International Journal of Modern Education IJMOE
EISSN: 2637-0905
Volume: 8 Issue: 31 (September 2026) PP. 387-402

INTERNATIONAL JOURNAL OF MODERN EDUCATION (IJMOE)
www.gaexcellence.com/ijmoe

GLOBAL ACADEMIC EXCELLENCE

THE IMPACT OF APPLYING GEN-AI TO KNOWLEDGE RETENTION AMONG STUDENTS IN EDUCATIONAL INSTITUTES: A SCOPING REVIEW

Khadijah Wan Mohd Ghazali[1]*, Aslina Saad[2], Norazlin Mohammed[3], Ariff Idris[4]

[1] Fakulti Teknologi Maklumat dan Komunikasi, Universiti Teknikal Malaysia Melaka, Malaysia
khadijah@utem.edu.my https://orcid.org/0000-0001-5426-4894

[2]Faculty Of Computing and Meta-Technology, Universiti Pendidikan Sultan Idris, Malaysia
aslina@meta.upsi.edu.my https://orcid.org/0000-0002-6831-7325

[3] Fakulti Teknologi Maklumat dan Komunikasi, Universiti Teknikal Malaysia Melaka, Malaysia
norazlin@utem.edu.my https://orcid.org/0009-0003-7338-843X

[4] Fakulti Teknologi Maklumat dan Komunikasi, Universiti Teknikal Malaysia Melaka, Malaysia
miariff@utem.edu.my https://orcid.org/0009-0005-1864-8424

*Corresponding Author

Article Info:

Article history:
Received date: 07.06.2026
Revised date: 28.06.2026
Accepted date: 30.08.2026
Published date: 15.09.2026

To cite this document:

Ghazali, K. W. M., Saad, A., Mohammed, N., & Idris, A. (2026). The Impact of Applying Gen-Ai to Knowledge Retention Among Students in Educational Institutes: A Scoping Review. *International Journal of Modern Education, 8*(31), 387-402.

Abstract:

This scoping review explores the use of generative artificial intelligence (GenAI) in higher education and its impact on student learning outcomes. This review, drawing on the six steps of Arthur Arksey and O'Malley, pooled the findings of 10 empirical studies across the selected time span of 2024-2026 to map the current use, implications for cognition development and variations in academic performance related to GenAI tools. The journals assessed were mainly from different geographic regions such as South Korea, Japan, Vietnam, Kuwait, Saudi Arabia, the UK, Morocco, Pakistan, Ireland, and the USA and were retrieved from Web of Science and Scopus. It is concluded from combined results that teaching and learning in the school environment is significantly influenced by pedagogical design, scaffolding of instruction, and human supervision. Within a structured framework for validation, in adaptive tutoring systems, or in immersive virtual reality settings, GenAI tools serve as collaborative partners that support the retention of factual knowledge, boost student engagement, and promote autonomy of the learner. However, in settings where workloads are overwhelming and time is of the essence, undirected use of GenAI can inadvertently lead to procrastination, memory loss, and a direct negative effect on actual student performance. This scoping review highlights the key gaps in longitudinal assessments and framework of structural evaluations. It also provides evidence-based suggestions for curriculum designers and education policy makers looking to balance technological

International Journal of Modern Education
EISSN: 2637-0905
Volume: 8 Issue: 31 (September 2026) PP. 387-402

innovation and the maintenance of critical thinking and academic integrity.

DOI: 10.35631/IJMOE.831024

Keyword:

Academic Performance, Cognitive Load, Generative Artificial Intelligence, Higher Education, Knowledge Retention, Learner Autonomy, Student Engagement

Introduction

Generative artificial intelligence (GenAI) technologies, particularly the Large Language Models (LLMs) with the generative pre-trained transformer (GPT) technology, is an emerging global trend in higher education (HE) and a widespread paradigm shift (Abbas et al., 2024), (Lee & Otani, 2025). These innovative systems utilize cutting-edge deep learning architectures, which are capable of producing human-like material in an automated manner (Trindade et al., 2025). Although students and teachers have readily adopted these tools for smooth operations and self-directed learning (Bachiri et al., 2025; Nguyen et al., 2025), the uptake of these tools has yet to be rigorously investigated and evaluated.

