Basic, Structured, or Strategic? A Diagnostic Typology of Generation Z's Untrained AI Prompting Skills

Henry Praherdhiono*, Yerry Soepriyanto, Citra Kurniawan, Taufik Ikhsan Slamet, Fauziah Nur Aisyah Rosyidah, Rahma Izzatul Hajjah

Universitas Negeri Malang, Semarang St. No. 5, Malang, East Java, 65145, Indonesia
*Corresponding author, email: henry.praherdhiono.fip@um.ac.id

Article History
Received: 8 November 2025
Revised: 13 December 2025
Accepted: 14 December 2025
Published: 14 December 2025

Keywords
AI literacy
Generation Z
Higher education
Human-AI interaction
Prompt engineering

Abstract
This study investigates the intuitive ("organic") capabilities of Generation Z students in designing Generative AI prompts, challenging the assumption that digital native status guarantees effective AI literacy. Through an in-depth qualitative content analysis of 125 prompts crafted by Educational Technology students at State University of Malang, this research maps their initial skill spectrum using a structured assessment rubric. The findings reveal a sharp polarization across three user typologies: Basic Users (42.4%) who tend to be ambiguous, Structured Users (32%) who are logical, and Strategic Users (25.6%) who demonstrate advanced control. This study concludes that general digital fluency does not automatically translate into AI literacy. Consequently, higher education institutions urgently need to explicitly integrate prompt engineering into the curriculum as a core future competency, rather than merely an adjunct technical skill.

How to cite: Praherdhiono, H., Soepriyanto, Y., Kurniawan, C., Slamet, T. I., Rosyidah, F. N. A., & Hajjah, R. I. (2026). Basic, Structured, or Strategic? A Diagnostic Typology of Generation Z's Untrained AI Prompting Skills. *Teaching, Learning, and Development*, *4*(1). 109–116. doi: 10.62672/telad.v4i1.130

1. Introduction

Generative Artificial Intelligence (AI), exemplified by platforms such as ChatGPT and Gemini, has rapidly emerged as a disruptive force within higher education (Wong, 2024). Its widespread adoption by students is fundamentally reshaping traditional paradigms of learning, research methodologies, and the very nature of academic task completion. The presence of generative AI is no longer a peripheral innovation but a central phenomenon (Storey et al., 2025). This shift necessitates urgent pedagogical adjustments and, critically, a deeper understanding of the new human-machine interaction dynamics occurring within intellectual and academic contexts (Dang et al., 2025).

The primary users in this transformation are Generation Z, a cohort widely described as "digital natives" (Agárdi & Alt, 2024; Chan & Lee, 2023). This generation is characterized by its high propensity to adopt and integrate new technologies into daily life, accelerating the shift from traditional learning models to digital first environments (Bagdi et al., 2023). However, a crucial paradox exists. Generation Z's digital fluency has been shaped by intuitive, interface-driven technologies like social media and keyword-based search engines (Chang & Chang., 2023). This "digital fluency" does not automatically equate to "AI literacy" the competency required for effective, logical, and structured communication with a dialogical AI (Hava & Babayiğit., 2024).

This distinction highlights the core problem: while numerous studies confirm Generation Z actively uses AI products (Al-Sharafi et al., 2023), a gap persists between mere usage and strategic mastery. Effective interaction, particularly for complex academic tasks, requires a specific competency known as AI literacy (Promma et al., 2025). This skill set moves beyond simple tool operation to encompass the systematic thinking needed for a successful human-AI partnership in learning and research (Kim, 2023; Ouyang et al., 2023).

