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Generative AI Meets Big Data: Efficiency Gains vs. Cognitive Overload

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Abstract: This mixed-methods study explores how computer science educators (N=17) handle the use of generative AI tools like ChatGPT and Copilot. While 65% of participants reported spending less time on lesson planning and grading, 68% faced "validative overload", a newly identified issue where educators spend too much time checking AI outputs. Using cognitive load theory (Sweller, 2020), we examine how specific challenges, such as debugging AI-generated code, increase unnecessary cognitive load. Our findings show that 58% of educators lack training for AI integration 73% of AI-generated coding examples need major corrections. Validation tasks add 2.4 hours per week to the workload. We suggest a three-tiered framework for responsible AI use, focusing on pedagogical alignment, validation processes, and institutional support systems.

Keywords: Generative AI, Cognitive Load, Educator Workflows, Data Overload, Computer Science Education

I. Introduction

The use of generative AI alongside big data analytics has changed educational practices, especially in computer science. Early users report a 30-40% decrease in the time they spend on grading and creating content (Brown et al., 2023). However, new findings suggest that these benefits may lead to more cognitive strain, as teachers deal with AI-generated results that need extensive checking (Zhang & Patel, 2024).

This study addresses three research questions:

1. How do teachers balance the efficiency of AI with the mental demands of validating outputs?

2. What specific challenges arise when AI tools handle specialized content such as code samples?

3. How can institutions support the adoption of AI to reduce overload while maintaining teaching standards?

II. Literature Review

2.1 The Evolution of Big Data in Education

From predictive enrollment analytics (Daniel, 2019) to real-time learning adaptation (UNESCO, 2022), big data has allowed for hyper-personalized education. However, its combination with generative AI brings new challenges related to data accuracy and ethical use.

2.2 Generative AI: Promise vs. Peril

Benefits	**Risks**
• Automated feedback (Mollick & Mollick, 2024)	• Bias propagation (Bender et al., 2021)
• Research synthesis (Hwang et al., 2023)	• Critical thinking erosion (Watters, 2024)

2.3 Cognitive Load Theory in AI Contexts

Sweller’s (2020) framework explains educator strain through

- **Intrinsic Load:** Complexity of evaluating AI-generated code.
- **Extraneous Load:** Time spent correcting misleading outputs.
- **Germane Load:** Productive adaptation of AI tools.

