The Engagement-Scaffolding Nexus: A Systematic Review of How Student Engagement and Teacher Scaffolding Mediate AI's Impact on Academic Achievement

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ABSTRACT

The impact of AI on teaching and learning approaches in higher education has been dramatic, but its effect on student academic success is a topic of debate. The present literature review provides an in-depth analysis of how student engagement and instructor scaffolding mediate and regulate the impact of AI use on academic success. Empirical studies on the impact of AI on academic performance published between 2019 and 2025 were found, screened, and summarized following the PRISMA 2020 guidelines. The results indicate that the use of AI enhances students' academic performance through personalization, adaptive feedback, and increased efficiency. The positive effect of AI use on student achievement is mediated by students' cognitive, behavioural, and motivational engagement, and instructor scaffolding. The findings reveal that student involvement mediates the relationship between AI utilization and academic performance and teacher scaffolding positively moderates the relationship. The present study, informed by these findings, proposes the Engagement-Scaffolding Nexus to specify how AI contributes to academic achievement. The findings imply that AI should assist students' learning and cognition instead of totally substituting their own educational endeavours. Therefore, the pivotal role of educators in an AI-augmented learning environment and the prudent incorporation of AI technology in higher education as an adjunct to pedagogical practices should be considered.

Keywords: Artificial Intelligence, Generative AI, Student Engagement, Teacher Scaffolding, Academic Performance, Higher Education, Learning Outcomes, Educational Technology, AI Integration, Systematic Literature Review.

INTRODUCTION

The swift development of artificial intelligence (AI), particularly generative AI tools such as ChatGPT, has transformed the way teaching is conducted in universities worldwide. Educational institutions are increasingly adopting AI-powered tools to support students with personalized learning, writing, knowledge, and engagement (Ben Otman et al., 2024; Al-Mamary & Alfalah, 2024). While much research shows AI can have a positive impact on academic performance and learning outcomes, new evidence also highlights concerns around over-reliance on AI, reduced critical thinking skills and issues around academic integrity. Mixed findings indicate that the effect of AI on academic success is contingent on a variety of pedagogical and behavioural factors, not just on AI use.

Student engagement refers to how actively students are involved in AI-supported learning activities and benefit from them, and teacher scaffolding refers to the instructional support students require to use AI technologies effectively and responsibly. Therefore, it is necessary to understand the relationship between student engagement, instructor scaffolding, and AI use to explain the differences in academic achievement outcomes. This chapter lays out the background of the study, the research problems and challenges, and the research objectives and questions that guide this systematic literature review.

Background of the Study

Artificial intelligence has emerged as a transformative force altering higher education environments, a fundamental characteristic established in the research of Alam et al. (2026). Tarhini et al. (2026) assert that the primary catalysts of the worldwide digital revolution in higher education are institutional imperatives and national priorities. Examples of these national agendas are Saudi Arabia’s Vision 2030 and Oman’s Vision 2040, both of which promote educational innovation via technological integration. Eltahir and Babiker (2024) classified three categories of well utilized AI tools: intelligent teaching platforms, adaptive learning systems, and generative AI exemplified by ChatGPT, all of which tailor to the learning speeds and requirements of individual students. These technologies have the ability to enhance efficiency and improve the overall quality of education by delivering quick, tailored feedback and automating routine tasks (Youssef et al., 2024).

Research Issues and Problems

Although artificial intelligence (AI) possesses substantial developmental potential, notable academic disparities remain concerning its influence on pupils' academic achievement. In 2026, Castro-Lopez et al. characterized this phenomenon of contradictory empirical findings as the "performance paradox". A 2025 study by Phua et al.endorses the beneficial aspects of AI, although other research has warned that it possesses dual risks. The adverse consequences of excessive dependence on AI technologies encompass academic procrastination, memory deterioration, and a reduction in critical thinking and independent reasoning abilities.