Within this new context, a crucial new competency has emerged: Prompt Engineering, now considered an essential component of modern AI literacy (Knoth et al., 2024; Walter, 2024). This skill refers to the ability to design precise, contextual, and structured instructions to guide an AI toward generating optimal and intended outputs (Federiakin et al., 2024). It is not merely a technical act but an interaction strategy, the effectiveness of which is profoundly influenced by an individual's level of AI literacy (Knoth et al., 2024). The relevance of

doi: 10.62672/telad.v4i1.130

ISSN: 2988-2834

mastering prompt engineering is increasingly urgent as AI becomes a deeply integrated partner in the contemporary classroom (Walter, 2024; Cain, 2023).

Despite this, a significant gap persists in the research literature. The majority of academic discourse focuses on the potential and impact of the AI technology itself, paying scant attention to the organic or baseline capabilities of its primary users the students who are often interacting without any formal training (Ng et al., 2023; Yim & Su., 2024). This creates a critical blind spot for educators: if students' "organic" interaction patterns are ambiguous and undirected, they risk producing shallow outputs, reinforcing misconceptions, and engaging in superficial learning. Educational institutions cannot design effective pedagogical interventions if they do not first understand the baseline skill level of their students.

This raises the fundamental research question: What is the actual quality of students' initial, "organic" interactions with AI when confronted with academic tasks? Are they intuitively capable of formulating precise and structured commands, or are their interactions conversely ambiguous and ineffective, thereby failing to fully leverage the potential of AI? Therefore, this study aims to analyze and map the spectrum of these organic prompt engineering skills among Generation Z students to provide an empirical foundation for developing targeted AI literacy curricula in higher education.

2. Method

2.1. Research Approach and Design

This study employs a mixed-methods sequential design embedded within a descriptive case study framework. This approach is optimal for capturing a nuanced understanding of a complex phenomenon within a specific context. The "case" is bounded by the Educational Technology student cohort (Classes A, B, C, D, and E) at the State University of Malang, focusing on their organic prompt engineering skills. The design was structured in two main phases:

a. Phase 1 (Qualitative): An initial qualitative analysis of a data subsample was conducted to inductively identify emergent themes and develop a structured assessment rubric.

b. Phase 2 (Quantitative & Interpretive): The developed rubric was systematically applied to the entire dataset (N=125) to quantitatively measure prompt quality. These quantitative findings were then interpreted qualitatively to build a rich description of the user typologies.

2.2. Participants and Data Collection

The participants were 125 Generation Z students enrolled in the Information Systems Management course within the Faculty of Education, State University of Malang.

The data consisted of 125 unique text-based commands (prompts) created by these students to instruct AI chatbots. These prompts were collected as part of a course assignment where students were asked to submit what they considered their 'best' prompt for a given academic-related task. This collection method provided insight into the students' perceived optimal capabilities without formal training.

2.2.1. Phase 1: Instrument (Rubric) Development

A formal assessment rubric was developed through a two-stage inductive and deductive process to ensure its validity.

a. Inductive Phase: A purposeful subsample of prompts (n=25, approximately 20% of the data) was first analyzed by the research team through an open-coding process. This initial analysis aimed to identify naturally emerging patterns. From this process, three distinct user typologies emerged: Type A (Highly Structured), Type B (Strategic & Contextual), and Type C (Ambiguous/General).

b. Deductive Phase: Informed by these emergent typologies and existing literature on AI literacy, the team deductively constructed a formal assessment rubric. The rubric consisted of four main criteria: (a) Clarity & Specificity, (b) Structure & Organization, (c) Context & Scope, and (d) Advanced: Output Control. Each criterion was assessed using a 5-point Likert-type scale (1 = Inadequate, 5 = Exceptional), with clear qualitative descriptors provided for each score level. This rubric served as the objective instrument for the quantitative analysis phase.

