
**ARTIFICIAL INTELLIGENCE, DIGITAL LITERACY, AND SELF-REGULATED LEARNING
AS DETERMINANTS OF ACADEMIC PERFORMANCE: A SYSTEMATIC LITERATURE
REVIEW OF COGNITIVE AND ORGANIZATIONAL MECHANISMS****Saefulah^{1*}, Zidan Ahmad², Jihaad Ahmad³**¹Industrial Engineering / Universitas Prof Dr Hafiz MPH / Cianjur, Indonesia²Mechanical Engineering / Universitas Gunadarma / Depok, Indonesia³Management Study Program/ Universitas Kahuripan Kediri / Kediri, IndonesiaE-mail: saeful.geo@mail.com¹

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Link Publish : <https://journal.aksarascentia.com/jiope/>**Abstract**

The rapid integration of artificial intelligence (AI), particularly generative artificial intelligence (GenAI), has transformed contemporary learning systems and raised new questions about how educational institutions should manage technology-enabled academic performance. Although recent studies report positive effects of AI-supported learning on academic achievement, the evidence remains conditional, suggesting that performance improvement depends not only on access to AI tools but also on students' AI literacy, digital literacy, self-regulated learning, cognitive load, and learning-environment support. This study aims to synthesize recent empirical and review-based evidence on the mechanisms through which AI-related factors influence students' academic performance and to propose an integrated performance-oriented framework for educational organizations. A systematic literature review was conducted on peer-reviewed studies published between 2021 and 2026, focusing on AI in education, GenAI, AI literacy, digital literacy, self-regulated learning, cognitive load, learning environment, and academic achievement. The synthesis identifies several interrelated findings. First, AI-supported learning can improve academic achievement when AI functions as instructional and cognitive support rather than as a substitute for students' reasoning. Second, AI literacy and digital literacy shape students' capacity to evaluate, interpret, verify, and use AI-generated information appropriately. Third, self-regulated learning serves as a key mechanism linking AI use with academic performance because students must plan goals, monitor understanding, regulate strategies, and verify AI outputs during learning. Fourth, cognitive load operates as a critical boundary condition because AI may reduce unnecessary mental effort but may also increase cognitive burden when information is excessive, unreliable, or poorly structured. The review also identifies important research gaps, particularly the limited integration of AI literacy, digital literacy, self-regulated learning, cognitive load, and learning-environment support within a unified educational performance model, as well as the need for stronger empirical evidence in secondary-school contexts. Based on these findings, the review proposes an integrated framework in which AI literacy, AI-supported learning, digital literacy, self-regulated learning, cognitive load, and learning-environment support interact to influence academic achievement. The findings suggest that educational institutions should manage AI adoption through measurable learning-performance indicators rather than technology-adoption metrics alone.

Keywords: *artificial intelligence; generative AI; AI literacy; digital literacy; self-regulated learning; cognitive load; academic achievement; educational performance.*

INTRODUCTION

Artificial intelligence (AI) has rapidly evolved from a specialized computational technology into a widely accessible component of contemporary learning environments. The emergence of generative artificial intelligence (GenAI), particularly large language model-based applications such as ChatGPT, has accelerated this transformation because students can now obtain explanations, examples, feedback, summaries, translations, and problem-solving assistance through natural-language interaction. Consequently, AI is increasingly becoming part of the operational environment of educational institutions rather than merely an optional technological innovation.

This transformation creates a fundamental performance-management problem. Educational organizations cannot evaluate the success of AI integration simply by measuring the number of students using AI applications or the availability of AI-enabled learning platforms. The relevant organizational question is whether AI adoption produces measurable improvements in learning processes and academic outcomes.

Recent empirical evidence provides support for this concern. A 2025 meta-analysis of 37 studies found that ChatGPT had a moderately positive effect on students' academic achievement, with an overall Hedges' g of 0.577 (Liu et al., 2025b). However, the magnitude of the effect varied according to intervention duration, discipline, knowledge type, instructional model, and other contextual factors. Similarly, Chen and Cheung's 2025 systematic review and meta-analysis of 57 studies involving 5,389 participants found a large overall effect of GenAI on university students' learning outcomes, including an effect of 0.633 for academic achievement, but no statistically significant effect for metacognition (Chen & Cheung, 2025).

