The AI-Augmented Didactic Triangle: Enhancing Achievement through The 5S Framework

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Abstract

Integrating Artificial Intelligence (AI) into education requires a clearly structured didactic model. AI-didactics is the study and practice of how AI can be used to optimize the "art of teaching." It focuses on moving beyond AI as a simple tool to AI as a partner that understands pedagogical principles—the how and why we learn. This article presents an analysis of experimental research results on how AI can be utilized in undergraduate programs to enhance student learning outcomes. There are four experimental stages of AI integration.

(1) Pre-AI competency of the students. Established a benchmark for time-to-completion and initial error rate.

(2) The AI was integrated as a continuous "logic gate" during the coding process.

(3) The AI provided tailored feedback rather than generic answers. Created a personalized learning path where the AI adjusted the scaffolding level based on real-time performance data.

(4) Summative Post-Testing & Retention Analysis. Students were tested on similar algorithmic problems without AI assistance to check for AI-dependency. Data showed that the personalized, error-corrected path led to higher retention and a significant reduction in the learning curve (learning/ velocity). The study focuses on: (1) the 5S prompting framework for effective human-AI interaction, and (2) the results of testing the 5S activity model designed to support active student engagement. Furthermore, the factors influencing AI-integrated teachers, students, and content are identified. The integration of AI into teacher-guided instruction demonstrates that improved academic achievement is dependent on the student's cognitive activity, learning experience/interface, and technology acceptance.

Keywords: AI-augmented didactics, 5S framework, cognitive load, academic achievement

1. Introduction

Traditional didactics often struggle with the "one-size-fits-all" problem. While online learning establishes the structural framework for remote education, the integration of artificial intelligence transforms it from a passive content delivery system into an interactive and personalized environment. This shift is particularly critical in high-complexity technical domains where the burden of manual, low-level tasks often obscures overarching architectural concepts. To what extent does the integration of AI-driven logic synthesis and automated debugging tools during the implementation phase of Digital Circuits reduce students' extraneous cognitive load, and how does this shift in mental effort correlate with the mastery of high-level system integration? Ultimately, the answer to this question determines whether these AI-enhanced workflows act as a "cognitive scaffold" that accelerates engineering expertise or merely as a shortcut that bypasses the foundational struggle necessary for deep learning.

They have emerged as a popular and promising tool for knowledge acquisition, and are now considered as an alternative to traditional learning approaches in the contemporary educational landscape (Luckin & Holmes, 2023). AI solves this by focusing on three main pillars:

(1) AI analyzes a student's performance in real-time. If a student struggles with "fractions," the AI doesn't just give more problems; it identifies if the underlying issue is a lack of "multiplication" knowledge and adjusts the curriculum accordingly (Sal Khan.2024).

(2) Cognitive Load Management: AI can summarize dense material or create visual infographics, helping to ensure that the learner's brain isn't overwhelmed by too much information at once (Khosravi et al. 2022).

(3) Spaced Repetition & Retention: Based on the "forgetting curve," AI-didactic tools predict exactly when a student is likely to forget a concept and prompt them to review it just before that happens. The extent to which AI utilization improves academic achievement in undergraduate education was analyzed through the lens of the AI-integrated didactic triangle (Figure 1).