2.2.2. Phase 2: Data Analysis Procedure

The data analysis procedure was systematic:

a. Quantitative Scoring: The primary researcher applied the validated rubric to all 125 prompts. Each prompt was scored (1-5) across the four criteria. This quantizing of the qualitative data allowed for a systematic mapping of the quality spectrum.

b. Categorization and Classification: Based on the scoring patterns, each prompt was classified into one of the three established typologies. This step connected the quantitative scores to the qualitative archetypes. For example, "Basic Users" (Type C) were characterized by low scores (1-2) in Clarity and Context; "Structured Users" (Type A) showed proficient scores (3-4) in Structure; and "Strategic Users" (Type B) demonstrated high scores (4-5) across all criteria, particularly in Output Control.

c. Synthesis and Interpretation: The quantitative findings (i.e., the frequencies and percentages of each typology, as shown in Table 1) were synthesized. This data was then interpreted qualitatively, using specific prompt examples as 'exemplars' to provide a thick description of the behaviors, strengths, and weaknesses associated with each user type.

2.3. Trustworthiness and Reliability

To ensure the rigor of this mixed-methods analysis, several techniques were employed:

a. Inter-Rater Reliability: To ensure the dependable application of the rubric, a second researcher (a co-author) independently coded a random subsample of 25 prompts (20% of the data). The initial agreement level was high (e.g., Cohen's Kappa > 0.85). Any minor discrepancies were discussed and resolved by consensus, which helped to refine the scoring rules before the primary researcher analyzed the remaining data.

b. Thick Description: Trustworthiness was enhanced by providing a thick description in the Results and Discussion sections. This was achieved by triangulating the quantitative data (scores and percentages) with rich, qualitative exemplars (direct quotes of student prompts) to illustrate the characteristics of each typology.

c. Systematic Procedure (Dependability): A clear audit trail was maintained. The consistent application of the same validated rubric to all 125 data points ensured the analysis was systematic and dependable, rather than a subjective assessment.

3. Results and Discussion

The analysis of 125 unique student prompts revealed a sharply polarized spectrum of prompt engineering skills. Rather than a homogenous group, students fell into three distinct typologies, quantitatively validating the digital fluency vs. AI literacy gap. The distribution of these typologies, as classified through the rubric-based analysis, is presented in Table 1.

Table 1. Classification of Student Prompt Engineering Skills

Prompt Type	User Typology & Key Characteristics	Number of Students	Percentage (%)
Type C	Basic User: Prompts are often ambiguous, general, and poorly structured. They fail to effectively define the task's context and scope.	53	42.40%
Type A	Structured User: Capable of formulating clear, logical, and specific prompts. They often utilize structures like bullet points to break down complex tasks.	40	32.00%
Type B	Strategic User: Demonstrates advanced mastery. Prompts are not only clear but also control for output format and style. This user can even collaborate creatively with the AI.	32	25.60%
Total		125	100%

3.1. Results

The following sections provide a detailed qualitative description of the characteristics and representative examples for each typology.

3.1.1. Typology C: The Basic User (42.40%)

This group, representing the largest cohort, struggled with the most fundamental aspect of AI interaction: contextual ambiguity. Their prompts were often short, vague, and failed to provide the AI with sufficient context or scope to perform the task effectively.

This user type reflects a mental model of the AI as an omniscient "mind-reader" rather than a logical system. They offload the cognitive burden entirely onto the AI. Common failures included using ambiguous deictic references (e.g., "this," "that") and assuming the AI shared their immediate knowledge.

a. Exemplar C1 (Lacks Scope): "Make a summary of the file I just uploaded." (Fails to specify length, style, or focus of the summary).

b. Exemplar C2 (Lacks Context): "Connect this file with the keyword: 'pedagogy'." (Fails to define what "connect" means e.g., find quotes, write an analysis, or list definitions).

c. Exemplar C3 (Ambiguous Reference): "Please explain this chapter's main concept." (Assumes the AI knows which chapter is being referenced).

3.1.2. Typology A: The Structured User (32.00%)

This group represents a crucial bridge between basic interaction and strategic control. These users understood that clarity and organization are essential for a good output. They often broke down complex tasks into logical, step-by-step instructions or used formatting, such as bullet points, to guide the AI.

