of the output is legally contested in most jurisdictions. Four developers in our treatment group independently flagged code suggestions that appeared to reproduce verbatim passages from well-known open-source libraries, raising concerns that the present study's authors lack the legal authority to fully adjudicate.

Model hallucination—the generation of plausible but factually incorrect code or documentation—was reported as a challenge by 67% of treatment group participants. In some cases, hallucinated API calls required significant debugging time, partially offsetting productivity gains. This challenge was particularly acute for developers working with recent framework versions whose documentation may not have been adequately represented in the model's training data.

Privacy and data security concerns were raised by participants from enterprise backgrounds, who noted that submitting code snippets to cloud-hosted AI APIs potentially exposes proprietary intellectual property. This concern aligns with reported enterprise policies at organizations including Samsung, Apple, and Goldman Sachs that have restricted or banned cloud-based AI coding tool usage on production codebases [28].

VII. Future Scope

This investigation opens several productive avenues for future research. The most pressing gap is longitudinal skill development assessment: our 16-week study was insufficient to determine whether junior developers who rely heavily on GenAI tools develop slower, faster, or differentially compared to non-assisted counterparts over a career span of two to five years. Longitudinal cohort studies tracking developer skill acquisition alongside AI tool usage intensity would substantially advance this question.

Second, the emergence of agentic AI systems—where LLMs autonomously plan, execute, and test multi-step coding workflows [29]—represents a qualitative shift beyond the single-turn code completion paradigm studied here. Tools such as Devin [30], SWE-agent, and OpenAI's Operator suggest that future developer productivity research must grapple with scenarios where AI completes entire tasks rather than individual code insertions. The implications for developer skill, accountability, and quality assurance in such settings are largely uncharted.

Third, team-level and organizational productivity effects remain underexplored. Prior studies, including ours, focus on individual developer metrics. However, software is predominantly a team endeavour, and GenAI tools may affect collaboration dynamics, code review culture, knowledge sharing, and architectural coherence in ways that individual productivity measures cannot capture. Multi-team field studies within real organizations would provide valuable ecological validity.

Fourth, multi-modal and domain-specific models present an interesting opportunity. General-purpose code LLMs trained on broad public repositories may perform sub-optimally in specialized domains such as embedded systems, safety-critical software (aerospace, medical devices), or domain-specific languages. Research into fine-tuned or retrieval-augmented models tailored to these domains, combined with productivity studies analogous to the present work, could inform highly consequential industry decisions.

Finally, ethical AI usage frameworks for development contexts remain nascent. Research intersecting software engineering, law, and ethics could produce actionable guidelines for IP risk management, bias auditing of AI-generated code, and transparent disclosure of AI assistance in software products—areas where academic engagement is urgently needed to precede regulatory action.

VIII. Conclusion

This paper has presented a rigorous empirical investigation into the productivity implications of Generative AI tools in professional software development. Through a 16-week randomized controlled study involving 128 developers across four experience tiers, we demonstrated that GenAI assistance yields significant and measurable productivity improvements across task completion time, code volume, cognitive load, and developer satisfaction. The mean 34.7% reduction in task completion time and 24.8% reduction in cognitive load represent substantively meaningful benefits for individual developers and, by extension, for the organizations that employ them.

However, these aggregate gains are accompanied by important qualifications that complicate any straightforward endorsement of GenAI tools as productivity panaceas. The counterintuitive increase in defect density—particularly among junior developers—reveals that speed and quality are in tension when AI assistance is deployed without adequate verification culture and skill development support. The experience-stratified analysis further reveals that the nature of GenAI's value shifts dramatically with expertise: where junior developers gain throughput, senior developers gain cognitive relief and creative support. Productivity measurement frameworks that fail to account for this differentiation will produce systematically misleading conclusions.

We conclude with three recommendations for practitioners and policymakers. First, organizations should implement experience-tiered GenAI adoption strategies that pair tool deployment with structured code review requirements for junior developers. Second, engineering education programs should explicitly teach AI failure mode recognition and critical evaluation of generated code as core competencies, rather than treating AI proficiency as synonymous with AI trust. Third, the research community should prioritize longitudinal and team-level studies that move beyond the isolated productivity snapshots that currently dominate the literature.

Generative AI represents neither the end of programming as a human skill nor a simple productivity multiplier to be uncritically adopted. It is a powerful cognitive augmentation tool whose value is contingent on the experience, judgment, and verification discipline of the developer wielding it. Understanding and shaping that contingency is the central challenge—and opportunity—of this technological moment in software engineering.

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