

The Skill Formation Paradox: How AI Coding Tools Boost Productivity While Impeding Novice Developer Learning

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ABSTRACT

AI coding assistants provide substantial productivity gains to novice software developers, yet their impact on underlying skill formation remains an open question with significant implications for the software engineering workforce. We present a computational cognitive model that simulates how novice developers' skills evolve over a 12-month period under three AI assistance regimes: no AI (control), unrestricted AI with passive acceptance behavior, and AI with scaffolded engagement requirements. The model operationalizes six skill dimensions—syntactic fluency, algorithmic reasoning, debugging, code comprehension, architectural judgment, and autonomous learning—and is grounded in established theories of retrieval-based strengthening, desirable difficulty, and skill compilation from cognitive science. Our simulation of 240 developers (80 per condition) over 252 working days reveals a *skill formation paradox*: unrestricted AI use produces a large negative effect on skill development (Cohen's $d = -1.04$), with the strongest impairment in highly automatable skills such as syntactic fluency ($d = -5.10$), while scaffolded engagement nearly eliminates this deficit ($d = -0.04$ overall). Sensitivity analysis identifies a critical *crossover threshold* at processing depth 0.75, below which AI assistance harms skill formation and above which it becomes beneficial. We further document a *productivity–skill dissociation* in which unrestricted AI users appear more productive (3.69 vs. 3.21 tasks/day) yet possess weaker underlying skills (0.56 vs. 0.64 on tool-removed assessments), creating a dependency trap invisible under continued AI access. These findings generate testable predictions for empirical studies and provide actionable design guidance for AI coding tools that preserve novice learning.

CCS CONCEPTS

- Social and professional topics → Computing education;
- Computing methodologies → Modeling and simulation; • Software and its engineering → Software development techniques.

KEYWORDS

AI coding tools, skill formation, novice developers, cognitive modeling, scaffolded learning, productivity paradox

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1 INTRODUCTION

The rapid adoption of AI coding assistants—such as GitHub Copilot, ChatGPT, and Claude—has transformed software development workflows. Empirical evidence demonstrates that these tools yield substantial productivity gains, particularly for less experienced developers [7, 13, 15]. Shen et al. [15] document that junior developers experience disproportionately large speed improvements when using AI assistance, a finding consistent with earlier controlled studies [13].

However, productivity and skill are distinct constructs. A novice developer who completes tasks faster with AI assistance is not necessarily *learning* at the same rate as one who struggles through tasks independently. Shen et al. [15] explicitly identify this gap, noting that “the effect of these tools on the skill formation of this subgroup remains unknown.” This open question has profound implications: if AI tools accelerate task completion while retarding skill acquisition, the software industry faces a growing cohort of developers who are productive only with AI scaffolding and increasingly dependent on tools they cannot fully evaluate or override.

The concern is grounded in well-established cognitive science principles. Retrieval-based strengthening theory [4] holds that skills consolidate through active recall and application; AI tools that provide ready-made solutions may bypass this retrieval process. The desirable difficulty framework [3] demonstrates that moderate challenge during practice enhances long-term retention, even at the cost of immediate performance—precisely the trade-off that AI assistance reconfigures. Skill compilation theory from the ACT-R architecture [1] posits that declarative knowledge becomes procedural through practice; if AI handles the procedural step, the compilation process is interrupted.

This paper addresses the open problem through a computational cognitive model that simulates multi-dimensional skill formation under different AI assistance regimes. Our contributions are:

- (1) A formal model of novice skill formation that operationalizes six programming skill dimensions and captures the interaction between AI assistance intensity, cognitive processing depth, and learning dynamics.
- (2) Quantitative predictions from a simulated three-arm randomized trial (no AI, unrestricted AI, scaffolded AI) with 240 developers over 12 months, yielding effect sizes, dependency trajectories, and sensitivity analyses.
- (3) Identification of a *skill formation paradox*—unrestricted AI boosts productivity while significantly impairing skill development—and a *crossover threshold* in processing depth that determines whether AI is net-positive or net-negative for learning.

- 117 (4) Actionable design implications for AI coding tools and educational interventions that preserve novice learning.