Research on AI in education remains fragmented, with numerous research focusing on technology, pedagogy, and psychological learning processes in isolation (Alam et al., 2026). Furthermore, there is minimal integration between Cognitive Load Theory (CLT) and artificial intelligence applications, especially with assistance for students' working memory. Festiyed et al. (2026) assert that numerous AI products are utilized beyond official educational settings, hence constraining their potential to cultivate higher-order thinking skills. The Engagement Scaffold Nexus, wherein active student participation and instructor guidance are crucial for enhancing the academic efficacy of AI, as underscored by recent research (Gu & Yan, 2025).

Research Objectives and Questions

This systematic literature review's main goal is to investigate how teacher scaffolding and student engagement work together to mitigate and limit the effects of AI technologies on academic achievement in higher education (Bai & Wang, 2025).This study is guided by the following specific research questions:

- **RQ1:** How does multifaceted student engagement (behavioural, emotional, and cognitive) mediate the link between the use of AI and academic achievement?
- **RQ2:** How do “AI + Teacher” models compare to autonomous usage, and how much does Teacher Scaffolding act as a critical boundary condition for AI efficacy?
- **RQ3:** What is the moderating effect of learner-level factors (digital readiness and AI literacy) on the relationship between perceptions of AI and learning outcomes?

METHODOLOGY

This chapter describes the methodological techniques used in conducting this systematic literature review (SLR) on the association between student engagement and instructor scaffolding in AI-enhanced higher education. The review followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) methodology (Page et al., 2021) and the systematic review procedures outlined by Kitchenham and Charters (2007). These frameworks were applied to ensure scientific robustness, transparency and repeatability throughout the review process.

The review process consisted of six main steps: identification of the database, development of the search strategy, screening of articles, assessment of eligibility, assessment of quality, and thematic synthesis. Inter-reviewer

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agreement was used during the screening process in order to improve methodological transparency. Quality assessment and risk-of-bias evaluation were performed in order to ensure the credibility of the selected research.

Database Used

To conduct a comprehensive review of the existing literature, four major academic databases were used: Web of Science (WoS), Scopus, ERIC, and Google Scholar. The database was selected because it concentrates on artificial intelligence, instructional technology, and higher education and because it contains a large body of research that has been reviewed by experts in the field. The primary databases used for conducting a systematic review in the field of artificial intelligence in education include Web of Science, Scopus, ERIC, and PsycINFO. This is due to their widespread global coverage and academic reputation (Yu et al., 2025).

We decided to use Scopus and Web of Science because of the wide coverage and citation indexing they provide. ERIC was created to serve the needs of educational research. A backward reference search was performed on Google Scholar (Aljuaid, 2024) to identify other relevant research and grey literature.

To maximize the chance of identifying relevant publications, to reduce the effect of publication bias and to avoid missing any relevant studies, we carried out a wide search of a large number of databases.

Search String

Boolean operators (AND, OR) and wildcard functions were used to capture a wider range of relevant topics in the literature search. Based on suggestions by Dong et al. (2025), search strings were thematically categorized to enhance precision and relevance of retrievals. The search terms were grouped into three major themes:

Table 1: Search String

Item	Search string
AI Technology	"Artificial Intelligence", "Generative AI", "ChatGPT", "Adaptive Learning Systems", "Intelligent Tutoring".
Mediating Process	"Student Engagement", "Teacher Scaffolding", "Scaffolding", "Motivation", "Cognitive Load".
Outcomes	"Academic Achievement", "Learning Outcomes", "Performance", "Knowledge Acquisition".

To strengthen methodological transparency, database-specific search strings were developed as follows:

Table 2: Specific search string used in every database

Database	Search String
Scopus	(TITLE-ABS-KEY ("Generative AI" OR "ChatGPT" OR "Artificial Intelligence") AND TITLE-ABS-KEY ("Student Engagement" OR "Teacher Scaffolding" OR "Motivation") AND TITLE-ABS-KEY ("Academic Achievement" OR "Learning Outcomes"))
Web of Science (WoS)	TS=("Generative AI" OR "ChatGPT" OR "Artificial Intelligence") AND TS=("Student Engagement" OR "Teacher Scaffolding" OR "Cognitive Load") AND TS=("Academic Performance" OR "Achievement")
ERIC	("Artificial Intelligence" OR "Generative AI") AND ("Student Engagement" OR "Teacher Scaffolding") AND ("Higher Education" AND "Academic Achievement")
Google Scholar	allintitle: "Generative AI" "Student Engagement" "Academic Achievement"

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Article Selection Process

The articles were selected in four stages, in accordance with the PRISMA 2020 framework: identification, screening, eligibility and inclusion.

