The AI Learning Pyramid for 21st-Century Educators

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Abstract: *The AI Learning Pyramid offers educators a structured framework for integrating artificial intelligence into teaching through three hierarchical components: "AI for a learning tool," "AI as a learning tool," and "AI of a learning tool." By leveraging concepts from Education 4.0, Learning Analytics, Human-Centered AI, and Precision Pedagogy, educators can create personalized, effective learning experiences that measurably improve educational outcomes. This framework helps teachers systematically implement AI technologies to meet diverse student needs in 21st-century classrooms.*

Keywords: Education 4.0, Learning Analytics, Human-centered AI, Precision Education, The AI Learning Pyramid

1. Introduction

The AI Learning Pyramid is a new framework proposed to help educators understand how AI can be applied in education and the benefits it can bring to educators and learners. The pyramid is designed to provide educators with a clear understanding of AI integration's different levels and applications. There are three components of the AI Learning Pyramid: "AI for a Learning Tool," "AI as a Learning Tool," and "AI of a Learning Tool." Educators can use this framework to distinguish whether AI is educational, designed for other purposes but still relevant to education, or based solely on AI. The authors propose that the AI Learning Pyramid can be an essential tool for educators to create effective and efficient learning experiences that substantially improve learning outcomes. By using the AI Learning Pyramid, educators can create an effective and efficient learning experience that meets the unique needs of learners.

2. Literature Review

2.1. Education 4.0

Education 4.0 represents a modern approach to education that emphasizes problem-based learning, self-determined learning, and the integration of disruptive technologies (Hussin, 2018). In today's rapidly changing world, new-age learners need to develop skills to thrive in evolving environments. As educators increasingly emphasize lifelong learning and emotional intelligence over IQ, personalizing instruction and adapting to student needs have become key aspects of Education 4.0 (Ciolacu et al., 2017). This approach encourages greater student independence while incorporating disruptive technologies like virtual reality, augmented reality, and artificial intelligence to improve learning outcomes and increase engagement (Moid, 2020). With its emphasis on needs-based education, goal-based learning, and integration of AI technologies, Education 4.0 aims to personalize the learning process and enhance educational quality through learning analytics (Mokhtar et al., 2019; Udvaros & Forman, 2023).

2.2. Learning Analytics

Learning analytics has become essential for institutions and educators seeking to improve educational quality by analyzing student performance and behavior (Papamitsiou & Economides, 2014). Following Gagne's "Events of Instruction," educators aim to capture attention, communicate goals, stimulate recall, connect content, provide guidance, motivate performance, offer feedback, assess learning, and reinforce retention (Tomei, 2008). Learning analytics enables a more personalized approach to teaching by creating customized study plans based on individual student behavior and outcomes (Mangaroska & Giannakos, 2017). This allows teachers to modify their teaching methods to meet student needs, providing necessary support to improve academic performance (Salas-Pilco et al., 2022). By analyzing performance data, educators can identify struggling or unmotivated students, offering additional support to ensure success (Sun et al., 2018). Learning analytics has played an important role in developing human-centered artificial intelligence, allowing for more personalized teaching, effective monitoring of student progress, and development of better educational policies (Dimitriadis et al., 2021).

2.3. Human-centered AI

Human-centered artificial intelligence (HCAI) considers human needs and perspectives when designing and implementing AI systems (Riedl, 2019). These systems continuously improve through human input and cooperation, providing efficient and positive human-machine experiences. As AI becomes more pervasive, understanding its impact on human life grows increasingly important (Auernhammer, 2020). HCAI researchers address AI challenges from a human perspective, considering human conditions and contexts in their approach. This involves developing students' cognitive thinking alongside computational thinking and incorporating human nature into AI algorithm design (Margetis et al., 2021). In education, HCAI can identify at-risk students for timely intervention, improve teaching quality, and enhance learning outcomes. Through smart learning analytics and assessment, HCAI can evaluate student behavior and difficulties, enabling teachers to adjust their instructional strategies and provide personalized feedback. As AI technology evolves, ensuring its development benefits humanity requires multidisciplinary collaboration between technology and humanities researchers (Kaluarachchi et al., 2021). Given limited existing teaching practices, further research on HCAI in education remains necessary (Chen et al., 2023).

2.4. Precision Education

Precision education transforms educational approaches using AI technology. Inspired by precision medicine, this pedagogy recognizes students' unique needs, learning behaviors, and strategies. Precision pedagogy follows four steps: diagnosis, prediction, treatment, and prevention (Yang et al., 2021). These steps involve analyzing students' learning behaviors, environments, and strategies to improve learning outcomes by creating personalized educational experiences that address individual needs and challenges.