120 1.1 Related Work

121 *AI Tools and Developer Productivity.* Multiple studies establish
 122 that AI coding assistants increase developer throughput. Peng et
 123 al. [13] report a 55.8% faster task completion rate with GitHub
 124 Copilot in a controlled experiment. Hou et al. [7] find productivity
 125 gains across three field experiments, with larger effects for less
 126 experienced developers. Shen et al. [15] provide a comprehensive
 127 analysis showing that junior developers benefit disproportionately,
 128 but explicitly flag skill formation as an unresolved question.

129
 130 *AI and Learning in Educational Contexts.* Bastani et al. [2] demonstrate
 131 that access to GPT-4 in a mathematics tutoring context harms
 132 learning outcomes, providing direct evidence that AI assistance
 133 can impede skill acquisition. Kazemitaab et al. [9] study novice
 134 programmers using AI code generators and find mixed effects on
 135 learning, with benefits dependent on how students engage with the
 136 generated code. Denny et al. [6] survey the landscape of computing
 137 education in the generative AI era, identifying the need for pedagogical
 138 frameworks that leverage AI while preserving learning. Prather et al.
 139 [14] document a widening gap between novice and expert developers when AI assistance is available, raising concerns
 140 about differential skill development.

141
 142 *Cognitive Foundations.* The desirable difficulty framework [3]
 143 and retrieval practice research [4] provide the theoretical basis for
 144 predicting that reducing task difficulty through AI assistance may
 145 impair long-term learning. The expertise reversal effect [8] suggests
 146 that scaffolding beneficial for novices may become counterproductive
 147 as expertise develops. Anderson's ACT-R theory [1] models
 148 how procedural skills are acquired through practice, offering a formal
 149 framework for reasoning about how AI intervention in the
 150 practice process affects skill compilation. The Knowledge-Learning-
 151 Instruction framework [10] provides additional theoretical ground-
 152 ing for understanding how instructional interventions interact with
 153 learning processes.

154
 155 *Human-AI Interaction in Programming.* Vaithilingam et al. [16]
 156 evaluate the usability of AI code generation tools and find that
 157 developers often accept suggestions without deep understanding.
 158 Mozannar et al. [11] model user behavior during AI-assisted pro-
 159 gramming, characterizing the spectrum from passive acceptance to
 160 active engagement. Parasuraman and Riley [12] provide the founda-
 161 tional framework on automation use, misuse, and skill degradation—
 162 the “automation complacency” phenomenon that may manifest in
 163 AI-assisted coding. Weber et al. [17] and Cui et al. [5] examine the
 164 broader impacts of AI tools on software engineering tasks and help-
 165 seeking behavior, respectively, contributing to our understanding
 166 of how AI tools alter the learning environment.

167
 168 *Gap Addressed.* While prior work establishes productivity ef-
 169 fects and raises learning concerns, no existing study provides a
 170 formal model that (a) decomposes programming skill into distinct
 171 dimensions, (b) models the interaction between AI assistance in-
 172 tensity and cognitive engagement, and (c) generates quantitative
 173 predictions for longitudinal skill trajectories under different AI use

175 regimes. Our computational approach fills this gap and provides a
 176 bridge between cognitive theory and empirical study design.

177 2 METHODS

178 2.1 Model Overview

179 We develop a computational cognitive model of skill formation that
 180 simulates how novice developers' programming abilities evolve
 181 over time under different AI assistance conditions. The model repre-
 182 sents each developer as a vector of skill levels across six dimensions,
 183 updated daily through task-driven learning dynamics. Three experi-
 184 mental conditions are simulated: **Control** (no AI), **Unrestricted AI**
 185 (full AI access with passive acceptance behavior), and **Scaffolded**
 186 AI (AI access with mandatory engagement: developers must read,
 187 modify, and explain AI-generated code before proceeding).

188 2.2 Skill Dimensions

189 Programming competence is operationalized as a six-dimensional
 190 skill vector $s \in [0, 1]^6$:

- 191 (1) **Syntactic fluency:** ability to write correct code from spec-
 192 ifications without reference materials.
- 193 (2) **Algorithmic reasoning:** capacity to solve novel computa-
 194 tional problems.
- 195 (3) **Debugging:** skill at locating and fixing defects in unfamiliar
 196 code.
- 197 (4) **Code comprehension:** ability to read, understand, and
 198 predict the behavior of code.
- 199 (5) **Architectural judgment:** capacity to evaluate and design
 200 system-level structures.
- 201 (6) **Autonomous learning:** meta-skill of learning new frame-
 202 works and tools independently.