These findings indicate that the relationship between AI and academic performance is not a simple technology-performance relationship. Instead, it is a socio-cognitive system involving the learner, technology, instructional process, and organizational environment.

One important determinant is AI literacy. AI literacy refers not merely to the ability to operate an AI tool but also to the ability to understand its capabilities and limitations, evaluate outputs, recognize ethical issues, and use AI appropriately (Chiu et al., 2024). Recent research emphasizes that conventional self-reported AI-literacy measurements may not adequately represent actual competence. For example, Wang et al. (2024) developed and validated an artificial intelligence literacy scale, demonstrating the need to distinguish perceived competence from measured competence in AI-related learning contexts.

A second determinant is digital literacy. Digital literacy provides the broader capability required to locate, evaluate, interpret, create, and communicate information through digital technologies. A 2025 meta-analysis found a causal relationship between digital literacy and academic achievement, reinforcing the argument that technological capability can function as an educational performance resource rather than merely a technical skill (Li et al., 2025 ; Saefulah et al., 2025).

A third factor is self-regulated learning (SRL). AI provides students with unprecedented access to information, but the availability of information does not automatically generate learning. Students must establish learning goals, select appropriate strategies, monitor comprehension, evaluate AI-generated responses, and regulate their behavior. A meta-analysis of 49 studies involving 5,786 university students found that self-regulated learning training programs improved academic performance, self-regulated learning strategies, and motivation, including a positive effect on academic performance (Theobald, 2021).

More recent research has also demonstrated a relationship between digital literacy, online self-regulated learning, and academic achievement (Chen, 2025; Ng et al., 2024).

A fourth factor concerns cognitive load. AI can reduce the effort required to retrieve or organize information, but poorly designed AI-supported learning can also produce excessive information, unreliable explanations, or dependence on automated answers. Recent research specifically argues that GenAI may impose problematic cognitive burden and recommends instructional approaches that reduce unnecessary cognitive demands while preserving independent problem-solving (Iqbal et al., 2025; Woo et al., 2024).

The fifth factor is the learning environment. Technology operates within an organizational context consisting of teachers, instructional design, infrastructure, policies, peer interaction, and institutional support. Research has shown that learning environment perceptions and learning strategies are related to academic outcomes (Faimau et al., 2022).

These findings reveal a significant research gap. Existing studies frequently investigate AI adoption, AI literacy, digital literacy, self-regulated learning, or cognitive load independently. However, fewer studies synthesize these variables as components of an integrated educational performance system.

Therefore, this study addresses the following research questions:

RQ1: How has recent research characterized the relationship between AI and students' academic achievement?

RQ2: What roles do AI literacy, digital literacy, self-regulated learning, and cognitive load play in AI-supported learning?

RQ3: What organizational and learning-environment factors condition the relationship between AI use and academic performance?

RQ4: What integrated framework can be proposed for managing AI-supported educational performance?

The contribution of this review is therefore not simply to determine whether AI improves learning. Rather, it seeks to identify under what conditions AI produces measurable educational performance improvements.

LITERATURE REVIEW

Artificial Intelligence and Academic Performance

The relationship between AI and academic achievement has become a rapidly growing area of research in educational technology. Overall, recent studies suggest that AI has the potential to support students' academic performance, particularly when it is used to assist learning rather than replace students' own thinking.

For example, Deng et al. reported that ChatGPT can improve academic performance, affective-motivational outcomes, and higher-order thinking, while also reducing students' mental effort (Deng et al., 2025). Similarly, Sun and Zhou's meta-analysis reviewed 28 articles, 65 independent studies, and 1,909 participants to examine whether GenAI improves college students' academic achievement (Sun & Zhou, 2024).

However, the findings are not entirely consistent. Observational studies show that simply using AI more often does not always lead to better academic results.

For instance, one study on essay-based assessment found that students who used permitted AI tools did not achieve higher scores than those who did not use AI, although higher-achieving students were more likely to adopt such tools (Weng et al., 2024).

Likewise, a 2026 study involving 2,307 Czech seventh-grade students found that frequent GenAI use was not positively associated with mathematics or Czech-language achievement. In fact, students who tended to use AI as a substitute for understanding showed lower academic achievement (Lintner et al., 2026).