An understanding of this phenomenon is important as it is a direct challenge to the academic standards given the dichotomy of how fast people adopt the technology and how slow their empirical understanding is of what long-term use does to the brain. With the students' workload and time constraints escalating, there is a critical need to understand the potential of GenAI as a catalyst for deep learning or as a shortcut that skips key mental processing steps (Abbas et al., 2024). Such research is significant when it comes to maintaining a focus on knowledge retention, serving as a foundation for academic mastery, in an increasingly AI-enhanced educational environment (Nguyen et al., 2025).

This is especially important as universities navigate the changing landscape of digital transformation, particularly regarding the impact of GenAI on the learning outcomes of their students (Nguyen et al., 2025), (Yao & González-Vélez, 2025). In this educational scenario, GenAI encompasses a wide range of automated tools such as conversational chatbots, adaptive e-tutors, multi-agent Retrieval-Augmented Generation (RAG) pipelines, and embodied non-player characters (NPCs) in virtual learning environments (Al Taqataq et al., 2025), (Yao &

González-Vélez, 2025). The student learning outcomes is a construct with multiple dimensions: academic attainment (quantitative data: Cumulative Grade Point Average), conceptual understandings, learner autonomy, cognitive load experience, and knowledge retention (Truong & Nguyen, 2025), (Lee & Otani, 2025), (Abbas et al., 2024).

The empirical relationship between the two variables is very complicated and bi-directional (Abbas et al,. 2024), (Nguyen et al., 2025). On the other hand, the adoption of GenAI in educational practice holds great promise for individualized learning and lowering students' learning anxiety while providing real-time and scalable feedback (Bachiri et al., 2025), (Nguyen et al., 2025). For example, in a specialized language-learning environment, the ChatGPT language learning tutor adjusts the difficulty of the language, the speed of the task, and the topicality to suit the needs of individual learners, which increases self-regulated learning and language learning motivation (Al Taqataq et al., 2025). Interactive AI-generated simulations and concept mapping are utilized as tools for active, deliberate practice to support visualization of complex and non-linear variables (Trindade et al., 2025), (Truong & Nguyen, 2025) in quantitative business/engineering areas. Such structured interactions are closely related to Self-Determination Theory (Ryan & Deci, 2000), meeting the psychological needs for autonomy and competence, and driving an individual's technology use into deep, cognitive engagement (Nguyen et al., 2025).

Conversely, extensive research cautions that the unrestricted use of GenAI can result in a phenomenon dubbed “cognitive offloading” and ultimately in a significant loss in the learning landscape (Abbas et al., 2024). GenAI can be a stand-in to perform tasks on behalf of students when they have high workloads and time pressures, leading to surface learning without critical thinking especially during the academic term (Abbas et al., 2024). This unguided shortcut directly distorts the active cognitive processes in the process of transferring knowledge from working memory to long-term schema retention, such as active retrieval and spacing (Bachiri et al., 2025). Prolonged use of generative tools creates a tendency towards procrastination, fosters poor memory retention, and negatively impacts academic outcomes, as noted by Abbas et al. (2024).

While there is increased interest in the arena of Educational Technology, there is a critical gap in studies in this area (Nguyen et al., 2025). A significant portion of the early literature is speculative commentaries, non-empirical editorials, or descriptive surveys lacking analysis of the modulation role of specific pedagogical designs and validation processes for student outcomes (Abbas et al., 2024). Lack of systematic scoping to map out the different technical configurations (Knowledge Graph-RAG integrations, virtual reality systems, and macro-powered human validation checklists) of GenAI and their direct consequences on student learning (Tracy & Spantidi, 2025; Trindade et al., 2025; Yao & González-Vélez, 2025). Therefore, the goal of this scoping review was to draw a picture of the empirical landscape of GenAI in higher education from 2024 to 2026. The ultimate research goal is to develop a mechanism-focused framework to explain how and when GenAI improves or hinders student learning outcomes.