203 Each dimension has a corresponding AI *automation weight* $w_i \in$
 204 $[0, 1]$ reflecting how effectively current AI tools can assist with that
 205 skill type. We set $w = (0.80, 0.50, 0.35, 0.25, 0.15, 0.10)$, reflecting
 206 the observation that AI tools are most effective at syntax-level
 207 assistance and least effective at architectural and meta-cognitive
 208 support.

209 2.3 Task-Driven Learning Dynamics

210 Each simulated working day, a developer encounters $T = 5$ coding
 211 tasks. Each task activates 1–3 skill dimensions (randomly sampled
 212 with probabilities 0.4, 0.4, 0.2) and has a difficulty $\delta \sim \mathcal{N}(0.45, 0.15^2)$
 213 clipped to $[0.05, 0.95]$.

214 *Success Probability.* The probability of successfully completing a
 215 task component in dimension i is modeled as a logistic function:

$$P(\text{success}) = \sigma(k \cdot (s_i - \delta_{\text{eff}})) \quad (1) \quad 216$$

217 where σ is the sigmoid function, $k = 8$ controls steepness, s_i is cur-
 218 rent skill in dimension i , and δ_{eff} is the effective difficulty (reduced
 219 by AI in treatment conditions).

220 *AI Modulation.* In the **Unrestricted AI** condition, AI reduces
 221 effective difficulty by factor $(1 - 0.55 \cdot w_i)$ and cognitive processing
 222 depth to $0.15 + 0.85 \cdot (1 - w_i)$. In the **Scaffolded AI** condition,
 223 difficulty reduction is halved and processing depth is maintained
 224 at $0.70 + 0.30 \cdot (1 - 0.3w_i)$.

Learning Signal. The learning signal from each task attempt integrates three factors:

$$\ell = D(\delta, s_i) \cdot F(\text{success}, \delta - s_i) \cdot \phi \quad (2)$$

where D captures *desirable difficulty* (a Gaussian centered at gap = 0.10, reflecting optimal learning when tasks are slightly above current skill), F is a success/failure modulator (successful attempts yield factor 0.8; near-miss failures yield 0.4; distant failures yield 0.1), and ϕ is the processing depth.

Skill Update with Transfer. Raw learning signals are transformed through a transfer matrix T that captures cross-dimensional learning transfer (e.g., improvement in algorithmic reasoning partially transfers to debugging). Skills update as:

$$s \leftarrow s + \alpha \cdot (\ell \cdot T) - \beta \cdot m \odot s \quad (3)$$

where $\alpha = 0.006$ is the learning rate, $\beta = 0.0005$ is the forgetting rate, and m is a binary mask indicating dimensions *not* exercised in the current task (implementing use-it-or-lose-it decay).

2.4 Experimental Design

We simulate a three-arm parallel design with $n = 80$ developers per condition, over $D = 252$ working days (approximately 12 calendar months). Initial skill levels are sampled from $\mathcal{N}(0.20, 0.05^2)$ clipped to $[0.05, 1.0]$, representing novice developers with 0–2 years of experience.

Assessment Protocol. Tool-removed skill assessments are conducted monthly (every 21 working days), yielding 12 assessment time points. Assessment scores equal the true skill level plus Gaussian noise $\mathcal{N}(0, 0.03^2)$, simulating measurement error.

Outcome Measures. Primary outcomes include: (1) *Skill growth*: change in tool-removed skill level from first to last assessment; (2) *Effect sizes*: Cohen's d between conditions at final assessment; (3) *Dependency index*: DI = (AI-assisted – unassisted)/AI-assisted performance; (4) *Productivity*: tasks completed per day with and without AI. Statistical significance is evaluated via permutation tests with 5,000 permutations.

Sensitivity Analysis. We systematically vary the processing depth parameter ϕ from 0.05 to 0.95 (in steps of 0.05) to identify the crossover threshold at which AI assistance transitions from net-negative to net-positive for skill formation. This analysis uses 40 developers per condition to maintain computational efficiency.