While proficient in structuring commands, this group generally did not demonstrate the advanced output control seen in Type B. They effectively told the AI what to do but not how to deliver it in a specific format or style.

a. Exemplar A1 (Logical Steps): "First, read the attached document on curriculum theory. Second, identify the main arguments by John Dewey. Third, list them as bullet points."

b. Exemplar A2 (Clear Breakdown): "I am a second-semester student. Help me understand the concept of 'constructivism'. Define it in simple terms. Give me an example of it in a classroom."

3.1.3. Typology B: The Strategic User (25.60%)

This group demonstrated an intuitive mastery of prompt engineering. They shifted their mental model from viewing the AI as a 'question-answering machine' to perceiving it as a customizable 'knowledge production tool'. Their prompts were not commands but detailed 'work contracts' that precisely defined inputs, processes, and outputs. Key techniques observed organically included:

a. Persona Adoption: Assigning a role to the AI (e.g., "Act as an academic reviewer...").

b. Format & Style Control: Explicitly defining the output (e.g., "bilingual table," "academic language," "single paragraph").

c. Constraint Control: Setting limitations (e.g., "in no more than 100 words," "without using bullet points").

d. Exemplar B1 (Advanced Control): “Act as a research assistant by reading the provided PDF on ‘Educational Technology Frameworks’ and then identifying the three most common frameworks, creating a two column table consisting of Framework Name and Key Principles, and writing a one-paragraph academic and systematic summary for each framework, with the entire output presented in both English and Indonesian”.

3.1.4. Overall Prompt Skill Profile

The individual scores, visualized in Figure 1, illustrate the polarization found in the typologies. The data shows high variance across all four criteria. Many students, even those in the 'Structured User' (Type A) category, scored high on 'Structure & Organization' but low on 'Context & Scope', indicating the failure to provide context is the most persistent and widespread weakness across the entire sample. Conversely, 'Strategic Users' (Type B) were the only group to consistently score high on the 'Advanced: Output Control' criterion, setting them apart. Visualization of individual student prompt quality assessment scores can be seen in Figure 1.