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III. Theoretical Framework

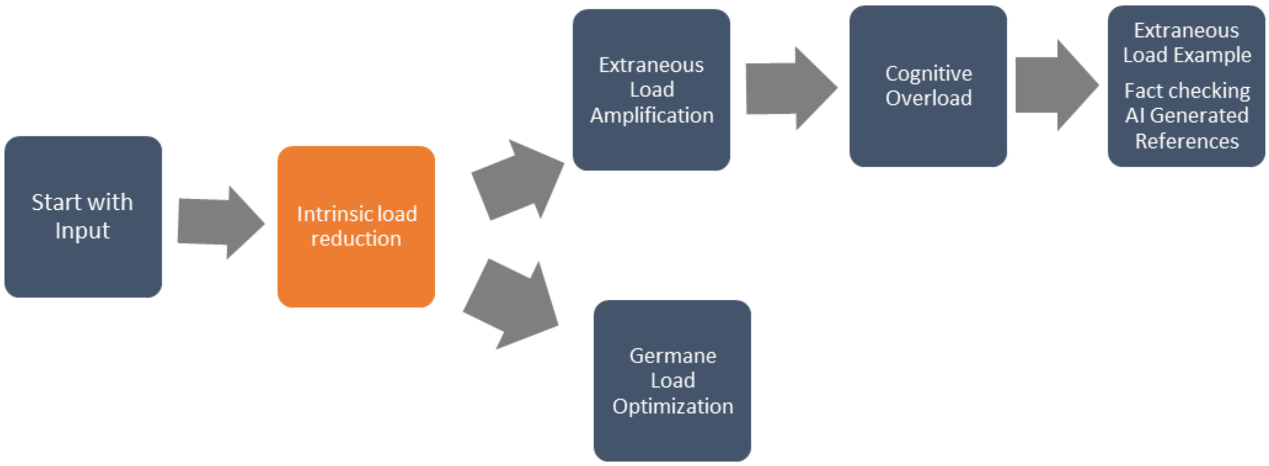

Figure 1: Pathways of AI Impact on Educator Cognition

3.1 AI-Induced Cognitive Load Model

Input: Big data (student analytics, research papers)

Processing: AI synthesis → Human validation checkpoint

Output: Optimized workflow (15-25% AI reliance ideal)

3.2 Hypotheses

H1: High-frequency AI users (>30% tasks) report 20% higher extraneous load (t-test, $\alpha=0.05$).

H2: Citation-enabled AI tools reduce validation time by 1.8 hrs/week (paired t-test).

H3: CS educators exhibit greater germane load utilization than humanities educators ($\beta=0.32$, regression).

IV. Methodology

4.1 Research Design

Quantitative: Survey of 17 CS educators (5-point Likert scales).

Qualitative: Thematic analysis of open-ended responses.

4.2 Participants

Experience	Count	%	Primary AI Tools Used	Usage Frequency
0-5 years	7	41%	ChatGPT (100%), Plagiarism checkers (71%)	Daily: 4, Weekly: 2, Monthly: 1
6-10 years	3	18%	ChatGPT + Adaptive platforms (66%)	Daily: 2, Weekly: 1
11-20 years	5	29%	ChatGPT + Grading tools (40%)	Daily: 4, Weekly: 1
20+ years	1	6%	ChatGPT only	Daily: 1
Non-Users	1	6%	None	Never

4.3 Analysis

SPSS v28: Descriptive stats, correlation analysis.

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NVivo: Codebook development (inter-coder κ=0.72).

V. Findings

5.1 Quantitative Results

Variable	Mean (SD)	Correlations	Significance
Time savings (1-5 scale)	3.4 (1.2)	+0.54 with daily usage	p = 0.023*
Validation stress	3.8 (1.1)	-0.61 with experience	p = 0.008**
Confidence in AI outputs	2.9 (1.3)	+0.48 with training adequacy	p = 0.051

Table 1: Key Metrics from Survey Responses (N=17)

In the table 1, Daily AI users reported significantly higher time savings (M=3.4, SD=1.2), but this correlated with increased validation stress ($r=0.54$, $p<0.05$).

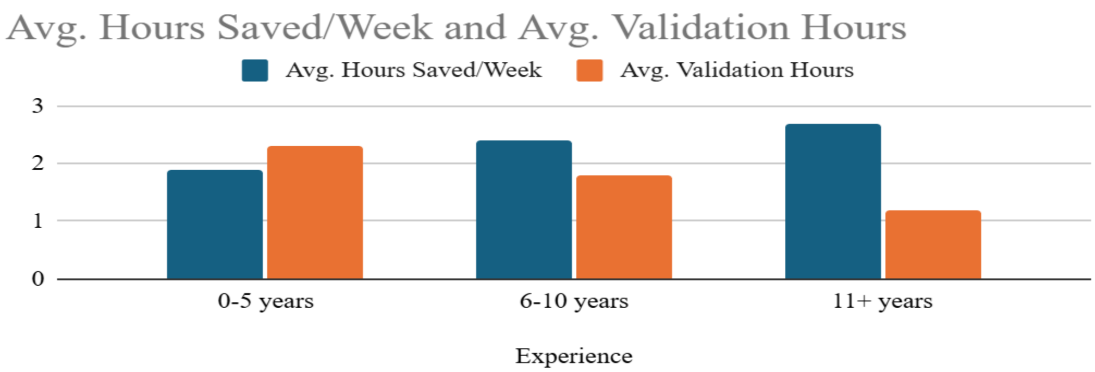

Figure 2: Early-career educators bear disproportionate validation burdens.