3. Proposed Model: The AI Learning Pyramid

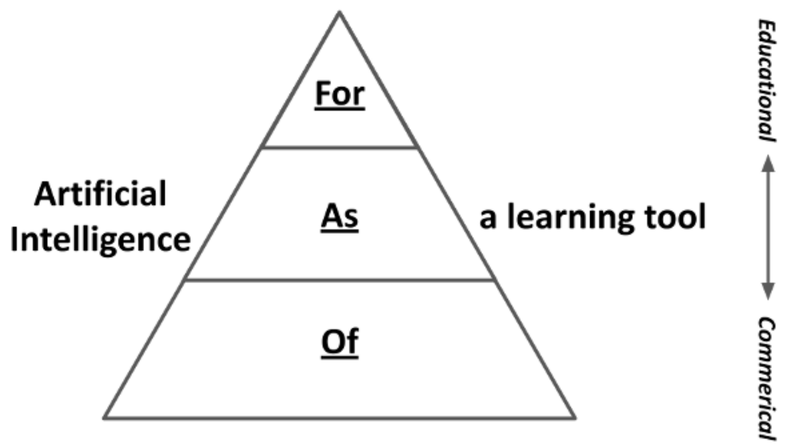

Figure 1. The AI Learning Pyramid

3.1. Description of The AI Learning Pyramid

The AI Learning Pyramid categorizes AI applications in education into three layers: "AI for a learning tool," focusing on purpose-built educational AI; "AI as a learning tool," repurposing existing AI for learning; and "AI of a learning tool," integrating AI into tool design. This framework highlights the interplay between design intention and pedagogical purpose, guiding educators in selecting and utilizing AI tools effectively to enhance learning outcomes.

The AI Learning Pyramid helps educators navigate the rapidly evolving landscape of AI in education. It provides a structured framework for understanding different levels of AI integration, their applications, and benefits. By categorizing AI educational technologies, this model enables teachers to make informed implementation decisions, better understand design principles, and create more effective learning experiences for students in the digital age.

3.2. Aim of The AI Learning Pyramid

To understand the AI Learning Pyramid, each level must be analyzed in detail. "AI for a learning tool" refers to AI systems specifically designed for education, built from the ground up to improve learning outcomes through tailored solutions. "AI as a learning tool" involves repurposing existing AI technologies, such as natural language processing or computer vision, to support learning processes without being deeply integrated into the tool's design. Meanwhile, "AI of a learning tool" embeds AI directly into the design and functionality of educational tools, enabling personalization, optimization, and adaptability. These distinctions are significant: "for" focuses on purpose-built educational AI, "as" adapts existing technologies for learning, and "of" transforms tools into immersive, adaptive systems that enhance both engagement and outcomes.

3.3. Structure of The AI Learning Pyramid

The AI Learning Pyramid emphasizes the progression of AI integration in education, focusing on the interplay between design intention and pedagogical purpose. At its base, "AI of a learning tool" refers to technologies embedded into a tool's design, enabling it to adapt dynamically to learners' needs. This foundational layer ensures robust functionality, making tools effective, reliable, and capable of personalizing the learning experience.

The middle layer, "AI as a learning tool," involves adapting existing AI technologies, such as natural language processing or machine learning, for educational purposes. While these tools are not initially designed for education, they extend learning possibilities by supporting activities like data analysis, creative problem-solving, or language practice. This layer bridges the gap between commercial AI applications and educational use, demonstrating how repurposed technologies can enhance the learning process.

At the apex, "AI for a learning tool" represents purpose-built AI systems designed specifically to address educational challenges. These tools align closely with pedagogical goals, offering tailored solutions to improve learning outcomes and foster engagement.

The pyramid's structure reflects a fluid relationship between layers, where tools can overlap in purpose and application. This flexibility allows educators to combine tools across layers, fostering innovative and adaptable learning environments that effectively address diverse student needs.