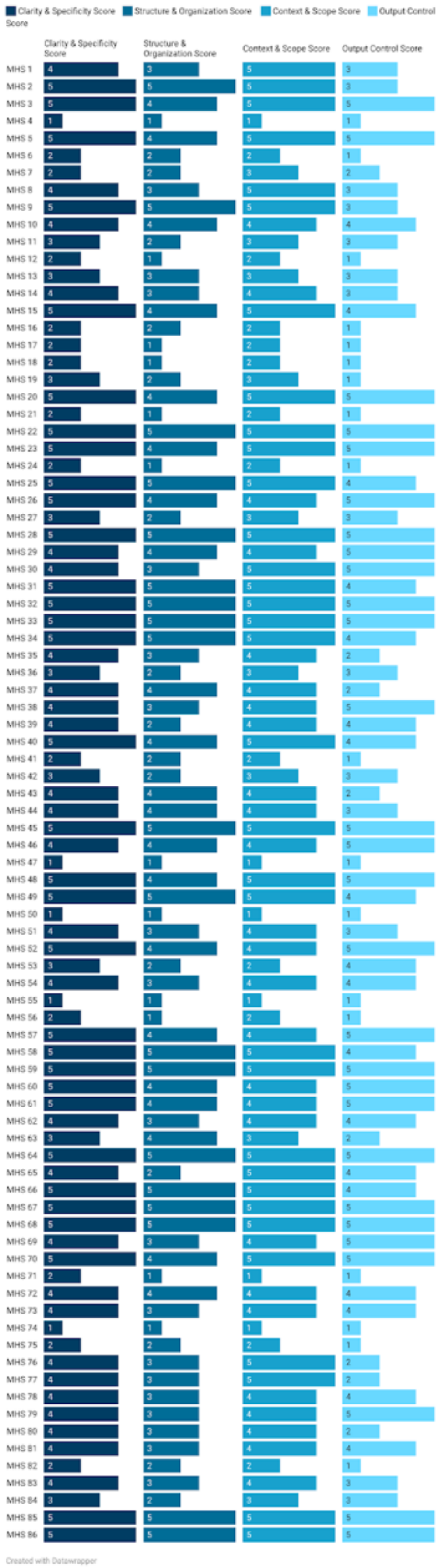

Figure 1. Visualization of Individual Student Prompt Quality Assessment Scores

3.2. Disscusion

This study's findings reveal a significant polarization in the organic prompt engineering skills of Generation Z students. Rather than a homogenous, tech-savvy cohort, the data shows a clear split in mental models. The prevalence of "Basic Users" (Type C) suggests that many students are misapplying the mental model of a "search engine" which rewards brief, transactional, and ambiguous keywords to Generative AI, which demands clear, contextual, and dialogical instructions. Conversely, the "Strategic Users" (Type B) intuitively grasp this new paradigm, treating the AI as a logical collaborator that must be instructed, not just queried.

3.2.1. Beyond the "Digital Native" Myth

The most significant theoretical contribution of this study is its direct challenge to the popular "digital native" narrative. The finding that a plurality of students (42.4%) defaulted to ambiguous, ineffective prompts (Type C) provides strong evidence that general digital fluency, defined by lifelong exposure to social media and apps (Agárdi & Alt, 2024; Tassoti., 2024), does not confer automatic AI literacy.

We propose a more nuanced distinction: Generation Z students are "Digital Interface Natives," not "AI Literacy Natives." They are adept at navigating intuitive graphical user interfaces but are not inherently skilled in the logical, structured communication required to command a non-intuitive AI (Knoth et al., 2024; Güner & Er, 2025). Their interaction patterns, shaped by platforms that infer context (like search engines), have left them unprepared for a technology that requires context to be explicitly provided (Walter, 2024).

3.2.2. Contextual Ambiguity: The Core Failure Point

The most persistent weakness observed across all typologies was "contextual ambiguity." The failure to define scope (e.g., using vague references like "this file" or "that chapter") was the primary differentiator between basic and advanced users. This finding is critical because it highlights the fundamental paradigm shift in human-computer interaction that Generative AI represents.

Previous technologies were designed to reduce the cognitive load on the user by inferring context (e.g., using location, search history, etc.). In contrast, Generative AI is a "blank slate" that demands the user provide all necessary context. The prevalence of Type C "Basic Users" is a direct symptom of this paradigm clash. Students are applying old habits to a new tool, leading to the unsatisfactory outputs that they themselves often critique, without realizing the failure lies in their own instruction.

3.2.3. Pedagogical Implications: A Diagnostic Framework

The implications for higher education are clear, urgent, and actionable. Simply granting access to AI tools is insufficient; it may even widen the gap between the "Strategic Users" who benefit and the "Basic Users" who fall behind.

The A-B-C typology presented in this study should be used not just as a finding, but as a diagnostic framework for educators. A one-size-fits-all approach to AI literacy will fail. Instead, a differentiated instructional approach is required:

a. For "Basic Users" (Type C): Training must focus on the single, most fundamental skill: defining context. Educators should design exercises that force students to move from ambiguous references ("my assignment") to concrete, bounded instructions ("Act as a tutor and critique the introduction of the attached essay on...").

b. For "Structured Users" (Type A): This group has mastered logic. The pedagogical goal is to move them to strategic control. Instruction should focus on advanced output control: defining persona, tone, style, and format, and using negative constraints (e.g., "write it without using bullet points").

3.2.4. Limitations and Future Research

The findings of this study must be viewed in light of several limitations. First, the data consisted of students' self-selected "best prompts." This selection bias means our findings are likely an optimistic representation of student ability. The 42.4% figure for "Basic Users" is a conservative baseline; the actual proportion in everyday, "messy" use is likely much higher.