The structure of this work is as follows: Part 1 provides literature review about GenAI and student learning outcomes; Part 2 explains the procedure in conducting this scoping review; and Part 3 presents the results of conducting the scoping review. Part 4 then concludes with a discussion of limitations, future research recommendations, implications, and conclusions.

International Journal of Modern Education IJMOE
EISSN: 2637-0905
Volume: 8 Issue: 31 (September 2026) PP. 387-402

Methodology

This is a scoping review; the literature was scoped in a structured way to ensure a rigorous, transparent and reproducible mapping of the literature. This was done using the six stages framework that was originally developed by Arksey & O'Malley (2005). Further, the Preferred Reporting Items for Systematic Reviews and Meta-Analyses Extension for Scoping Reviews (PRISMA-ScR) guidelines (Ramdan et al., 2024) were used to inform the study. The six steps which are carried out for this research are explained on following paragraphs.

Step (1): Research Question to be addressed. Research questions for this review were developed around specific dynamics. The focus was on the structural and cognitive relationship between generative AI and student outcomes. The main question was, "How does the use of GenAI in tertiary education affect students' cognitive, behavioural, and affective learning outcomes?" Secondary questions were designed to investigate specific configurations of GenAI. The setups that make the cognitive load optimal were explored. The connection between self-directed uses of AI and academic procrastination was also investigated. Lastly, methods for improving knowledge retention over long periods of time using human-in-the-loop validation techniques were explored.

Step (2): Review literature relevant to the aim of the scoping review. A thorough search was conducted in two electronic databases. The Web of Science and Scopus were these databases. The search included publications in the time period January 2024 to May 2026. This time period was chosen to capture the fast-paced evolution of empirical studies. This rapid growth followed the widespread availability of consumer-grade LLMs. Boolean combinations of high-level terms were employed in the search strings. The specific query used was: ("generative artificial intelligence" OR "GenAI" OR "ChatGPT" OR "large language models" OR "LLM") AND ("learning outcomes" OR "academic performance" OR "cognitive load" OR "knowledge retention" OR "student engagement") AND ("higher education" OR "university" OR "college" OR "tertiary"). Next, this automated query was supplemented with manual searches. The previous reviews of tables of contents from the best journals in the field of education technology were checked.

Step (3): choose the articles appropriate for analysis. Using a reference management software, sourced citations were gathered to efficiently exclude duplicate citations. Study selection was conducted using a two-stage screening process. The screening process starts with screening the titles and abstracts. A complete text assessment against strict, well-defined inclusion/exclusion criteria then ensued. The following basic parameters were used in selecting the sites. In a first step, only peer-reviewed journal articles were selected to guarantee a sufficient level of academic rigor and to ensure a high quality of the study papers and methodological transparency (Hodgkinson & Ford, 2014). This strategy took advantage of a powerful indexing system, of this kind Web of Science database covers more than 760 million multidisciplinary records (Sánchez et al., 2017). Second, only papers that adopted empirical research methodologies (quantitative, qualitative, or mixed methods) were included in the review since it is known that in the study of education, such methods are generally more suitable and prevalent than other research methodologies (Johnson & Christensen, 2020). Third, only articles that were in English were considered eligible, because English is the main linguistic medium of academic communication all over the world. Finally, a major focus was the intersection of GenAI tools and student learning outcomes, with a focus on higher education populations. Allowances have been made for highly structured health or safety educational

International Journal of Modern Education
IJMOE
EISSN: 2637-0905
Volume: 8 Issue: 31 (September 2026) PP. 387-402
studies, but the relevance to the adult learning frameworks is clearly stated. Lastly, there was a selection criterion, ensuring only recent literature was considered, from 2024 to 2026, so that the synthesis can benefit from the latest technology advancements and high quality scholarships that are part of such a quickly developing field as current research.