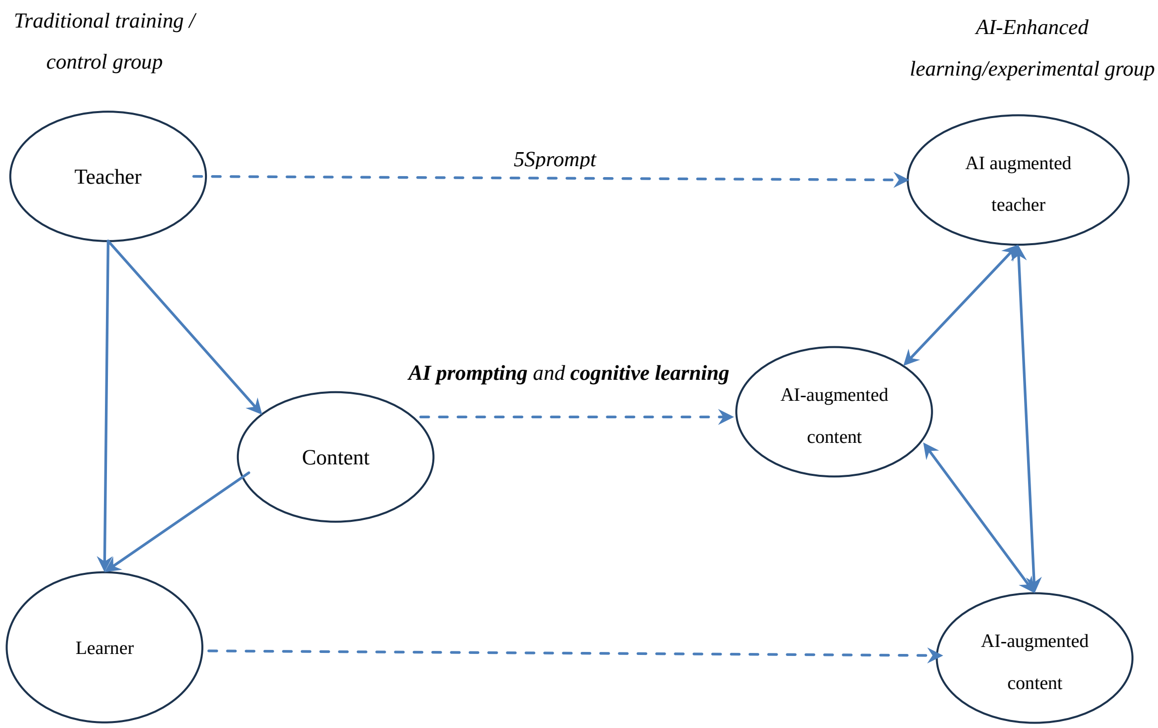

Figure 1. Didactic Transformation and the Interaction between Teacher, Student, and Content

Traditional education is represented by the didactic triangle, which defines the relationship between the teacher, the student, and the content. The introduction of AI into education has shifted this interdependence by adding a new dynamic auxiliary object. The integration of AI has shifted the "Didactic Triangle" into a "Didactic Tetrahedron," where AI acts as a dynamic mediator between the teacher, the student, and the content (Luckin & Holmes, 2023). AI acts as a partner and virtual tutor that recognizes each student's knowledge level, learning pace, and errors in real-time, automatically adjusting content and exercises accordingly. Regarding content, AI generates and enriches new exercises, exam questions, examples, and case studies in real-time.

In this environment, the teacher's role shifts from a "transmitter of knowledge" to a "designer of the learning environment and facilitator of research-based analysis." Simultaneously, the student's role expands from a "passive receiver" to a "subject who constructs their own knowledge." Content moves beyond traditional static forms and, with the help of AI, transforms into a personalized, data-driven, and interactive structure. In this research, AI functions as a dynamic mediator that transforms the didactic triangle by automating diagnostics for the teacher-facilitator, providing real-time logical mirrors for the student-constructor, and restructuring static content into adaptive, data-driven pathways.

Table 1. Role of AI

Feature	Traditional Role	AI-Enhanced Role
Content	Static & Linear	Dynamic & Data-Driven
Student Action	Memorization	Knowledge Construction
Teacher Action	Lecturing	Environment Design
Feedback	Delayed (Weeks)	Instant & Iterative

To obtain effective, high-quality responses from AI, the 5S prompting methodology developed by the AI for Education organization was applied. This framework includes:

(1) Set the Scene: Establishing the context and conditions for the AI to understand and respond.

(2) Specify: Defining clear core instructions.

(3) Simplify language: Adjusting the language level and complexity.