These findings highlight an important distinction: using AI is not the same as learning effectively with AI.

The impact of AI on academic performance depends on how students integrate the technology into their learning process, how critically they evaluate AI-generated information, and whether AI supports rather than replaces their cognitive engagement.

AI Literacy as a Performance Capability

AI literacy represents a more specific and performance-oriented capability than general digital literacy because it concerns students' ability to understand, evaluate, and apply artificial intelligence within academic learning contexts.

Recent research suggests that AI literacy encompasses multiple dimensions, including cognitive, behavioral, affective, and ethical aspects (Chiu et al., 2024). A 2025 study involving 1,669 middle-school students identified heterogeneous AI-literacy profiles ranging from poor to excellent (Kong & Yang, 2025). This finding indicates that students may demonstrate substantially different levels of AI competence, even when they share similar exposure to digital technologies.

Similarly, research involving 622 secondary-school students found significant relationships among students' attitudes toward AI learning, AI literacy, and interest in AI-related careers, suggesting that AI literacy is associated not only with technical competence but also with learning orientation and future academic pathways (Zhang et al., 2025).

In academic learning, AI literacy is therefore important because students must be able to: (1) formulate appropriate questions or prompts; (2) evaluate AI-generated information critically; (3) recognize hallucinations, inaccuracies, and unsupported claims; (4) distinguish evidence-based information from AI-generated assertions; (5) understand the capabilities and limitations of AI tools; (6) use AI ethically and responsibly; (7) verify AI outputs through independent and credible sources; and (8) integrate AI assistance with their own reasoning, reflection, and academic judgment.

Consequently, AI literacy should be conceptualized as a performance-enabling academic capability rather than merely as a technical skill for operating AI applications.

Digital Literacy and Academic Achievement

Digital literacy provides the foundational capability that enables students to participate effectively in AI-supported learning environments.

A 2025 meta-analysis examining the causal relationship between digital literacy and academic achievement concluded that digital literacy has a meaningful association with students' academic outcomes, indicating that digital competence functions as an educational performance resource rather than merely a technical skill (Li et al., 2025).

Empirical studies further clarify the mechanisms through which digital literacy contributes to academic performance.

Chen's 2025 study of 894 college students found that digital literacy positively predicted academic achievement, while learning adaptation and online self-regulated learning sequentially mediated this relationship (Chen, 2025).

Similarly, Zakir et al. reported that digital literacy was related to academic performance through digital informal learning, self-efficacy, and digital competence (Zakir et al., 2025).

These findings suggest that digital literacy influences academic achievement not only through direct technology use, but also by strengthening students' capacity to adapt to digital learning environments, regulate learning behavior, evaluate information, and use digital resources strategically.

Self-Regulated Learning

Self-regulated learning is particularly important in AI-mediated environments because AI increases the volume, accessibility, and speed of information available to students.

Zimmerman's model conceptualizes self-regulated learning as a cyclical process involving forethought, performance, and self-reflection (Zimmerman, 2002). In AI-supported learning, these processes can be operationalized as follows:

(1) Forethought: students establish learning objectives, determine the appropriate role of AI, and select suitable learning strategies.

(2) Performance: students interact with AI, solve learning problems, compare AI-generated outputs, and monitor their understanding during the learning process.

(3) Self-reflection: students evaluate learning outcomes, verify information, identify errors, and modify future learning strategies.

Recent empirical research supports the relevance of this mechanism. Ng et al. examined 74 secondary students using generative AI and rule-based AI chatbots in science learning and investigated how these tools influenced students' self-regulated learning processes (Ng et al., 2024).

The evidence indicates that AI can support self-regulated learning when learning designs require active student participation, critical monitoring, verification of AI-generated information, and reflection on learning strategies.

Cognitive Load in AI-Supported Learning

Cognitive Load Theory provides an important explanation for why AI-supported learning may produce both positive and negative educational outcomes.

Learning occurs within the limitations of working memory. AI may reduce extraneous cognitive load by simplifying complex information, providing explanations, organizing content, and supporting students' initial understanding of difficult concepts.