Table 1: Inclusion and Exclusion Criteria

Criterion	Inclusion Criteria	Exclusion Criteria
Publication Type	• Peer-reviewed journal articles	• Gray literature, book chapters, conference proceedings, conference abstracts, opinion pieces, non-empirical conceptual papers, and reviews
Study Design	• Empirical studies utilizing quantitative, qualitative, or mixed-methods designs	• Non-empirical or purely theoretical studies
Language	• Articles written in English	• Non-English publications
Publication Year	• Published between the years 2024 and 2026	• Published before 2024
Topic / Focus	• Explicitly focused on the intersection of Generative AI tools and student learning outcomes	• Unrelated to generative AI or cognitive/learning outcome
Target Population	• Centered on higher education populations (with minor allowances for highly structured health or safety educational studies relevant to adult learning frameworks)	• Non-higher education populations (unless fitting the adult learning exception)

Source: Authors' Research

Step (4): Charting the data to be presented. A common data-charting spreadsheet was created. A template of the characteristics was systematically extracted from each eligible study using this tool. Extracted key fields are authors, year of publication, geographical location and target student group. The type of GenAI system used, and their technical set-up were also included. The recording of research design, target variables and measuring instruments were conducted. Lastly, important quantitative or qualitative results were gleaned. Absolute data fidelity was ensured by this structured mapping. There was also a high level of inter-study efficiency.

Step (5): Collating, summarizing and reporting the data. Convergent thematic synthesis was used to analyse the charted data. This method was applied to identify recurring patterns, contradictions, and structural relationships across the heterogeneous literature. Results that were relevant were grouped into three main themes: The first theme that came out was "Scaffolded Autonomy versus Unscaffolded Cognitive Offloading". The second was classified under the Cognitive Load Optimization. The third was titled: The Paradox of Immediate Performance and Long-Term Retention. These themes offered a structured framework which was vital for integrating the cognitive implications of AI between the disciplines.

International Journal of Modern Education
IJMOE
EISSN: 2637-0905
Volume: 8 Issue: 31 (September 2026) PP. 387-402
Step (6): Discussion of the results. The created themes have been analyzed and assessed as part of the final stage of research work. These were contrasted to well-known concepts in the field of educational psychology. The frameworks included Self-Determination Theory (Ryan & Deci, 2000), Cognitive Load Theory (Sweller, 1988), the Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2012), and the Information Adoption Model (Sussman & Siegal, 2003). This critical evaluation resulted in actionable recommendations. In addition to this, second- and third-order guidance was provided to curriculum designers, educational administrators and technology developers. The purpose of this guidance is to support implementing responsible AI-supported instructional systems.

Findings

The results of the screening and selection process ultimately resulted in the isolation of high-quality, empirical studies meeting all of the primary research variables, as shown in Figure 1.