Second, this was a case study in a single department at one university. The skill distribution may differ in other disciplines. These limitations provide clear directions for future research.

a. First, studies should analyze full interaction histories (entire chat logs) rather than single-best prompts to understand the "trial-and-error" and "prompt refinement" processes.

b. Second, experimental, pre-test/post-test studies are needed to determine if pedagogical interventions based on this A-B-C typology can effectively and measurably transition students from "Basic" to "Strategic" users.

4. Conclusion

This study sought to analyze the organic prompt engineering capabilities of Generation Z students, and the findings confirm a sharp polarization in skill, providing clear empirical evidence that the “digital native” label is dangerously misleading. The results show a fundamental distinction between general digital interface fluency the intuitive ability to operate apps and true AI literacy, which requires logical, structured, and contextual communication. The high prevalence of “Basic Users” (42.4%) underscores a critical pedagogical failure, as these students continue to apply a “search engine” mental model to a “collaborator” tool, resulting in ambiguous interactions and diminished output quality. This persistent struggle is not rooted in technical limitations but in the inability to define context, reflecting the misalignment between mental models and the nature of generative AI interaction. Beyond these findings, the key contribution of this research is the development of the A-B-C (Basic, Structured, Strategic) user typology, positioned as an actionable diagnostic framework rather than merely a descriptive classification. The pedagogical implications are significant: higher education must transition from uniform AI instruction to differentiated approaches tailored to learner competence levels. This typology enables educators to assess students accurately and deliver targeted interventions that help “Basic Users” develop contextual clarity and “Structured Users” gain advanced control over output. Ultimately, the challenge posed by generative AI in education lies not in the technology but in the pedagogy required to harness it, and equipping all students to become “Strategic Users” must be regarded as an essential competency for academic and professional success in the 21st century.

Author Contributions

All authors have equal contributions to the paper. All the authors have read and approved the final manuscript.

Funding

This research was funded by the Department of Educational Technology, Faculty of Education, Universitas Negeri Malang, through the Decentralized Research Grant scheme.

Declaration of Conflicting Interests

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Acknowledgement

The authors would like to express their gratitude to the Department of Educational Technology, Faculty of Education, Universitas Negeri Malang, for the funding and support provided through the Decentralized Research Grant scheme.

References

Agárdi, I., & Alt, M. A. (2024). Do digital natives use mobile payment differently than digital immigrants? A comparative study between generation X and Z. *Electronic Commerce Research*, *24*(3), 1463–1490. https://doi.org/10.1007/s10660-022-09537-9

Al-Sharafi, M. A., Al-Emran, M., Arpaci, I., Iahad, N. A., AlQudah, A. A., Iranmanesh, M., & Al-Qaysi, N. (2023). Generation Z use of artificial intelligence products and its impact on environmental sustainability: A cross-cultural comparison. *Computers in Human Behavior*, *143*, 107708. https://doi.org/10.1016/j.chb.2023.107708

Bagdi, H., Bulsara, H. P., Sankar, D., & Sharma, L. (2023). The transition from traditional to digital: Factors that propel Generation Z's adoption of online learning. *International Journal of Educational Management*, *37*(3), 695–717. https://doi.org/10.1108/IJEM-01-2023-0003

Cain, W. (2024). Prompting change: Exploring prompt engineering in large language model AI and its potential to transform education. *TechTrends*, *68*, 47–57. https://doi.org/10.1007/s11528-023-00896-0

Chan, C., & Lee, K. (2023). The AI generation gap: Are Gen Z students more interested in adopting generative AI such as ChatGPT in teaching and learning than their Gen X and millennial generation teachers? *Smart Learning Environments*, *10*, 1–23. https://doi.org/10.1186/s40561-023-00269-3

Chang, C., & Chang, S. (2023). The impact of digital disruption: Influences of digital media and social networks on forming digital natives' attitude. *SAGE Open*, *13*, 1–12. https://doi.org/10.1177/21582440231191741