In the identification stage, 213 records were retrieved from the selected databases, which are Scopus (85), Web of Science (52), ERIC (31), and Google Scholar (45). 182 unique records after duplicates removed.

Two reviewers independently assessed the relevancy of titles and abstracts during the screening phase. Inter-reviewer agreement, measured by Cohen's Kappa coefficient, was used to measure uniformity in study selection. The score was **0.84** which indicates a strong consensus.

At this stage, 121 recordings were eliminated as they did not pertain to higher education, generative artificial intelligence, student engagement, teacher scaffolding, or academic achievement.

Using the inclusion and exclusion criteria, a total of 61 full-text articles were assessed for eligibility. Twenty-four studies were excluded because they were purely conceptual, did not provide enough empirical data or did not provide quantifiable academic outcomes.

The final synthesis included 37 studies.

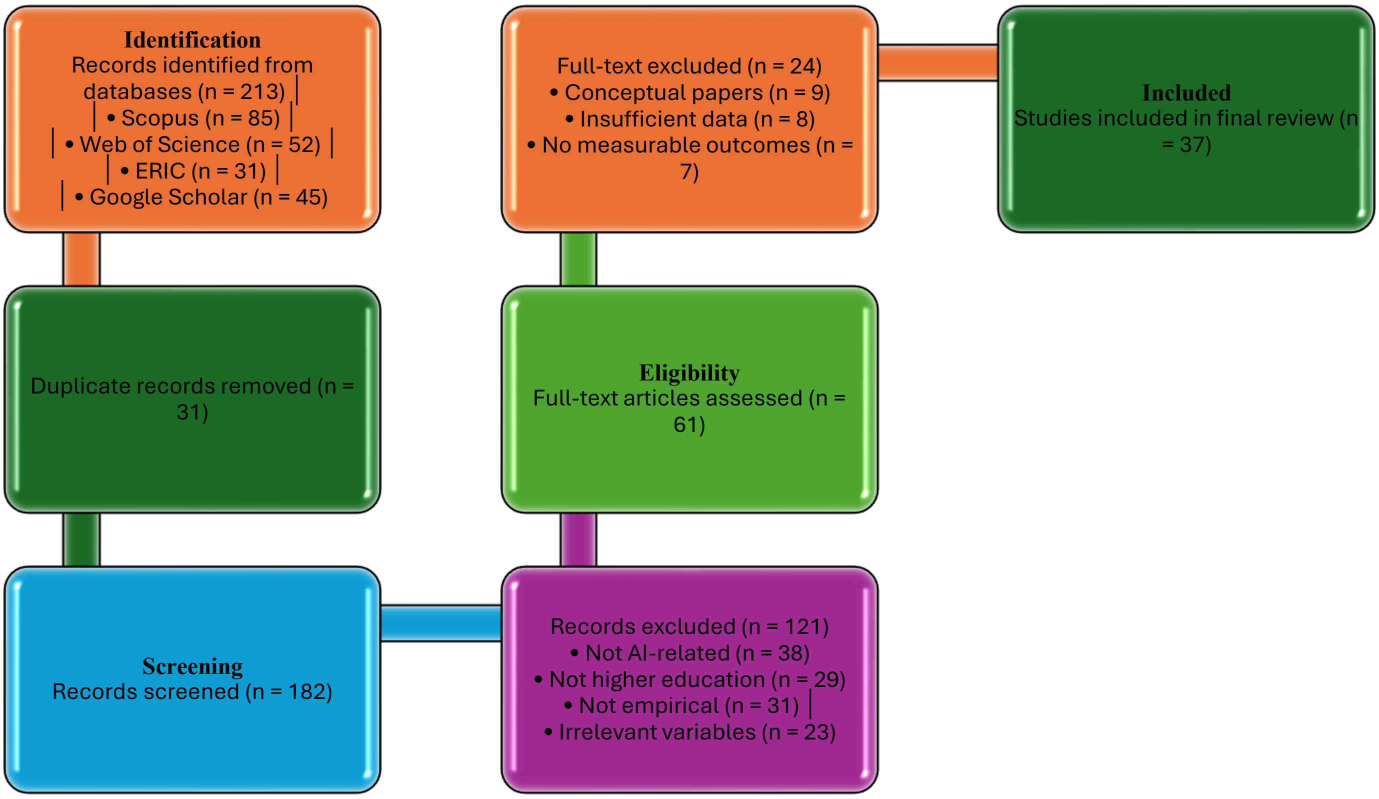

Figure 1: PRISMA Framework Flow

Inclusion and Exclusion Criteria

This study employed the PICOS framework—Participants, Interventions, Comparisons, Outcomes, and Study Design—to ensure the accuracy and reliability of the findings. The selected studies focused on university students in higher education environments to fulfill participant criteria (Gu & Yan, 2025). The studies were required to utilize AI-powered tools for assignments or academic purposes (Yu et al., 2025). The comparison criteria emphasized studies that contrasted AI-based learning tactics with traditional teaching methods or non-

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AI learning environments (Dong et al., 2025). Only studies that provided measurable academic success indicators—such as GPA, test scores, or measures of student engagement—were included for outcomes (Dong et al., 2025). The review focused on empirical research methodologies, including quasi-experimental designs, experimental studies, and Partial Least Squares Structural Equation Modeling (PLS-SEM) techniques (Aljuaid, 2024).