However, AI can also increase cognitive burden through: (1) excessive information; (2) lengthy AI-generated responses; (3) contradictory outputs; (4) unreliable explanations; (5) unnecessary prompting; (6) frequent switching between applications; and (7) dependence on AI-generated answers.

A 2025 study examining GenAI and load-reduction instruction concluded that GenAI may impose problematic cognitive burden when it is not pedagogically structured, and therefore requires scaffolding, feedback, practice, and problem-solving support to manage cognitive demands (Iqbal et al., 2025).

Another 2025 phenomenological study found that ChatGPT could reduce cognitive load by simplifying complex problems; however, verification of AI-generated answers remained essential for schema construction and deeper understanding (Woo et al., 2024).

Thus, cognitive load should not be conceptualized only as a negative learning condition. The central issue is whether students' cognitive resources are directed toward meaningful learning, verification, reasoning, and schema construction, or instead consumed by unnecessary processing and dependence on automated responses.

METHOD

Research Design

This study employed a systematic literature review (SLR) design to synthesize recent empirical and review-based evidence on the relationship between artificial intelligence, digital literacy, self-regulated learning, cognitive load, learning environment, and academic performance (Page et al., 2021).

The review focused on peer-reviewed studies published between January 2021 and September 2026. This period was selected because it captures the rapid development of AI-supported education, including the emergence and increased use of generative AI tools in formal learning contexts.

The review procedure was guided by the logic of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework, particularly in relation to transparent identification, screening, eligibility assessment, and synthesis of relevant studies (Page et al., 2021).

Search Strategy

The literature search was conducted using combinations of keywords related to the core constructs of the study. The main search string was organized as follows:

("artificial intelligence" OR "generative AI" OR "ChatGPT")

AND ("academic achievement" OR "academic performance" OR "learning outcomes")

AND ("AI literacy" OR "digital literacy" OR "self-regulated learning" OR "cognitive load" OR "learning environment")

Additional targeted searches were conducted for each major construct to identify relevant empirical studies, systematic reviews, and meta-analyses that addressed the cognitive, behavioral, technological, and organizational mechanisms of AI-supported learning.

Studies were included when they met the following criteria: (1) published between 2021 and 2026; (2) published as peer-reviewed journal articles; (3) written in English; (4) designed as empirical studies, systematic reviews, or meta-analyses; (5) focused on education or learning; (6) examined AI, GenAI, AI literacy, digital literacy, self-regulated learning, cognitive load, learning environment, academic achievement, or related learning outcomes; and (7) provided sufficient bibliographic information, including DOI or a stable publisher record, for verification.

Studies were excluded when they met one or more of the following conditions: (1) opinion or commentary articles without empirical or systematic evidence; (2) studies focused exclusively on AI engineering without educational application; (3) studies that did not address learning processes, educational outcomes, or academic performance; (4) duplicate publications; and (5) publications lacking sufficient bibliographic information for verification.

Analytical Procedure

The selected literature was analyzed using thematic synthesis, a method used in systematic reviews to identify recurring patterns, develop descriptive themes, and generate analytical interpretations across studies (Thomas & Harden, 2008). This procedure was used to identify recurring patterns, conceptual relationships, and performance-related mechanisms across the reviewed studies.

The synthesis was organized around analytical dimensions that connect technological, capability-based, cognitive, organizational, and performance-related aspects of AI-supported learning:

Table 1. Analytical dimensions used in the thematic synthesis

Category	Main construct	Performance implication
Technology	AI/GenAI use	Access and learning assistance
Capability	AI literacy	Quality of AI interaction
Capability	Digital literacy	Information evaluation and technology use
Cognitive mechanism	Self-regulated learning	Goal setting, monitoring, reflection
Cognitive mechanism	Cognitive load	Mental effort and information processing
Organizational context	Learning environment	Institutional and instructional support
Outcome	Academic achievement	Measurable educational performance

The synthesis then examined relationships among the constructs rather than treating each variable as an isolated factor. This approach enabled the review to develop an integrated performance-oriented interpretation of AI-supported learning.

RESULTS AND DISCUSSION

Evidence Pattern: AI Improves Performance Under Specific Conditions

The reviewed literature indicates that AI-supported learning can improve academic achievement; however, this effect is conditional rather than automatic.