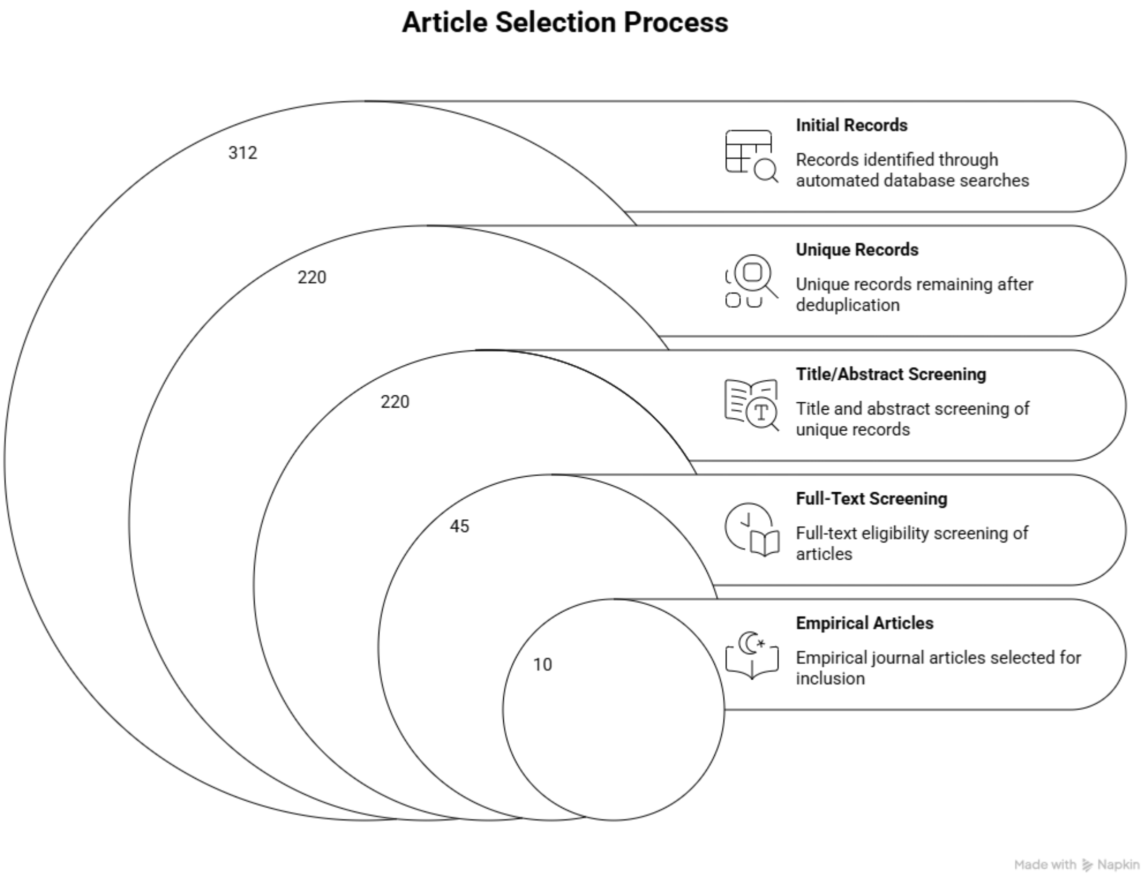

Figure 1: Flow Diagram of Research Selection Process Using Preferred Reporting Items for Systematic Reviews (PRISMA)

Source: Adapted from Moher et al. (2015)

The database search yielded a total of 312 papers of which were considered for this scoping review. After removing duplicate papers (92 papers), 220 papers are left which can be used for this study. Of these 220 articles, there were 175 articles which were excluded because they were not empirical research or were not related to the objectives of this scoping review. The

International Journal of Modern Education
IJMOE
EISSN: 2637-0905
Volume: 8 Issue: 31 (September 2026) PP. 387-402
publications from 2024 to 2026, and the article from the field of education and generative AI with scientific status were only 45 publications that were qualified based on the inclusion criteria for empirical articles. Lastly, only 10 articles were included, using quantitative approach as well as the mixed-methods approach because it was found that these articles' reporting items supported the objective of the study and were more relevant and supported the research aim as presented in Figure 1.

Findings and Discussions

Table 1 shows the 10 research articles that were selected for a scoping review according to methodology criteria. Results identified three main areas that are significantly affected by the use of generative AI: cognitive structures, behavioural patterns, and academic outcomes.