To maintain the review's relevance, certain exclusion criteria were employed. This review is confined to the higher education sector, excluding non-English publications, conceptual papers, and studies related to K–12 education (Dong et al., 2025; Aljuaid, 2024).

Table 3: Inclusion and exclusion criteria

Criterion	Inclusion Criteria	Exclusion Criteria
Participants (P)	Higher education students (undergraduate/postgraduate)	K-12 students, professionals outside academic context
Intervention (I)	AI-powered learning tools (GenAI, ChatGPT, adaptive learning systems, tutoring systems)	General ICT tools or administrative AI systems
Comparison (C)	Traditional learning, unguided AI usage, non-AI scaffolded environments	No baseline or control comparison
Outcomes (O)	Academic achievement, engagement, motivation, learning outcomes, knowledge acquisition	Social media use, satisfaction-only studies
Study Design (S)	Quantitative, experimental, quasi-experimental, mixed methods, PLS-SEM	Editorials, dissertations, conceptual papers, theoretical reviews

To enhance methodological transparency and consistency of selection, the PICOS framework was applied. This was done through setting boundaries to the investigation.

Quality Assessment and Risk of Bias

To improve the reliability of the review findings, a systematic assessment of quality for all selected papers was conducted following established systematic review frameworks (Kitchenham & Charters, 2007). The studies were evaluated against five criteria:

- Accuracy of research goals
- Method appropriateness
- Adequacy of Sample
- Rigour in Data Analysis
- Accuracy of result

Each criterion was scored as:

* **1 = Yes**

* **0.5 = Partially**

* **0 = No**

Studies scoring below 3.0 were excluded from the final review.

In addition, a formal risk-of-bias assessment was conducted to identify possible weaknesses in study design. The review considered:

- selection bias
- reporting bias
- measurement bias
- publication bias

The majority of the studies we reviewed presented a moderate to low risk of bias. Nevertheless, publication bias could still be a limitation as good AI-related results are more likely to be published (Aljuaid, 2024). In order to overcome this some databases and grey literature sources were incorporated.