The strongest evidence comes from recent meta-analyses. Liu et al. synthesized 37 studies published between 2022 and 2025 and found a moderate positive effect of ChatGPT on academic achievement ($g = 0.577$) (Liu et al., 2025b). Similarly, Chen and Cheung’s 2025 meta-analysis synthesized 57 studies involving 5,389 participants and reported a large overall effect of GenAI on learning outcomes, including a positive effect on academic achievement ($g = 0.633$) (Chen & Cheung, 2025). Nevertheless, this positive pattern should be interpreted alongside studies reporting neutral or negative relationships between AI use and academic outcomes.

For example, the 2024 study on AI-assisted essay assessment found no meaningful performance advantage attributable to AI use itself (Weng et al., 2024).

More recently, Lintner et al. found that GenAI-use frequency among 2,307 Czech seventh-grade students was not positively associated with achievement. More importantly, the study indicated that students who relied on AI as a substitute for developing their own understanding tended to show lower academic achievement (Lintner et al., 2026).

Taken together, these findings suggest that AI-use frequency is an insufficient indicator of educational performance. A more appropriate interpretation is that academic outcomes depend on the

quality of AI interaction, students' AI literacy, their self-regulated learning capacity, their level of cognitive engagement, and the instructional conditions under which AI is used.

Accordingly, AI-supported academic performance can be understood as a developmental sequence in which AI availability enables learning support, but performance improvement occurs only when students possess the literacy, regulatory, and cognitive capabilities required to use AI productively.

In this sequence, AI availability should lead to meaningful academic outcomes through AI literacy, quality of AI interaction, self-regulated learning, cognitive engagement, learning outcomes, and ultimately academic achievement.

This sequence provides a stronger explanation of why students exposed to the same AI technology can achieve substantially different outcomes.

AI Literacy, Digital Literacy, and Self-Regulation as Performance Mechanisms

The first major finding concerns the interaction among technology-related competencies and students' capacity for self-regulated learning.

AI literacy determines whether students are able to understand the functions, limitations, and risks of AI tools and use them appropriately for academic purposes (Chiu et al., 2024). Digital literacy determines whether students are able to evaluate, organize, and integrate information from digital sources (Li et al., 2025). Self-regulated learning determines whether students can plan, monitor, control, and evaluate their own learning process (Ng et al., 2024).

These three constructs therefore perform complementary but conceptually distinct functions in AI-supported learning:

(1) AI literacy addresses students' ability to understand, evaluate, and use AI appropriately in learning tasks. (2) Digital literacy addresses students' ability to evaluate, manage, and apply digital information effectively. (3) Self-regulated learning addresses students' ability to control goals, strategies, monitoring, and reflection during the learning process.

This distinction is important because frequent AI use does not necessarily indicate effective learning. A student may demonstrate high technical familiarity with AI tools but still show weak self-regulation, leading to superficial engagement, overreliance on generated answers, or limited independent reasoning.

Conversely, students with stronger self-regulated learning may use AI more selectively as a cognitive support tool while maintaining active monitoring, verification, and independent problem-solving.

Recent empirical evidence supports this interpretation. Digital literacy has been shown to predict academic achievement directly and indirectly through learning adaptation and online self-regulated learning (Chen, 2025; Li et al., 2025).

Similarly, evidence from self-regulated-learning interventions indicates positive effects on academic achievement and metacognitive strategies, suggesting that students' capacity to manage their own learning remains central even in technology-rich environments (Baars et al., 2022; Ng et al., 2024).

These findings imply that educational institutions should not evaluate AI implementation exclusively through adoption metrics, such as the percentage of students using ChatGPT, the frequency of AI use, the number of AI-supported assignments, or the number of AI-enabled courses.

Instead, institutions should monitor capability and performance indicators, including: (1) AI literacy; (2) digital literacy; (3) verification behavior; (4) independent problem-solving; (5) metacognitive monitoring; (6) cognitive engagement; (7) learning efficiency; and (8) academic achievement.

This represents an important shift from technology-adoption management toward AI-enabled educational performance management, in which the primary concern is not whether students use AI, but whether AI use strengthens measurable learning processes and outcomes.