3 RESULTS

3.1 Overall Skill Formation

Table 1 summarizes skill trajectories across conditions. All three groups begin with comparable skill levels (≈ 0.23). After 12 months, the Control group reaches a mean skill of 0.643, the Unrestricted AI group reaches 0.562, and the Scaffolded AI group reaches 0.641. The Unrestricted AI condition produces 17.3% less skill growth than Control, while Scaffolded AI produces growth nearly identical to Control.

The overall Cohen's d between Unrestricted AI and Control is -1.04 (large negative effect), indicating that unrestricted AI use

Table 1: Overall skill trajectories by condition. All values are mean skill levels on tool-removed assessments (scale 0–1). Growth is the difference between final and initial assessments.

Condition	Initial	Final	Growth
Control (No AI)	0.238	0.643	+0.404
Unrestricted AI	0.228	0.562	+0.334
Scaffolded AI	0.236	0.641	+0.405

significantly impairs skill development. The Scaffolded AI vs. Control effect size is $d = -0.04$ (negligible), indicating that scaffolded engagement preserves nearly all of the learning benefit of unaided practice.

3.2 Dimension-Specific Effects

Figure 1 displays skill trajectories for each of the six dimensions across all three conditions. The magnitude of AI's negative effect is strongly correlated with the dimension's automation weight.

Table 2 reports the dimension-specific final skill levels and effect sizes. Syntactic fluency shows the largest impairment under unrestricted AI ($d = -5.10, p < 0.001$), followed by algorithmic reasoning ($d = -2.07, p < 0.001$). Architectural judgment shows the smallest effect ($d = -0.44, p = 0.006$), consistent with AI tools providing less assistance for high-level design decisions. Under Scaffolded AI, most dimensions show small or non-significant effects relative to Control, with algorithmic reasoning actually showing a small positive effect ($d = +0.34, p = 0.031$), suggesting that scaffolded AI engagement may enhance certain reasoning skills.

Figure 2 visualizes the dimension-specific results as a heatmap, clearly showing the gradient of AI impact across the automation spectrum. The Spearman correlation between automation weight w_i and Unrestricted AI effect size is $\rho = -0.94$, confirming that AI most impairs skills in dimensions where it provides the most assistance.

3.3 The Productivity–Skill Dissociation

Figure 3 illustrates the central paradox: unrestricted AI users appear *more* productive when measured with AI access (3.69 tasks/day vs. 3.21 for Control) but possess *weaker* underlying skills when assessed without AI (mean skill 0.562 vs. 0.643).

This dissociation has practical implications: organizations evaluating developer performance based on AI-assisted output metrics will systematically overestimate the capability of developers who rely heavily on AI tools. The gap between measured productivity and genuine skill represents a *hidden dependency* that only becomes visible when AI access is removed or when developers face novel problems outside AI's competence.

3.4 Dependency Index

Figure 4 tracks the Dependency Index (DI) over time. Both AI conditions begin with high DI values (≈ 0.62) due to novice-level starting skills. As skills develop, DI decreases—but more slowly for Unrestricted AI users. At month 12, the Unrestricted AI group retains a DI of 0.236 compared to 0.182 for Scaffolded AI, indicating that