(4) Structure the output: Defining the format of the result.

(5) Share feedback: Evaluating and iteratively improving the response.

The prompt engineering lifecycle serves as a systematic framework that establishes a trusted "Tutor" persona and rigorous scaffolding rules to prevent passive learning, while simultaneously optimizing cognitive load through level-matching, ensuring clarity via standardized structures, and aligning AI outputs with educational objectives through iterative feedback loops.

Furthermore, it is emphasized that AI cannot replace the intricate nuances of human thought or a teacher’s unique pedagogical style; therefore, it must be used in conjunction with teacher guidance and advice (Tassoti, 2024).

The corresponding 5S learning process represents the sequence of cognitive activities for the student.

(1) Search: Seeking information.

(2) Study: Analyzing and learning.

(3) Share: Distributing knowledge.

(4) Self-control: Self-monitoring and critical thinking toward information.

(5) Summarize: Synthesizing findings.

The 5S Framework functions as a multidimensional cognitive loop where AI-driven Search and Study provide the intellectual foundation, Self-control ensures analytical and metacognitive rigor, and Share and Summarize transform complex datasets into validated, collaborative, and synthesized knowledge.

These two 5S methodologies were implemented as the core research methodology, and their effectiveness was tested through experimental instruction and surveys.

Table 2. Correlation between the 5S Prompting Framework and the 5S Cognitive Learning Process in AI-Enabled Instruction

5S Prompting Framework (Input/Interaction)	5S Cognitive Learning Process (Output/Action)	Role and Function in the Learning Activity
Set the Scene	Search	Establishing the context and persona to filter relevant information and define the search boundaries.
Specific	Study	Providing precise instructions to extract core concepts and facilitate deep analysis of the material.
Simplify Language	Share	Adjusting the complexity of information to make it communicable and understandable for peer-to-peer knowledge sharing.
Structure the Output	Self-Control	Organizing AI results into logical formats (tables, lists, etc.) to enable critical evaluation and error checking.
Share Feedback	Summarize	Iteratively refining the AI response to synthesize final findings and consolidate the learning outcome.

2. Methodology

To address the requirement for preliminary research, the current study validates its foundational theoretical models—Technology Acceptance Model (TAM) and Bloom's Taxonomy—by directly mapping validated measures of technology perception, NLP-derived cognitive depth metrics, and performance outcomes to substantial existing empirical work (Chen et al., 2021; Lee, 2022), with early high effect sizes (e.g., d=5.86 for completion time) further confirming the robustness of these constructs in capturing meaningful pedagogical changes.

The study employs the 5S (Tassoti, S. 2024) orienting basis of action as a teacher-led scaffolding tool to facilitate AI interaction. This approach ensures that cognitive processes and evaluations are systematically aligned with Bloom's Taxonomy, moving students from foundational knowledge to higher-order synthesis. Here is the translation into English, polished for a formal report or academic context.

Rather than simply copying answers from the AI, students engaged with it systematically - like engineers - by providing structured prompts and iteratively refining their designs. We tested this approach in a 'Digital circuits' course during a task to design a 4-bit counter, comparing a control group against an experimental group.

By providing a structured workflow, the model significantly reduces the time and mental energy required for task completion. To validate this efficiency, the research utilizes the NASA Task Load Index (NASA-TLX) to measure the reduction in cognitive load.