Table 4: Quality Assessment and Risk-of-Bias Matrix

Assessment Domain	Criteria	Evaluatin Scale
Research objective clarity	Clearly stated aim and objectives	Yes / Partial / No
Methodological	Appropriate design and procedures	Yes / Partial / No
Sample adequacy	Sufficient sample size and representativeness	Yes / Partial / No
Data analysis validity	Appropriate statistical or thematic analysis	Yes / Partial / No
Findings reliability	Findings supported by evidence	Yes / Partial / No
Selection bias	Risk of biased participant selection	Low / Moderate / High
Reporting bias	Selective reporting of outcomes	Low / Moderate / High
Measurement bias	Reliability of instruments used	Low / Moderate / High
Publication bias	Overrepresentation of positive findings	Low / Moderate / High

Social Cognitive Theory (SCT): The Role of Self-Efficacy

The main theoretical framework used in this review to understand the impact of self-efficacy on AI-assisted learning programs is the social cognitive theory (SCT). Social Cognitive Theory explains learning as a dynamic relationship among personal components, environment, and behavior through triadic reciprocal determinism (Shahzad et al., 2024).

Self-efficacy is one of the basic elements of self-competence theory (SCT), which means students' belief in their ability to successfully complete academic activities (Bećirović et al., 2025). AI-enhanced learning settings can also improve self-efficacy by using artificial intelligence technologies. This is done through providing rapid feedback, adaptive guidance, and opportunities for repeated mastery (Shahzad et al., 2024b).

Another topic presented in this study is the "self-efficacy paradox. According to Tarhini et al. (2026), an overreliance on AI-assisted problem-solving may cause students to become too dependent on the technology, which may then impede their capacity for critical thinking.

Table 5: Theoretical Mapping of the Engagement-Scaffolding Nexus

Theoretical Framework	**Core Concept Applied**	**Role in the Nexus**	**Contribution to the SLR**
Cognitive Load Theory (CLT)	Extraneous vs. Germane Load	Efficiency Mechanism	Explains how AI reduces "noise" (extraneous load) so students can focus on engagement (germane load).
Constructivism & ZPD	Zone of Proximal Development	Scaffolding Mechanism	Defines AI as a "conditional scaffold" that must be guided by a teacher to stay within the student's learning zone.
TAM / UTAUT / TPB	Perceived Usefulness & Attitude	Usage Initiation	Explains the psychological drivers (PU, PEOU) that lead a student to adopt AI in the first place.
Social Cognitive Theory (SCT)	Self-Efficacy & Reciprocal Determinism	Persistence Mechanism	Explains how a student's confidence in their AI skills drives deeper, sustained cognitive engagement.

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RESULTS

Descriptive analysis of the retrieved studies

Thirty-seven empirical studies published from 2019 to 2026 were retrieved according to PRISMA 2020 protocol for this review. They were a variety of experimental, quasi-experimental, survey-based and Structural Equation Modelling (SEM) studies which focused on exploring the effect of AI, student engagement, teacher scaffolding on academic achievement in higher education. Geographically, the retrieved studies were from Asia, Europe, Middle East and some emerging higher education environments like Afghanistan and Pakistan. The studies predominantly from Asian countries are evidence that the usage of AI technology in higher education has greatly expanded in this region.

The following AI technologies are included in the reviewed literature:

- Generative AI (ChatGPT + other tools)
- Adaptive learning systems
- Intelligent Tutoring System
- Artificial Intelligence Driven Feedback
- Mechanisms learning analytics systems

Most studies found positive correlations between AI use and academic achievement, although some studies identified risks of over-reliance on AI technologies.

Quality assessment of included studies

All included studies were assessed for methodological quality using the MMAT criteria adapted.

Table 4 : Quality assessment of included studies

Quality Indicator	% of studies
Clear objectives of research	100%
Sound methodological design	94.6%
Use of valid measure	91.9%
Acceptable sample size	89.2%
Statistical robustness	86.5%
Discussion of limitations	78.4%

In conclusion, studies generally provided moderate to high methodological quality data; however, some had a strong reliance on self-reported measures and cross-sectional data, thus having potential for response bias and precluding causally interpretable relationships.