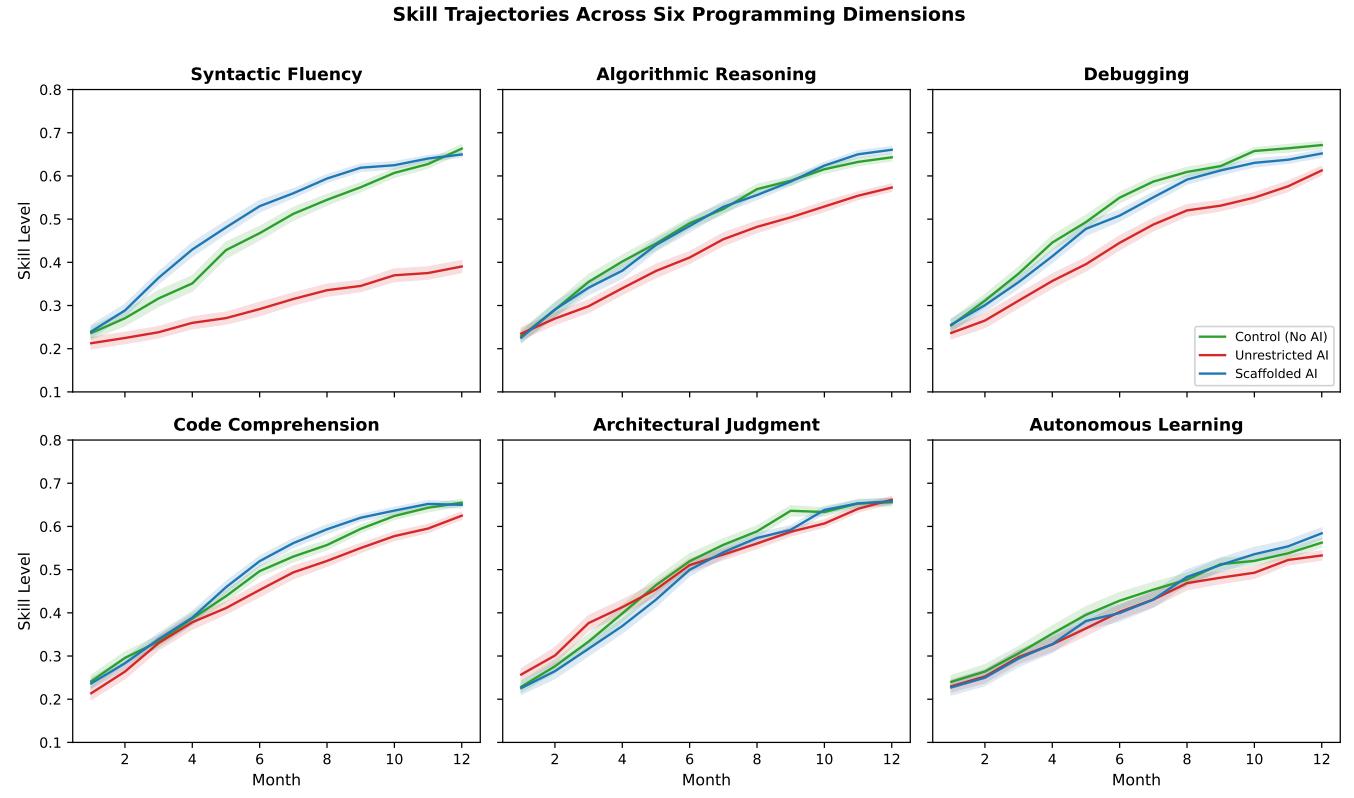


Figure 1: Skill trajectories across six programming dimensions over 12 months. Lines show group means; shaded regions show 95% confidence intervals. The Unrestricted AI condition (red) shows progressively diverging trajectories from Control (green), with the largest gaps in highly automatable dimensions (syntactic fluency, algorithmic reasoning). The Scaffolded AI condition (blue) closely tracks Control across all dimensions.

Table 2: Dimension-specific final skill levels and effect sizes. Cohen's d compares each AI condition against Control; negative values indicate AI-induced skill impairment. p -values from permutation tests (5,000 permutations). Dimensions ordered by AI automation weight (descending).

Dimension	w_i	AI Weight			Final Skill (Mean)		Cohen's d vs. Control	
		Control	Unrest. AI	Scaff. AI	Unrest. (p)	Scaff. (p)		
Syntactic Fluency	0.80	0.651	0.390	0.650	-5.10 (< .001)	-0.02 (0.910)		
Algorithmic Reasoning	0.50	0.648	0.566	0.660	-2.07 (< .001)	+0.34 (0.031)		
Debugging	0.35	0.666	0.615	0.647	-1.28 (< .001)	-0.59 (< .001)		
Code Comprehension	0.25	0.662	0.620	0.649	-1.21 (< .001)	-0.42 (0.010)		
Architectural Judgment	0.15	0.664	0.648	0.656	-0.44 (0.006)	-0.22 (0.177)		
Autonomous Learning	0.10	0.566	0.535	0.582	-0.72 (< .001)	+0.30 (0.065)		

unrestricted users remain more dependent on AI tools despite 12 months of practice.