Table 1: Charting the Data

No.	Study	Cohort	AI Tool	Research Design	Variables	Key Findings
1	Lee & Otani (2025)	Undergraduate (N = 57)	ChatGPT	Survey	Motivation, Cognitive Load, Satisfaction	High motivation (mean (M) = 3.79, standard deviation (SD) = 0.818); significant mental effort (M = 3.18, SD = 0.909); enthusiasm (M = 3.60, SD = 0.884)
2	Truong & Nguyen (2025)	STEM (N = 570)	Napkin AI	Structural Equation Modeling (SEM)	Knowledge Retention (KR) and Loss of Retention (LOR)	Actual use of mind mapping (AUM) has strong direct positive effect on KR (beta (β) = 0.320, $p < 0.001$), and direct negative effect on

International Journal of Modern Education
IJMOE
EISSN: 2637-0905
Volume: 8 Issue: 31 (September 2026) PP. 387-402

						LOR (β = -0.206, $p < 0.001$).
3	Habeeb & Dashti (2026)	Preschoolers (N = 65)	AI - generated animation	Quasi-Experiment	KR	Experimental scores rose from 3.71 to 10.85/12 ($\eta2$ = 0.9763, d = 10.88, $p < 0.001$).
4	Nguyen et al. (2025)	Higher learning (N = 488)	GenAI	Survey with Partial least squares structural equation modelling (PLS-SEM)	Engagement, Usability	Engagement has a positive significant effect on Knowledge Acquisition (β = 0.672, p = 0.000) and Retention and recall (β = 0.742, p = 0.000).
5	Bachiri et al. (2025)	MOOCs (N = 50)	AI-generated flashcards	Survey	Active Retrieval, Retention	AI flashcard helpfulness 4.1 (SD = 0.9), relevancy 4.2 (SD = 0.8); enhanced memory retention 75%.
6	Tracy & Spantidi (2025)	University (N = 52)	GPT-powered virtual reality class	Experiment	engagement, cognitive load, knowledge retention, and performance	Positive increase in understanding (M = 4.06, SD = 0.78); Lower intrinsic

						cognitive load ($F = 4.58$, $p = 0.005$); enhanced conceptual knowledge transfer ($\chi 2 = 8.74$, $p = 0.012$)
7	Abbas et al. (2024)	University (N = 494)	ChatGPT	PLS-SEM	Procrastination, memory loss, and academic performance	Use of ChatGPT positively related to procrastination ($\beta = 0.309$, $p < 0.001$) and memory loss ($\beta = 0.274$, $p < 0.001$), and negative effect on academic performance ($\beta = -0.104$, $p < 0.05$)
8	Al Taqataq et al. (2025)	EFL Female (N = 60)	ChatGPT	Experiment	Adaptability, autonomy and language retention	Gains in perceived adaptability ($F = 31.95$, $p < 0.001$, partial η^2 $eta^2 = 0.35$), autonomy ($F = 6.28$, $p = 0.015$, partial η^2 $eta^2 = 0.09$), and language retention ($F = 16.30$, $p < 0.001$,

International Journal of Modern Education
IJMOE
EISSN: 2637-0905
Volume: 8 Issue: 31 (September 2026) PP. 387-402

						partial η^2 eta2 = 0.22).
9	Trindade et al. (2025)	Business (N = 41)	ChatGPT	Pre-Post	Trade-offs	The experimental group achieved superior post-test understanding of trade-offs ($p < 0.01$).
10	Yao & González-Vélez (2025)	Simulated (N = 100)	KG-RAG	Benchmark	Performance	KG-RAG improved domain F1 scores (ML +64%, Biology +44%) and resolved length bias.

Source: Authors' Research

This comparative analysis of these 10 studies yields four major themes that describe the multi-faceted nature of the relationship between generative AI and student learning outcomes. This is because sourced findings have demonstrated that GenAI is not a neutral tool. Rather, it serves as a structural mediator of cognitive functions, behavioral routines, and memory consolidation (Abbas et al., 2024), (Nguyen et al., 2025), as illustrated in Table 2. Theme and sub-theme mapping and description of research is provided in the Table 2 below.