AI and Academic Performance (RQ1)

There is empirical support showing that AI is positively related to academic performance. There was considerable effect sizes reported in meta-analytic research:

Study	Effect Size
Dong et al. (2025)	0.924
Gu & Yan (2025)	g = 0.683
Multiple-study synthesis	SMD = 0.961

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Some empirical studies had reported significant improvements in:

- GPA
- Test scores
- Knowledge retention
- Problem solving
- Assignment quality

The study which adopted the adaptive learning system increased average test scores by 68.4% to 82.7%, whereas one involving AI supported instructional methods led to an increase of course grades by approximately 75% to 86%.

In roughly 1/4 of the articles analysed there was evidence of negative or zero impact, these typically showed links between high levels of AI use and:

- Decreased critical thinking
- Shallow learning techniques
- Procrastination in academia
- Over-reliance on AI generated text

These suggest an "AI performance paradox," where effectiveness is mediated by AI use.

Mediating Mechanism-Student Engagement (RQ1)

Student engagement was identified as the most persistent mediating factor between AI usage and academic achievement. There were four different definitions that were applied to the concept of student engagement: Cognitive Engagement, Behavioural Engagement, Emotional Engagement and Social Engagement. These were defined as students putting more of their mental resources into their learning to comprehend, analyse and use what they know. Students are more involved in learning tasks and carry them out more reliably. Students are more interested, enthusiastic and are in the mood to learn. Students learn collaboratively and from others around them. AI mediated students' academic success indirectly by enhancing these measures of engagement rather than directly enhancing achievement. The pathway to the mediator between AI usage and academic achievement can be shown as below:

Figure 2: Mediation Pathway Linking AI Use, Student Engagement, and Academic Achievement

Students who use AI because it is effective are also more likely to be highly engaged with their studies, and in turn are likely to achieve greater academic results.

Teacher scaffolding moderates AI impacts (RQ2)

Teacher scaffolding proved a key moderator influencing the effectiveness of AI. The results showed clear distinctions between structured and unstructured use of AI.

Table 2 : Comparison of Effect Size for AI use by teacher scaffolding

Learning Context	Effect Size
AI with teacher scaffolding	g = 1.426
Autonomous AI use	g = 0.077

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Teacher scaffolding facilitates the following:

- Critical appraisal of AI output
- Ethical use of AI
- Reflective learning and knowledge application
- The development of higher-order thinking and metacognition
- The promotion of academic integrity

In contrast, students who did not receive scaffolded use of AI tended to use AI for the purpose of generating answers rather than building knowledge. The results indicate that AI has the potential to have greatest impact when it is used in a pedagogically supported context.

Digital readiness and AI literacy mediate AI impact (RQ3)

Two distinct studies highlight AI literacy and digital readiness as significant boundary conditions that can modulate impact. Specifically, students who showed more high digital literacy, high AI self-efficacy, and high technological proficiency had more positive learning experiences and academic gains in AI environments. However, AI literacy alone did not seem sufficient in determining academic impact as shown in two different studies.

Engagement-Scaffolding Link

The integration of findings provides the foundation for a conceptual framework, the Engagement–Scaffolding Nexus.

The framework states that:

- AI offers personalized and adaptive feedback to learning.
- The effect of AI on learning outcomes is mediated by student engagement.
- Teacher scaffolding moderates and strengthens this relationship.
- Digital literacy and AI readiness are contextual factors.

Conceptually:

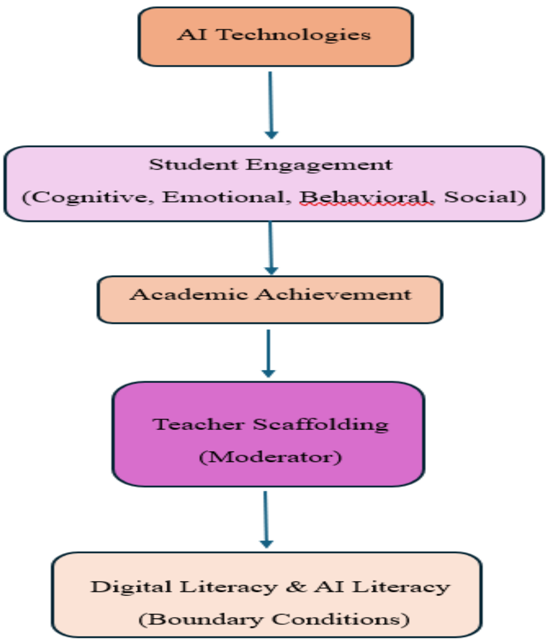

Figure 3: The Engagement–Scaffolding Nexus Framework

DISCUSSION

Synthesis of Main Study Results

The conducted systematic literature review presents evidence gathered from a total of 37 scholarly articles exploring the role of AI, student engagement, teacher scaffolding, and academic achievement in higher education environments. According to the results of this research, AI, especially generative AI applications like ChatGPT, demonstrates a positive effect on the learning outcomes of students in HEIs. As can be inferred from this review, there are three factors that contribute to enhanced learning outcomes facilitated by AI: personalized assistance provided to students; availability of timely feedback; and reduced cognitive load. Nevertheless, this positive effect is not automatic and requires certain pedagogical conditions to become evident. Namely, the use of AI is effective when student engagement levels are high and there is sufficient teacher scaffolding. It is worth noting that some researchers report the lack of impact or even adverse effects associated with the implementation of AI applications in educational processes. Such neutral or negative results were registered only in instances of unassisted usage of AI or substitution tasks instead of providing learning assistance.

The Mediating Effect of Student Engagement

In terms of mediating effects, student engagement has shown itself to be the most reliable means for explaining AI's influence on academic success. Specifically, across different studies, engagement emerges as the mediator through which AI helps achieve better learning outcomes. It is important to note that engagement can be understood as cognitive, behavioural, affective and social aspects of learning. AI improves cognitive engagement by promoting reflection and deep processing of materials. In turn, AI promotes higher levels of behavioural engagement in terms of increased task persistence and completion. Finally, it improves both motivational and emotional engagement through increasing motivation and reducing learning anxiety. Social engagement benefits from the availability of collaborative AI-powered learning experiences. As for theoretical models, the present study suggests that student engagement should be understood as part of Cognitive Load Theory and Self-Determination Theory. Namely, by providing automation of some processes and thus reducing extraneous cognitive load, AI creates conditions under which individuals are more able to engage in learning through applying cognitive resources actively. Therefore, it can be assumed that AI does not promote academic success independently; rather, it helps create the necessary environment in which engagement can occur.

The Moderating Influence of Teacher Scaffolding

Teacher scaffolding is one significant moderator affecting the success of the AI's contribution in higher education settings. The research conducted in this study consistently reveals a significant superior learning experience for the AI, particularly when the AI's operation takes place within a more structured and a teacher-directed learning setting. Firstly, teacher scaffolding serves the function of reinforcing the relationship between the use of AI with specific learning goals and course objectives. Second, teacher scaffolding can ensure the critical interrogation of information delivered through AI in order to prevent over-reliance. Thirdly, the use of AI can be guided through teachers to assist students with their tasks associated with the highest levels of cognitive processes, such as analysis, synthesis, and problem solving. A particularly noteworthy finding from the available literature concerns the contrast between AI use within a structured as opposed to unguided manner. Studies focusing on teacher-directed or structured integration of AI have generally shown positive results for students' academic performance and the depths of their learning experiences, whereas, an unguided application of AI appears to promote superficial learning, a loss of critical reasoning capacity and a dependence on automatic responses. Thus, the results lend to an understanding of AI as a "conditional scaffold" instead of a substitute for the teacher in terms of higher education instruction. Within the context of Vygotsky's Zone of Proximal Development (ZPD), the use of AI in a student's education can only be truly beneficial when appropriately mediated by a teacher that guarantees adequate difficulty and the appropriate level for development of the student.

The Engagement-Scaffolding Nexus

This review makes a significant contribution by proposing the Engagement-Scaffolding Nexus that clarifies the role of AI in student achievement through the intersection of student engagement and teacher scaffolding.