Cognitive Load and Learning Environment as Boundary Conditions

The second major finding concerns the role of cognitive load and the learning environment as boundary conditions that shape the effectiveness of AI-supported learning.

AI does not operate independently of the learning environment. Rather, students interact with AI within an instructional system that includes teachers, curriculum, assessment practices, learning platforms, institutional policies, digital infrastructure, peer interaction, and learning resources.

Therefore, the effectiveness of AI-supported learning is partly determined by system design, particularly the extent to which instructional arrangements guide students to use AI for explanation, comparison, verification, reasoning, and reflection rather than for passive answer generation.

The cognitive-load perspective provides a useful explanation for this condition. AI can reduce extraneous cognitive load by simplifying difficult concepts, generating examples, providing immediate explanations, summarizing large amounts of information, and offering feedback that supports students' initial understanding (Woo et al., 2024).

However, AI can also increase extraneous cognitive load when responses are excessively long, when multiple interpretations are generated, when information is inaccurate, when students must repeatedly verify outputs, when students lack sufficient prior knowledge, or when they switch between multiple digital platforms.

Recent research therefore recommends integrating GenAI with instructional strategies that reduce unnecessary cognitive burden while preserving students' active reasoning, practice, and problem-solving processes (Iqbal et al., 2025; Woo et al., 2024).

This implies that cognitive load should be treated as a system-performance variable rather than merely as an individual learning difficulty. In AI-supported learning, the central issue is whether mental effort is directed toward productive cognitive processing or consumed by unproductive cognitive processing.

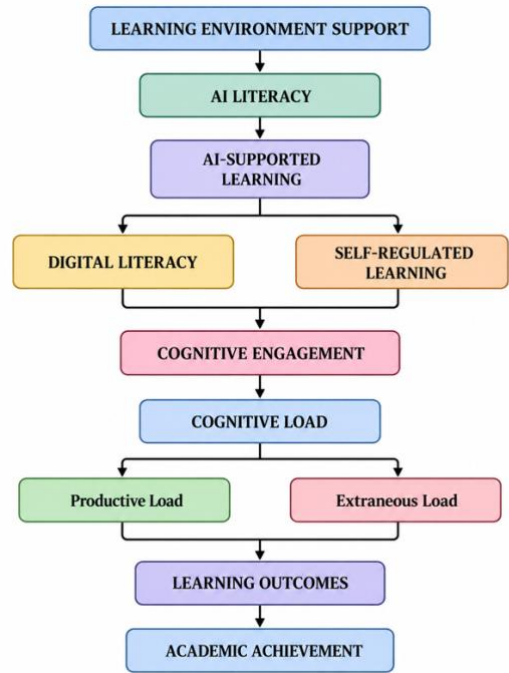
A useful conceptual distinction can therefore be made between two forms of AI-supported cognitive processing: (1) Productive cognitive processing occurs when AI assistance supports explanation, comparison, verification, reasoning, reflection, and schema construction. (2) Unproductive cognitive processing occurs when AI assistance leads to information overload, answer copying, excessive prompting, source confusion, or cognitive outsourcing.

The organizational challenge is therefore not simply to maximize AI utilization, but to increase the proportion of AI-supported learning activities that contribute to productive cognitive processing. From a performance-management perspective, learning environments should be designed to reduce unnecessary cognitive load while strengthening students' verification behavior, reasoning quality, and independent learning capacity.

Integrated Performance Framework

Based on the reviewed literature, this study proposes an integrated performance framework that explains how AI-supported learning influences academic achievement through a combination of technological, cognitive, capability-based, and organizational mechanisms (Chen & Cheung, 2025; Chiu et al., 2024; Li et al., 2025; Ng et al., 2024; Woo et al., 2024).

Figure 1. Proposed AI-Supported Educational Performance Framework



The framework positions academic achievement as the ultimate performance outcome, whereas AI use is treated as an enabling mechanism rather than as a final indicator of educational performance. In this model, AI adoption becomes meaningful only when it strengthens students’ AI literacy, digital literacy, self-regulated learning, cognitive engagement, and capacity to manage cognitive load within a supportive learning environment.

This distinction is important for educational organizations because high levels of AI adoption do not necessarily reflect high levels of educational performance.