Table 2: Themes in Reviewed Articles

Theme	Sourced Studies	Cognitive / Pedagogical Dynamics
Theme 1: Scaffolded Autonomy vs. Unscaffolded Cognitive Offloading	Abbas et al. (2024); Al Taqataq et al. (2025); Nguyen et al. (2025)	Evaluates how self-regulated learning and personalization foster autonomy, contrasted with task-driven shortcuts and procrastination under workload pressures.
Theme 2: Cognitive Load Optimization	Tracy & Spantidi (2025); Lee & Otani (2025); Habeeb & Dashti (2026)	Analyzes how structured instruction (e.g., VR agents, multi-phase courses, or animated media) reduces intrinsic load and supports germane processing.
Theme 3: Paradox of Immediate Performance vs. Long-Term Retention	Truong & Nguyen (2025); Bachiri et al. (2025)	Explores the "desirable difficulties" introduced by active recall and mind mapping, which enhance long-term recall despite initial scoring dips.

International Journal of Modern Education
IJMOE
EISSN: 2637-0905
Volume: 8 Issue: 31 (September 2026) PP. 387-402

Theme 4: Human-in-the-Loop Validation and KG Engineering	Trindade et al. (2025); Yao & González-Vélez (2025)	Details the programmatic and manual frameworks (Excel validation checklists, RAG pipelines, Knowledge Graphs) that mitigate AI hallucinations.

Source: Authors' Research

Scaffolded Autonomy versus Unscaffolded Cognitive Offloading is the first important theme. This is a significant moderator of learning outcomes of students in all disciplines studied (Al Taqataq et al., 2025), (Nguyen et al., 2025). Based on Self-Determination Theory (Ryan & Deci, 2000), learning technologies are very effective if they can meet the psychological needs of students for autonomy and competence (Nguyen et al., 2025). Al Taqataq et al. (2025) and Nguyen et al. (2025) provided as proof that personalized and interactive GenAI platforms allow and promote self-regulated learning autonomy. This enables students to set their own targets, pick their own tasks and get instant feedback on progress. That, however, is a workload-shortcut loop, which results from the integration of these tools without pedagogical scaffolding under high academic workloads and time constraints (Abbas et al., 2024). Abbas et al. (2024) established that overburdened students utilise ChatGPT as a substitute proxy actor, copying and pasting assignments to bypass the cognitive effort required for learning. This replacement use is the direct cause of academic procrastination, reduced memory retention and actual reduction of overall academic achievement as evidenced by decreasing Cumulative Grade Point Averages.

The second theme is **Cognitive Load Optimization Paradigm**. Under Cognitive Load Theory (Sweller, 1988), learning is optimised when the extraneous cognitive load is blocked from working memory, leaving space for both internal and germane cognitive load (Tracy & Spantidi, 2025). Tracy & Spantidi (2025) proved that having a GPT-powered teaching assistant (TA) in an Immersive Virtual Reality (VR) environment is effective in reducing intrinsic cognitive load (ICL) arising from complex algorithms. This scaffolding enables students to allocate greater amounts of germane load and to achieve better conceptual knowledge transfer without the cognitive overload. In the more conventional world of textbook-based learning, however, studying prompt engineering and conducting AI output evaluations at the same time may create significant cognitive friction, as identified by Lee & Otani (2025). In order to avoid overloading, this calls for a very structured, multi-phase curriculum scaffolding.

The third big theme is **The Paradox between Immediate Performance and Long-term Retention**. The structural trade-off is well illustrated in the study by Truong & Nguyen (2025) where they use concept-mapping to investigate the essence of STEM. It was found that there was a direct positive effect of the use of Napkin AI mind mapping on the outcomes of the long-term knowledge retention and there was a direct negative effect on the outcomes of the immediate short-term knowledge. Active, generative learning methods enable to infuse "desirable difficulties" into the learning process (Bachiri et al., 2025), (Truong & Nguyen, 2025). Such challenging actions increase the initial level of mental effort, and therefore temporarily lower the immediate test scores, but they help to deeply encode schemas. This leads to much better knowledge retention and recall over long periods of time than conventional teaching methods where the student is the recipient of the imparted knowledge.