Table 1. A summary of the relationships within the AI Learning Pyramid

AI	**For** a learning tool	**As** a learning tool	**Of** a learning tool
Position	Created for learning	Used for learning	Embedded to learning
Designed for Learning	Purposely	Non-purposely	Purposely / Non-purposely
Contribution	Empirical / Theoretical	Empirical	Theoretical
Adaptivity	Formative / Summative	Summative	Formative

Educational approach <--> ***Commercial approach***

4. A Case Study: Data Encryption and Artificial Intelligence Technology

4.1. Research Purpose

This case study explores how the AI Learning Pyramid framework can be implemented in STEAM curriculum and analyzes different AI collaboration modes' impact on learning effectiveness. Using the "Data Encryption and Artificial Intelligence Technology" course as an example, we recorded and analyzed how Secondary 2 students interact with AI in encryption and decryption tasks and the resulting educational effects. Through empirical observation, this research reveals how junior secondary students utilize different levels of AI interaction to enhance their problem-solving abilities and how this collaboration affects task success rates. This research not only enriches AI education theory but also provides practical course design references for educators, demonstrating effective AI integration in secondary school STEAM education.

4.2. Course Design and Background

The "Data Encryption and Artificial Intelligence Technology" course is divided into three stages corresponding to the AI Learning Pyramid levels, progressively developing students' AI literacy and encryption/decryption abilities. The first stage focuses on "AI for a learning tool," training students to select appropriate AI chatbots for specific encryption and decryption problems by analyzing different AI tools' characteristics and applicable scenarios. The second stage embodies "AI as a learning tool," establishing effective personalized communication models through deep AI interaction to build human-machine understanding for problem-solving. The third stage explores "AI of a learning tool," utilizing AI's logical analysis strengths for complex encryption and decryption problems while gaining understanding of AI's underlying mechanisms.

This progressive teaching strategy moves students from selecting appropriate AI tools to establishing effective human-machine interaction models to deeply understanding and strategically utilizing AI's capabilities. The design ensures students develop comprehensive AI literacy throughout the learning process, mastering encryption knowledge while cultivating abilities to select, interact with, and understand AI. The research subjects were 76 Secondary 2 students aged 13-14 with basic computer skills but limited AI experience.

4.3. Research Methodology

This study employed a straightforward method focusing on students' success rates in encryption and decryption tasks. We designed a controlled experiment with 76 Secondary 2 students divided into two groups: Group A (40 students using AI with selection strategy guidance) and Group B (36 students working without AI). Both groups completed three core tasks: defining encryption rules, encrypting specified messages, and decrypting others' encrypted messages after obtaining the encryption pattern. The experimental design ensured fair comparison with identical prior knowledge, task time, and difficulty levels. Group A could use any AI assistant based on learned selection strategies, while Group B used only traditional references. By comparing task success rates between groups, we could assess AI collaboration's impact on students' problem-solving processes.

4.4. Research Findings

The task success rate data clearly demonstrated a significant difference in performance between students who used AI and those who did not. In the task of decrypting others' messages after obtaining the encryption pattern, all 40 students in Group A achieved successful decryption, resulting in a 100% success rate. In contrast, only 24 out of 36 students in Group B were successful, yielding a 67% success rate (24/36). This represents a 33% absolute difference in success rate, or a 50% relative improvement in success rate for the AI-assisted group, strongly indicating that AI assistance significantly enhances students' decryption success even when encryption rules are known. Detailed success rate data is summarized in Table 2.

Table 2. Study Group * Decryption Success Crosstabulation

			Code Modification		
			Modified	***Not modified***	***Total***
Academic Year Period	***With AI (Group A)***	***Count***	***40***	***0***	***40***
		Expected Count	***33.7***	***6.3***	***40***
		% within Academic Year Period	***100.0%***	***0.0%***	***100.0%***
	Without AI (Group B)	***Count***	***24***	***12***	***36***
		Expected Count	***30.3***	***5.7***	***36.0***
		% within Academic Year Period	***66.7%***	***33.3%***	***100.0%***
Total		***Count***	***64***	***12***	***76***
		Expected Count	***64.0***	***12.0***	***76.0***
		% within Academic Year Period	***84.2%***	***15.8%***	***100%***

To further evaluate the statistical association between study group and decryption success, a Chi-Square test was conducted. Table 3 presents the detailed results of the Chi-Square tests. The Pearson Chi-Square value was 15.79 ($df = 1$, $p < .001$), indicating a highly statistically significant positive association between study group and decryption success. Furthermore, Fisher's Exact Test also demonstrated a high level of significance ($p < .001$ for both 2-sided and 1-sided), reinforcing the statistical robustness of these findings.