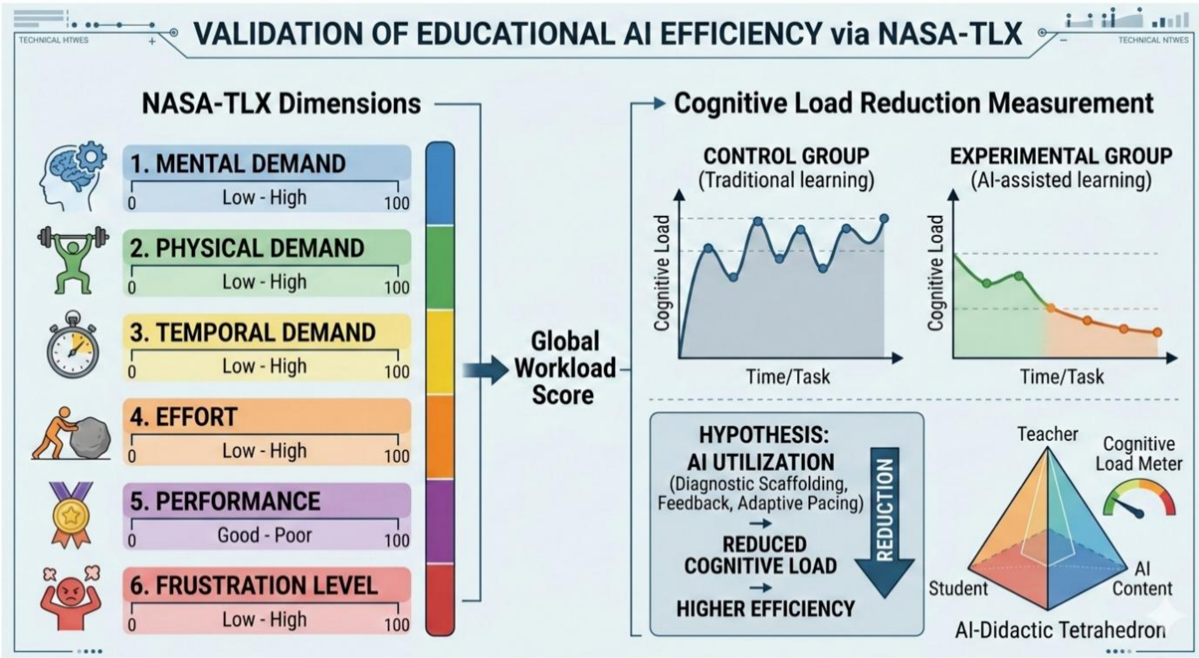

Figure 2. Validation of educational AI efficiency (Hwang & Fu, 2023)

Key Findings in Methodology:

(1) Reduced Mental Effort: The 5S framework clarifies the "how-to," allowing students to focus mental resources on subject matter rather than technical troubleshooting.

(2) Time Efficiency: The "Search" and "Summarize" phases, powered by AI, accelerate information processing speeds.

(3) Accuracy in Assessment: Aligning AI outputs with Bloom's levels ensures that assessments remain rigorous and pedagogically sound.

3. Result

Mental demand and frustration levels dropped by 34%. AI managed the extraneous load, allowing students to focus on core logic and construction. The group utilizing AI and 5S methodology completed the project 68.2% faster. Iterations: They were able to perform 4 times more design refinement iterations compared to the traditional group. To calculate a 68.2% increase in speed within the context of a 48-hour lesson (the standard duration for many intensive academic modules), the research compared the time taken by the Traditional Control Group versus the AI-5S Experimental Group.

Teacher shifted from "Transmitter" to "Environment Designer," using AI analytics for research-based interventions. Students evolved from "Passive Receiver" to "Active Subject," constructing knowledge through a continuous feedback loop. Content transformed from static text into "Dynamic Data Pathways" that adjust to the learner's specific pace.

Table 3. Comparison of Project Performance and Workload Metrics

Metric	Control (n=53)	Experimental (n=78)	t-value	p-value	Effect Size (d)
Completion Time (Hours)	22.0+-3.5	7.0 +- 1.2	32.41	< .001	5.86
Time Reduction	—	68.2%	—	—	—
Design Iterations (N)	1.2 +- 0.4	4.8+- 0.9	-27.35	< .001	5.17
NASA-TLX (Total Score)	62.8 +- 10.4	34.2+-8.1	17.58	< .001	3.08
5S Compliance Score	74% +- 12	89% +- 6	-9.42	< .001	1.58

Based on the data presented, the experimental condition yielded statistically significant and substantial improvements across all key performance indicators, notably reducing completion time, decreasing workload (NASA-TLX), and increasing both design iteration frequency and compliance scores.