For example, an institution may demonstrate high AI adoption while students still have limited AI literacy, weak self-regulated learning, and insufficient verification behavior, resulting in poor or inconsistent learning outcomes.

Conversely, moderate AI adoption may produce stronger educational performance when it is accompanied by high AI literacy, strong self-regulation, purposeful use of AI, and appropriate instructional support.

This proposition is consistent with the broader evidence pattern showing that AI-use frequency alone does not adequately explain academic achievement (Lintner et al., 2026; Weng et al., 2024). Instead, educational performance depends on how AI is embedded within students’ learning strategies, cognitive processes, and institutional support systems (Faimau et al., 2022; Ng et al., 2024).

Implications for Organizational Performance Engineering

The proposed framework has direct implications for organizational performance engineering in education because it shifts the evaluation of AI implementation from technology adoption toward measurable learning-performance improvement.

Educational institutions can be understood as complex socio-technical systems in which technology, human capability, instructional processes, organizational support, and academic outcomes interact. From this perspective, AI implementation should not be treated as a stand-alone technological initiative, but as an educational performance system that requires planning, monitoring, evaluation, and continuous improvement.

Accordingly, AI implementation should be managed through a performance-control cycle consisting of five stages: (1) planning AI-supported learning objectives; (2) implementing AI-supported instructional practices; (3) measuring relevant capability, process, and outcome indicators; (4) evaluating whether AI use contributes to meaningful learning improvement; and (5) improving instructional design, student support, and institutional policy based on performance evidence.

For example, educational institutions may define performance indicators across the following dimensions: (1) AI readiness, measured through students' AI literacy; (2) digital capability, measured through digital literacy; (3) AI utilization, measured through both frequency and purpose of AI use; (4) learning process quality, measured through cognitive engagement and verification behavior; (5) self-management, measured through self-regulated learning; (6) cognitive efficiency, measured through cognitive load; (7) learning outcomes, measured through assessment results; and (8) final academic performance, measured through academic achievement.

This approach is more consistent with performance engineering than a simple technology-adoption perspective because it links AI readiness, AI utilization, learning processes, cognitive efficiency, and academic achievement into a measurable improvement system.

At the institutional level, this performance-control logic can be operationalized through a balanced AI-learning performance dashboard that integrates input, process, output, and improvement indicators.

Table 2. Balanced AI-learning performance dashboard

Indicator category	Examples of indicators	Performance function
Input indicators	AI infrastructure, teacher AI competence, student AI literacy, and digital resources	Assess institutional readiness for AI-supported learning
Process indicators	Quality of AI interaction, verification behavior, engagement, self-regulation, and cognitive load	Monitor whether AI supports productive learning processes
Output indicators	Learning outcomes, assessment performance, and academic achievement	Evaluate measurable educational results
Improvement indicators	Intervention effectiveness, reduction in unnecessary cognitive load, improvement in AI literacy, and improvement in independent learning	Guide continuous improvement of AI-supported learning systems

Source: Author's synthesis based on the reviewed literature.

Such a framework enables educational institutions to evaluate whether AI investment generates measurable performance improvement in student capability, learning process quality, cognitive efficiency, and academic achievement. It also provides a practical basis for evidence-informed decisions about AI policy, teacher development, instructional design, and student support.

Research Gap

The review identifies four major research gaps that should be addressed in future studies on AI-supported educational performance.

First, existing studies provide limited integration of key constructs. Many studies examine AI use, AI literacy, digital literacy, self-regulated learning, or cognitive load as separate variables. However, the evidence reviewed in this study suggests that these constructs operate as interrelated components of a broader educational performance system. Therefore, future research should develop and test more integrated models that explain how technological, cognitive, capability-based, and environmental factors interact to influence academic achievement.

Second, empirical evidence from secondary-school contexts remains limited. Recent meta-analyses are still dominated by studies involving university students, even though secondary-school learners differ from university students in autonomy, prior knowledge, self-regulation, and institutional supervision (Chen & Cheung, 2025; Liu et al., 2025a; Liu et al., 2025b). The 2026 Czech study involving 2,307 seventh-grade students represents an important development because it provides large-scale evidence from secondary education (Lintner et al., 2026). Recent studies on GenAI in secondary education and middle-school mathematics learning also indicate growing interest in this context, but the evidence remains insufficient for explaining integrated performance mechanisms across AI literacy, digital literacy, self-regulated learning, cognitive load, and academic achievement (Wu & Zhang, 2025; Xing et al., 2025). Nevertheless, additional studies are required to examine how AI-supported learning affects younger learners who are still developing independent learning and metacognitive capabilities.