Table 3. Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	15.79[a]	1	<.001		
Continuity Correction	13.51	1	<.001		
Likelihood Ratio	20.66	1	<.001		
Fisher's Exact Test				<.001	<.001
Linear-by-Linear Association	15.58	1	<.001		
N of Valid Cases	76				

Table 4 summarizes the symmetric measures, with both Phi and Cramer's V coefficients at .456 ($p < .001$), suggesting a moderate to strong strength of association between study group and decryption success.

Table 4. Symmetric Measures

	Value	Approximate Significance
Nominal by Nominal	Phi	.456
	Cramer's V	.456
N of Valid Cases		76

The analysis of Group A's performance highlights a powerful synergy: integrating skills across the AI Learning Pyramid's stages significantly boosted decryption efficiency. Beyond mere success, AI collaboration fostered critical cognitive flexibility, enabling students to dynamically adjust strategies through AI interaction, a stark contrast to the less adaptable approaches of Group B. These observations strongly suggest that AI, when implemented within a structured framework, not only enhances problem-solving outcomes but also cultivates essential metacognitive abilities vital for navigating complex challenges.

5. Discussion

The findings validate the AI Learning Pyramid as a valuable framework for integrating AI into education. By categorizing AI technologies based on their design intention and pedagogical purpose, the pyramid provides a clear roadmap for educators to systematically incorporate AI into their teaching practices. The significant difference in decryption success rates between Group A (100%) and Group B (67%) highlights the effectiveness of AI collaboration when implemented within a structured framework.

One key insight is the progressive synergy between the pyramid’s layers. Moving from "AI of a learning tool" to "AI for a learning tool," students develop increasingly sophisticated skills, from understanding AI’s underlying mechanisms to leveraging purpose-built educational tools. This progression fosters both cognitive and metacognitive abilities, enabling students to navigate complex problem-solving scenarios with greater flexibility and efficiency.

The findings also suggest that the distinction between the layers is not rigid but fluid, with tools and applications often overlapping in their design intention and pedagogical purpose. For example, while "AI as a learning tool" may originate from commercial applications, its adaptation for educational purposes demonstrates the potential for hybrid approaches that combine technical innovation with pedagogical insight. This flexibility allows educators to optimize the use of AI tools across different layers, ensuring they meet diverse learning needs.

To address the comment’s concern regarding practical implementation, the pyramid serves as a guide for educators to systematically plan AI integration. This includes selecting tools that align with pedagogical goals, promoting AI literacy, and training students in human-AI collaboration. Educators must also focus on developing critical thinking and strategic decision-making skills, ensuring students understand how to interact with AI effectively. By applying the pyramid’s framework, teaching practices can become more adaptable and responsive to the evolving demands of education in the AI era.

6. Conclusion

This case study powerfully demonstrates the AI Learning Pyramid framework's practical value in secondary school "Data Encryption and Artificial Intelligence Technology" courses. Results clearly show that organically integrating the pyramid's three levels significantly improves student success rates in complex data decryption tasks, providing strong empirical support for AI as an effective educational tool for enhancing problem-solving abilities.

Particularly striking is the contrast in success rates when decrypting messages with known encryption rules: 100% in Group A versus 67% in Group B. This confirms AI collaboration's significant educational effect and highlights students' comprehensive ability development through three-stage progressive learning. These abilities likely extend beyond specific encryption/decryption scenarios to broader STEAM complex problem-solving. Statistical analyses further validate these findings' significance and reliability.

Theoretically, this research empirically validates the AI Learning Pyramid as an effective framework for secondary AI education design, revealing the critical role of cross-level AI literacy integration in enhancing problem-solving abilities. Practically, it establishes an operational, replicable curriculum implementation model demonstrating how to transform abstract theoretical frameworks into concrete, implementable, and assessable teaching activities.

While currently focused on task success rates without deeply examining AI-collaborative teaching's impact on higher-order cognitive abilities or non-cognitive factors, our findings sufficiently support comprehensive AI integration in secondary STEAM education. Future research should explore the framework's adaptability across broader subject areas and conduct longitudinal studies on its impact on students' cognitive development and long-term learning motivation.

As AI increasingly integrates into educational ecosystems, systematically developing future-oriented AI literacy has become a core mission of digital-age educational transformation. This research provides theoretically grounded, practically valuable approaches for achieving this strategic goal, emphasizing a progressive AI education pathway from "rational AI tool selection" to "human-machine collaboration optimization" to "basic understanding of AI operational mechanisms." Through this multidimensional, integrated approach, we can help students develop future-oriented problem-solving abilities for success in an increasingly intelligent, digital, and complex society.

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