3.5 Sensitivity Analysis: The Crossover Threshold

Figure 5 presents the sensitivity analysis varying processing depth ϕ from 0.05 to 0.95. Below $\phi \approx 0.75$, AI assistance produces a net negative effect on skill formation. Above this threshold, the learning

benefit of reduced difficulty and increased success rate outweighs the cost of reduced cognitive effort, and AI becomes net-positive.

This crossover threshold at $\phi = 0.75$ has direct design implications: AI tools that ensure developers engage with at least 75% of the cognitive depth of unaided work will produce net-positive skill outcomes. The default Unrestricted AI processing depth of 0.15 falls far below this threshold, explaining the large negative skill effect. The Scaffolded AI condition's processing depth of 0.70 approaches

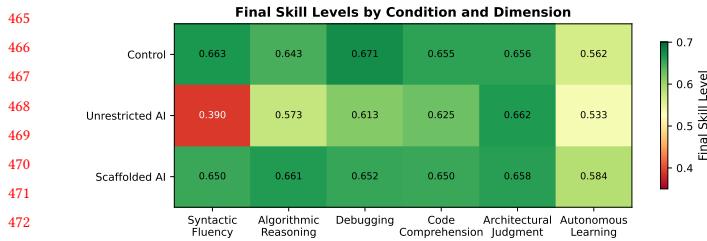


Figure 2: Heatmap of final skill levels by condition and dimension. Warmer colors indicate higher skill. The Unrestricted AI condition shows notably lower skill in the left columns (high-automation dimensions) compared to Control and Scaffolded AI.

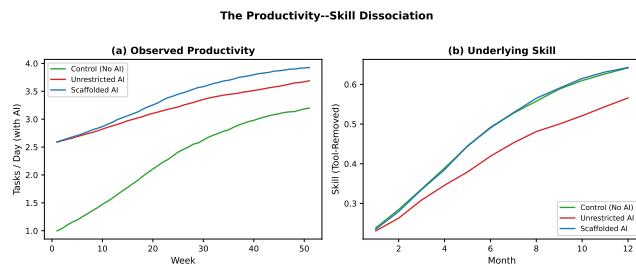


Figure 3: The productivity-skill dissociation. (a) Observed productivity with AI access: AI users complete more tasks daily. (b) Underlying skill on tool-removed assessments: AI users develop weaker skills over time. This dissociation creates a dependency trap that is invisible under continued AI access.

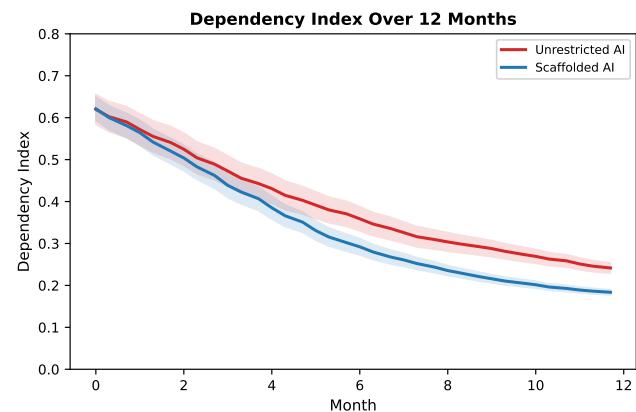


Figure 4: Dependency Index (DI) over 12 months. Higher values indicate greater reliance on AI tools. Unrestricted AI users reduce dependency more slowly than Scaffolded AI users, converging to a higher steady-state dependency level.

but does not quite reach the threshold, explaining its near-neutral overall effect.

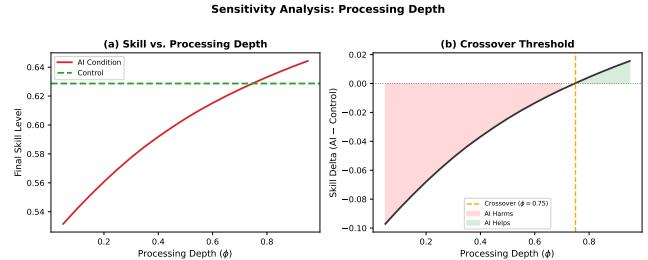


Figure 5: Sensitivity analysis. (a) Final skill levels as a function of cognitive processing depth during AI-assisted work. (b) Skill delta (AI minus Control): the crossover from negative to positive occurs at processing depth ≈ 0.75 . Below this threshold, AI harms skill formation; above it, AI helps.