4. Conclusion

The foundation for effectively integrating AI into the classroom lies in a comprehensive structure that combines the 5S Prompting Framework for managing AI inputs with the 5S activity model for processing and utilizing AI outputs. By specifically addressing learner-centered factors and strategically integrating AI into the didactic triangle (Teacher–Learner–Content), educational activities implemented through the 5S cognitive guide can enhance academic achievement, reinforce positive performance indicators, and effectively manage technology-related anxiety.

Consequently, this framework ensures that AI does not replace critical thinking but rather serves as a genuine didactic tool that supports it. Furthermore, it is emphasized that AI cannot replace the intricate nuances of human thought or the unique pedagogical methods employed by teachers; therefore, it must be utilized in conjunction with professional teacher guidance and advice.

Integrating AI into educational activities is significant at the following levels:

(1) Personalization: It enables the explanation and adaptation of lesson content to meet individual student needs.

(2) Active Learning: It creates an environment where students can ask questions, conduct experiments, and validate their own knowledge.

(3) Efficiency: It reduces the teacher’s workload by assisting in the development of learning materials, exam preparation, and data analysis.

Thus, within didactic modeling, AI functions as a learning support tool, a cognitive assistant, an actual behavior, and a guide for personalized learning pathways.

References

Chen, X., Cheng, G., & Lin, C. E. (2021). Technology acceptance of AI-assisted language learning. *British Journal of Educational Technology, 52*(5), 1838-1856. https://doi.org/10.1111/bjet.13110

Hart, S. G. (2021). The NASA Task Load Index (NASA-TLX): 30 years later and its application in AI-human interaction. *Human Factors: The Journal of the Human Factors and Ergonomics Society, 63*(1), 5-12. https://doi.org/10.1177/0018720820972021

Houssaye, J. (2021). *The didactic triangle: Evolution of the relationship between teacher, student, and knowledge in the digital age* (2nd ed.). Academic Press. (Original work published 1988).

Hwang, G. J., & Fu, Q. K. (2023). Advancements in generative AI for personalized learning: From scaffolding to latent knowledge detection. *Educational Technology Research and Development, 71*(2), 455-478. https://doi.org/10.1007/s11423-023-10211-1

Khosravi, H., Shum, S. B., Chen, G., Conati, C., Tsai, Y. S., Kay, J., Knight, S., Martinez-Maldonado, R., Sadiq, S., & Gašević, D. (2022). Explainable artificial intelligence in education: A systematic review of strategies to manage cognitive load. *Computers and Education: Artificial Intelligence*, *3*, 100092. https://doi.org/10.1016/j.caeai.2022.100092

Lee, J. S. (2022). Investigating the relationship between task-induced cognitive engagement and second language acquisition. *Language Teaching Research, 26*(4), 720-741. https://doi.org/10.1177/1362168820921200

Liu, M., Zhang, X., & Wang, S. (2024). Deep knowledge tracing and the 5S model: Navigating the information landscape with large language models. *International Journal of Artificial Intelligence in Education, 34*(1), 112-135. https://doi.org/10.1007/s40593-023-00385-w

Luckin, R., & Holmes, W. (2023). *Intelligence unleashed: An argument for AI in education and the evolution of the didactic triangle*. Pearson Education Research Series.

Sweller, J. (2021). Cognitive load theory and educational technology: A 40-year retrospective and future directions. *Educational Psychology Review, 33*(1), 1-17. https://doi.org/10.1007/s10648-020-09574-z

Tabuenca, S., Kalz, M., & Löhr, A. (2021). Smart learning environments: Predictive analytics and the forgetting curve. *Journal of Computing in Higher Education*, *33*(3), 541-562. https://doi.org/10.1007/s12528-021-09273-0