Third, AI use is frequently measured in terms of frequency rather than learning function. Measuring how often students use AI provides only limited insight into whether AI contributes to academic performance. Future research should distinguish among different types of AI use, including: (1) information retrieval; (2) explanation; (3) brainstorming; (4) feedback; (5) problem solving; (6) answer generation; and (7) AI dependence. This distinction is important because these forms of AI use may have different implications for cognitive engagement, self-regulation, and academic achievement.

Fourth, cognitive load requires stronger empirical integration within AI-supported learning models. Although recent studies increasingly recognize cognitive load as an important mechanism, it is still less frequently incorporated into integrated quantitative models than AI adoption, technology acceptance, or self-efficacy (Iqbal et al., 2025; Woo et al., 2024). Future research should examine whether cognitive load mediates or moderates the relationship between AI-supported learning and academic achievement, particularly in contexts where students must process large amounts of AI-generated information.

CONCLUSION

This systematic literature review synthesized recent evidence on the relationship between artificial intelligence, digital literacy, self-regulated learning, cognitive load, learning environment, and academic performance within contemporary educational systems.

The findings indicate that AI and GenAI can contribute positively to students' academic achievement; however, their effects are not determined by technology use alone. Recent meta-analytic evidence shows positive effects of ChatGPT and GenAI on academic achievement and broader learning outcomes, while empirical studies also demonstrate that frequent AI use does not automatically lead to better academic performance.

This review identifies five interrelated components that shape AI-supported educational performance: AI literacy, AI-supported learning, digital literacy, self-regulated learning, and cognitive load within a supportive learning environment.

AI literacy enables students to understand, evaluate, and use AI-generated outputs responsibly. Digital literacy provides the broader capacity to locate, assess, manage, and integrate digital information. Self-regulated learning allows students to plan goals, monitor understanding, regulate strategies, and reflect on learning outcomes. Cognitive load determines whether AI reduces unnecessary mental effort or creates additional cognitive burden. The learning environment, including instructional design, teacher support, assessment practices, and institutional policy, determines how these capabilities are translated into effective learning processes.

The main theoretical implication of this review is that AI should not be conceptualized as an independent predictor of academic achievement. Rather, AI should be understood as part of a socio-cognitive performance system in which technological access interacts with learner capability, cognitive regulation, instructional support, and organizational conditions.

The main practical implication is that educational institutions should move beyond technology-adoption metrics and develop AI-enabled educational performance management systems. Such systems should incorporate measurable indicators of AI literacy, digital literacy, self-regulated learning, quality of AI interaction, verification behavior, cognitive engagement, cognitive load, learning outcomes, and academic achievement.

For future empirical research, the proposed framework can be tested using quantitative structural equation modeling, particularly partial least squares structural equation modeling (PLS-SEM) or covariance-based structural equation modeling (CB-SEM). Such research would enable scholars to examine direct, mediating, and moderating relationships among AI literacy, AI-supported learning, digital literacy, self-regulated learning, cognitive load, learning-environment support, and academic achievement.

The framework is particularly relevant for secondary education because students at this level are increasingly exposed to GenAI while still developing the cognitive and metacognitive capabilities required for independent learning. Therefore, future studies should examine not only whether students use AI, but also how AI use contributes to measurable improvements in learning quality, cognitive efficiency, and academic achievement.

AI-ASSISTED RESEARCH DISCLOSURE

Artificial intelligence (AI) tools were used to support the preparation of this manuscript, particularly for literature-search assistance, language refinement, organization of ideas, and visualization of the conceptual

framework. The authors remain fully responsible for the accuracy, originality, interpretation, and scholarly integrity of the content. All references and scientific claims were independently reviewed and verified against their original sources. AI tools were not used to replace the authors' critical analysis, methodological decisions, or scientific judgment.

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