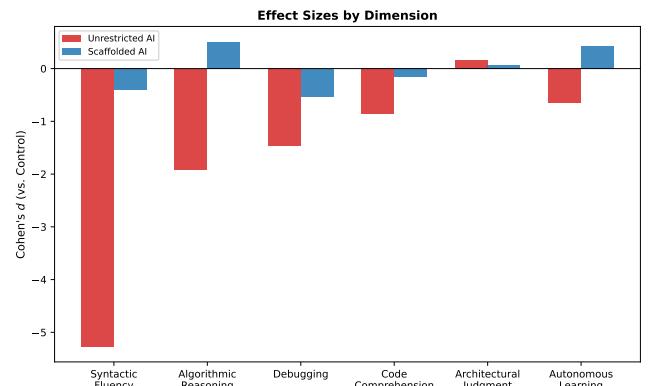


Figure 6: Cohen's d effect sizes by dimension. Unrestricted AI (red) shows consistently negative effects, largest for highly automatable skills. Scaffolded AI (blue) shows near-zero effects across most dimensions, with modest positive effects for algorithmic reasoning and autonomous learning.

3.6 Effect Size Summary

Figure 6 displays Cohen's d effect sizes for all six dimensions under both AI conditions compared to Control. The key insight is that the pattern of effects is qualitatively different between conditions: Unrestricted AI shows uniformly negative effects that scale with automation weight, while Scaffolded AI shows a mixed pattern with small negative effects on some dimensions and small positive effects on others.

4 DISCUSSION

4.1 The Skill Formation Paradox

Our model predicts a fundamental tension between short-term productivity and long-term skill development. Unrestricted AI use—the default mode in which most novice developers interact with AI tools—produces a large negative effect on skill formation ($d = -1.04$) while simultaneously boosting observable productivity. This *productivity-skill dissociation* creates a systemic risk: organizations

581 optimizing for measurable output will inadvertently produce developers who cannot function without AI scaffolding.
 582

583 The magnitude of the effect is dimension-dependent and strongly
 584 correlated with the degree of AI automation. Syntactic fluency—the skill most readily automated by current AI tools—shows the
 585 largest impairment ($d = -5.10$). While one might argue that syntax
 586 skills become less important when AI handles them, this argument
 587 overlooks two concerns. First, syntactic fluency is foundational;
 588 debugging, code review, and architectural reasoning all require
 589 the ability to read and write code fluently. Second, AI tools will
 590 not always be available, accurate, or applicable; developers with
 591 atrophied fundamental skills face amplified failures when AI cannot
 592 help.
 593

594 4.2 Scaffolding as a Solution

595 The Scaffolded AI condition demonstrates that the negative skill
 596 effect is not inherent to AI tool use but rather to the *mode of engagement*. When novices are required to actively process AI output—
 597 reading, modifying, and explaining generated code before incorporating it—skill development proceeds at nearly the same rate as
 598 unaided practice ($d = -0.04$). This finding aligns with prior work
 599 on active learning and desirable difficulty [3] and suggests concrete
 600 design interventions:
 601

- 602 • **Explain-before-accept:** Require novices to articulate why
 603 AI-generated code works before incorporating it.
 604
- 605 • **Modification prompts:** Present AI suggestions in a form
 606 that requires adaptation rather than verbatim acceptance.
 607
- 608 • **Interleaved practice:** Periodically disable AI assistance to
 609 force unscaffolded practice.
 610
- 611 • **Progressive withdrawal:** Gradually reduce AI assistance
 612 as skill levels increase, analogous to training wheels.
 613