In this model, student engagement acts as the inner mechanism of student learning where AI exerts its impact on student cognition, whereas teacher scaffolding acts as the outer regulation mechanism that guides the application of AI in learning contexts.

The integration of empirical evidence implies that AI provides the greatest benefit when both student engagement and scaffolding are high, fostering deep learning, meaningful engagement, and better academic outcomes. When engagement and scaffolding are low, AI loses some of its effectiveness. The Nexus is consistent with existing learning theories such as Cognitive Load Theory, Self-Determination Theory, Social Cognitive Theory and Vygotsky's socio-cultural theory, as they all help illustrate how cognitive, motivational and instructional elements interplay to affect learning outcomes in AI-driven learning environments.

From a practical standpoint, the Engagement-Scaffolding Nexus recommends the harmonious coexistence of technology implementation and pedagogical practices. It stresses that technology cannot be implemented in isolation, but it should be integrated within a coherent learning system in which students are highly motivated to learn and where teachers actively orchestrate scaffolds.

Discipline-related, Geographical and Cultural Factors

The results show clear discipline-related, geographical and cultural disparities in terms of effectiveness of AI. The disciplinary aspect of the differences implies that the implementation of AI is more effective in STEM disciplines in comparison to humanities disciplines. The reason for this can be seen in the difference between the nature of learning activities. STEM requires students to perform certain procedures which are similar to what AI systems can perform. The geographical aspect implies that most of the research comes from the Asian context, as it is evident from the support from institutions and governments encouraging the digital transformation in higher education. At the same time, there is no enough research coming from Africa and Latin American countries. The cultural aspect may affect the adoption of AI as well as learning outcomes due to differences in educational values, the structure of teacher authority and technological acceptance. Nevertheless, there is not enough research to make any conclusion about it.

Ethical and Institutional Implications

This review highlights a number of ethical and institutional problems connected with the use of artificial intelligence in higher education. Among the main ethical problems are the ones associated with the academic integrity, since the students might use AI to submit assignments without real learning process. The other problem is associated with cognitive offloading, when the excessive reliance on artificial intelligence does not allow developing critical thinking and problem-solving skills. The other ethical problems are associated with the potential algorithmic bias, data privacy, and accuracy of AI-generated content. From the institutional standpoint, the implications are connected with the creation of proper policies regulating the use of artificial intelligence in the academic context. Universities should create guidelines which would differentiate between appropriate usage of AI and its substitution in assessments. Moreover, universities should provide faculty development programs in order to help educators integrate artificial intelligence in pedagogy. Just as importantly, universities should promote development of students' AI literacy.

Limitations of the Review and Future Research Directions

There are several limitations to discuss. First of all, only studies written in English were reviewed. Second, the vast majority of those are cross-sectional, limiting the possibilities to draw causational relationships. Third, there is considerable heterogeneity in AI tools, assessment approaches, and educational context, making the results incomparable.

In addition, the fast development of AI tools can make the results of the review obsolete due to constantly changing environment. Secondly, the large share of studies from Asian countries can limit the global validity of results.

In the future, researches should concentrate on longitudinal and experimental studies in order to clarify causation of AI effects. It is necessary to conduct more cross-cultural researches in order to see how the contextual variables impact on the effects of AI. Long term impact of AI on critical thinking, creativity, and independence of learners should be explored too. Finally, it is needed to validate the Engagement-Scaffolding Nexus empirically.

CONCLUSION

Synthesizing the 'Gap-Bridging' Evidence

The evidence suggests that GenAI tools successfully bridge the engagement-performance gap by bolstering motivation and self-efficacy, particularly when output quality is high. However, the R^2 = 0.9075 predictive power must be balanced against the existence of "High Usage, Low Belief" clusters, which indicate that many students utilize AI for utilitarian efficiency rather than deep learning. Digital Literacy remains the fundamental moderator; without it, the bridge to performance gains leads only to surface-level academic inflation. The future of higher education necessitates a strategic balance between leveraging innovation for efficiency and preserving the rigorous, independent critical thought that defines the university experience.

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