Dang, B., Huynh, L., Gul, F., Rosé, C., Järvelä, S., & Nguyen, A. (2025). Human–AI collaborative learning in mixed reality: Examining the cognitive and socio-emotional interactions. *British Journal of Educational Technology*, *56*(5), 2078–2101. https://doi.org/10.1111/bjet.13607

Federiakin, D., Molerov, D., Zlatkin-Troitschanskaia, O., & Maur, A. (2024). Prompt engineering as a new 21st century skill. *Frontiers in Education*, *9*, Article 1366434. https://doi.org/10.3389/feduc.2024.1366434

Güner, H., & Er, E. (2025). AI in the classroom: Exploring students' interaction with ChatGPT in programming learning. *Education and Information Technologies*, *30*, 12681–12707. https://doi.org/10.1007/s10639-025-13337-7

Hava, K., & Babayiğit, Ö. (2024). Exploring the relationship between teachers' competencies in AI-TPACK and digital proficiency. *Education and Information Technologies*, *30*, 3491–3508. https://doi.org/10.1007/s10639-024-12939-x

Kim, J. (2023). Leading teachers' perspective on teacher–AI collaboration in education. *Education and Information Technologies*, *29*, 8693–8724. https://doi.org/10.1007/s10639-023-12109-5

Knoth, N., Tolzin, A., Janson, A., & Leimeister, J. M. (2024). AI literacy and its implications for prompt engineering strategies. *Computers and Education: Artificial Intelligence*, *6*, 100225. https://doi.org/10.1016/j.caeai.2024.100225

Ng, D., Su, J., Leung, J., & Chu, S. (2023). Artificial intelligence (AI) literacy education in secondary schools: A review. *Interactive Learning Environments*, *32*, 6204–6224. https://doi.org/10.1080/10494820.2023.2255228

Ouyang, F., Wu, M., Zheng, L., Zhang, L., & Jiao, P. (2023). Integration of artificial intelligence performance prediction and learning analytics to improve student learning in an online engineering course. *International Journal of Educational Technology in Higher Education*, *20*(1), 4. https://doi.org/10.1186/s41239-022-00372-4

Promma, W., Imjai, N., Usman, B., & Aujirapongpan, S. (2025). The influence of AI literacy on complex problem-solving skills through systematic thinking skills and intuition thinking skills: An empirical study in Thai Gen Z accounting students. *Computers and Education: Artificial Intelligence*, *8*, 100382. https://doi.org/10.1016/j.caeai.2025.100382

Storey, V., Yue, W., Zhao, J., & Lukyanenko, R. (2025). Generative artificial intelligence: Evolving technology, growing societal impact, and opportunities for information systems research. *Information Systems Frontiers*. https://doi.org/10.1007/s10796-025-10581-7

Tassoti, S. (2024). Assessment of students' use of generative artificial intelligence: Prompting strategies and prompt engineering in chemistry education. *Journal of Chemical Education*, *101*(6), 2475–2482. https://doi.org/10.1021/acs.jchemed.4c00212

Walter, Y. (2024). Embracing the future of artificial intelligence in the classroom: The relevance of AI literacy, prompt engineering, and critical thinking in modern education. *International Journal of Educational Technology in Higher Education*, *21*(1), 15. https://doi.org/10.1186/s41239-024-00448-3

Wong, W. K. O. (2024). The sudden disruptive rise of generative artificial intelligence? An evaluation of their impact on higher education and the global workplace. *Journal of Open Innovation: Technology, Market, and Complexity*, *10*(2), 100278. https://doi.org/10.1016/j.joitmc.2024.100278

Yim, I. H. Y., & Su, J. (2025). Artificial intelligence (AI) learning tools in K–12 education: A scoping review. *Journal of Computer Education*, *12*, 93–131. https://doi.org/10.1007/s40692-023-00304-9