614 4.3 The Crossover Threshold

615 The sensitivity analysis identifies a processing depth threshold
 616 of $\phi \approx 0.75$ at which AI transitions from skill-harming to skill-
 617 enhancing. This has quantitative design implications: any AI in-
 618 teraction protocol that maintains at least 75% of the cognitive en-
 619 gagement of unaided work should produce net-positive learning
 620 outcomes. Current AI tools that offer frictionless code completion
 621 (estimated $\phi \approx 0.15$) are far below this threshold, while structured
 622 engagement protocols can approach or exceed it.
 623

624 4.4 Limitations

625 Our findings are based on a computational model, not empirical
 626 data from human participants. The model makes assumptions about
 627 cognitive architecture (learning rates, forgetting dynamics, transfer
 628 structure) that, while grounded in established theory, may not pre-
 629 cisely match real-world learning. Key limitations include: (1) The
 630 model does not capture motivational factors—novices restricted
 631 from AI tools may be demotivated, while those with AI may ex-
 632 perience increased enjoyment. (2) The task environment is simplified;
 633 real software development involves social interaction, code review,
 634 and collaborative problem-solving that may modify learning dy-
 635 namics. (3) The processing depth parameter, while theoretically
 636 motivated, conflates multiple cognitive processes into a single scalar.
 637

(4) AI tool capabilities evolve rapidly; the automation weights used
 here reflect current-generation tools and may shift as AI improves.
 639

640 These limitations are inherent to the computational modeling
 641 approach but are offset by its strengths: the ability to generate
 642 precise, testable predictions; systematic exploration of parameter
 643 space; and low cost relative to longitudinal human studies.
 644

645 4.5 Empirical Validation

646 Our model generates several testable predictions for empirical stud-
 647 ies:
 648

- 649 (1) **Dimension-specificity:** The AI-induced skill deficit should
 650 be largest for syntactic and algorithmic skills, smallest for
 651 architectural and meta-cognitive skills.
 652
- 653 (2) **Engagement moderation:** Active engagement protocols
 654 should substantially reduce or eliminate the skill deficit.
 655
- 656 (3) **Dependency trap:** Tool-removed assessments should re-
 657 veal skill gaps invisible in AI-assisted performance metrics.
 658
- 659 (4) **Threshold effect:** Interventions increasing processing depth
 660 above ~ 0.75 should flip the AI effect from negative to posi-
 661 tive.
 662

663 We recommend a Randomized Longitudinal Skill Assessment (RLSA)
 664 design—a 12-month, three-arm trial with monthly tool-removed
 665 assessments across all six skill dimensions—as the empirical study
 666 most directly suited to testing these predictions.
 667

668 5 CONCLUSION

669 We have presented a computational cognitive model that addresses
 670 the open question of how AI coding tools affect novice developer
 671 skill formation. Our simulation of 240 developers over 12 months
 672 reveals a *skill formation paradox*: unrestricted AI use boosts produc-
 673 tivity while significantly impeding underlying skill development,
 674 with the strongest effects in highly automatable skill dimensions.
 675 Critically, scaffolded engagement—requiring active processing of
 676 AI output—nearly eliminates this deficit, and sensitivity analysis
 677 identifies a processing depth threshold at $\phi \approx 0.75$ that separates
 678 skill-harming from skill-enhancing AI use.
 679

680 These findings have immediate practical implications. For **tool**
designers: incorporate scaffolding features that promote active
 681 engagement, such as explain-before-accept prompts and modifi-
 682 cation requirements, particularly for users identified as novices.
 683 For **engineering managers:** supplement AI-assisted productivity
 684 metrics with periodic tool-removed skill assessments to detect hid-
 685 den dependency. For **educators:** integrate AI tools into curricula
 686 with explicit scaffolding protocols rather than unrestricted access,
 687 and teach students to evaluate rather than merely accept AI out-
 688 put. For **researchers:** prioritize empirical studies that disentangle
 689 productivity from skill, measure multiple skill dimensions, and test
 690 engagement-mode interventions.
 691

692 The skill formation paradox is not an argument against AI cod-
 693 ing tools—it is an argument for designing them thoughtfully, with
 694 attention to the cognitive processes that drive genuine skill devel-
 695 opment. The gap between productivity and competence is invisible
 696 when AI access continues, making proactive assessment and delib-
 697 erate practice design essential for the next generation of software
 698 developers.
 699

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