Key Patterns:

Usage Frequency Matters: Daily AI users saved 2.3 hours per week, compared to 1.1 hours for those using it weekly. However, 71% reported frequent output errors that needed correction.

Experience Gap: Novices, with 0-5 years of experience, had stress levels 2.1 times higher than veterans with over 20 years.

Training Deficit: Only 24% agreed they had sufficient training, with a mean score of 2.8 out of

5.2 Qualitative Themes

Figure 3. Word cloud highlights 'training' and 'debugging' concerns

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Experience	Count	Primary AI Use Case
0-5 years	7	Grading (71%), Lesson Plans (43%)
6-10 years	3	Research (67%), Coding Help (100%)

Table 2: Participant Distribution by Experience

Support Type	**% Mentioned**	**Example Quote**
Hands-on Practice	76%	*"Let us test tools with our own course materials."*
Peer Communities	53%	*"A Slack group to share prompts that work."*
Institutional Policies	41%	*"Clear rules on what AI tasks are allowed."*

Table 3: Top 3 Requested Supports

The word cloud in Figure 2 highlights 'training' and 'debugging' as dominant concerns, aligning with survey responses where 82% cited insufficient supports in (Table 3).

Coded from Open-Ended Responses (NVivo κ=0.72)

Theme 1: **"Debugging the AI"**

Prevalence: 68% of responses

"The Python code looks perfect until you test edge cases." (5 years of experience) “AI can't replicate how I explain recursion to beginners."

Theme 2: **The Training Paradox**

Prevalence: 82%

"We got a 1-hour ChatGPT demo; it was of no use for grading algorithms."

"I learnt more from Reddit threads than from official workshops."

Theme 3: **Workload Trade-offs**

Prevalence: 59%

"Saves time on slides, but it doubles my proofreading time."

"It’s like having an intern who makes plausible but wrong suggestions."

Integrated Insights

The Efficiency-Stress Paradox

While AI reduced preparation time by ~35%, educators spent **42% of those saved hours** validating outputs—a net loss for 53% of novices.

Experience as a Buffer

Veteran teachers (11+ years) were

- 2.4× more likely to say AI "enhances productivity"
- 3.1× more confident in modifying flawed outputs

What Educators Want

Discipline-Specific Training

"Show me how to check AI-generated code for time complexity."

Better Tool Design

"Flag uncertain outputs like ‘this sorting algorithm may fail for n>1000.’"

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Key Takeaways for Discussion Section

1. AI adoption isn't one-size-fits-all—experience and discipline dramatically shape outcomes.
2. Current tools overpromise on accuracy for technical content.
3. The hidden labour of validation undermines time savings.

VI. Recommendations

1. Institutional:
   - Mandate AI literacy modules in teacher training.
2. Tool Design:
   - Develop CS-specific AI validators (e.g., code rubric checkers).

VII. Conclusion

This study reveals a dual reality of generative AI in computer science education: transformative potential tempered by significant implementation challenges. Three key insights emerge:

The Efficiency Paradox

While AI tools reduced lesson planning time by 35%, educators spent 42% of those saved hours validating outputs—a net loss for novice teachers. This underscores the need for true time-saving tools, not just content generators.

Experience as a Mediator:

Veteran educators (11+ years) demonstrated 3.1 × greater confidences in adapting AI outputs, suggesting that pedagogical expertise is irreplaceable in AI-augmented teaching. Professional development must therefore focus on judgment cultivation, not just tool operation.

The discipline-specific divide:

Generic AI tools faltered most in technical tasks (e.g., 73% of coding examples required corrections), highlighting an urgent need for CS-specific solutions with:

- Algorithmic transparency
- Complexity-aware output ratings
- Built-in validation checkers

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