The next large theme is **Human-in-the-Loop Validation and Knowledge Graph Engineering**. However, as LLMs can generate some kind of math-related mistakes, hallucination, or significant bias, successful adoption in education should include a structured

International Journal of Modern Education
IJMOE
EISSN: 2637-0905
Volume: 8 Issue: 31 (September 2026) PP. 387-402

verification system (Trindade et al., 2025), (Yao & González-Vélez, 2025). Trindade et al. (2025) confirmed that when a validation sheet is built in a macro-powered Excel sheet along with a business game powered by ChatGPT, students can actively verify and adjust the AI's calculations. The validation process turned a potentially unpredictable AI interaction into a trustworthy teaching tool, so that the students feel more confident and understand better on the level of concept about what cost tradeoffs mean. Yao & González-Vélez (2025) at the system level showed that combining a structural Knowledge Graph (KG) with a RAG pipeline reduced the likelihood of hallucinations. It also has a great impact on the quality and accuracy of the domain specific and customized outputs in specialized science fields. This programmatic emphasis on source credibility and structural quality seems to be quite consistent with Information Adoption Model's (Sussman & Siegal, 2003) underlying theoretical tenets regarding the critical evaluation of argument quality and structural trustworthiness that heavily mediate the adoption of dynamically generated knowledge.

Background of the Research Included in the Review

The empirical literature is geopolitically varied and shows a worldwide reaction from scholars to the quick surge of GenAI in Higher Education (Table 3).

Table 3: Number Of Research Based On Country

Country/Region	Number of Studies
Morocco	1
Kuwait	1
Saudi Arabia	1
South Korea/JP	1
Vietnam	1
Pakistan	1
United Kingdom	1
Ireland	1
United States	2

Source: Qwn Finding

The countries of these researched studies are shown in Table 3. The reviewed works were undertaken in eight different countries, i.e., South Korea and Japan (Lee & Otani, 2025), Vietnam (Truong & Nguyen, 2025), Kuwait (Habeeb & Dashti, 2026), the United Kingdom (Nguyen et al., 2025), Morocco (Bachiri et al., 2025), Pakistan (Abbas et al., 2024), Saudi Arabia (Al Taqataq et al., 2025), Ireland (Yao & González-Vélez, 2025), and the United States (Tracy & Spantidi, 2025), (Trindade et al., 2025). Most of the research investigations are held in an Asian and Middle Eastern context where the educational models are facing a rapid digital transformation (Abbas et al., 2024), (Al Taqataq et al., 2025).

International Journal of Modern Education
IJMOE
EISSN: 2637-0905
Volume: 8 Issue: 31 (September 2026) PP. 387-402

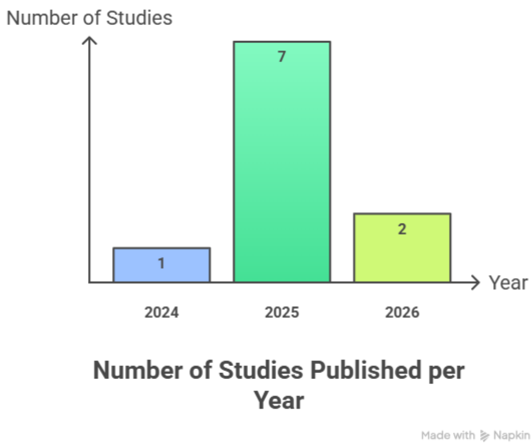

Figure 2: Year of publication in the WoS and Scopus databases

Figure 2 shows the number of papers published on WoS and Scopus based on the year of publication between 2024 and 2026. One was published in 2023/2024 (Abbas et al., 2024). A dramatic surge was observed in 2025, which yielded seven peer-reviewed publications (Bachiri et al., 2025), (Lee & Otani, 2025), (Nguyen et al., 2025), (Al Taqataq et al., 2025), (Tracy & Spantidi, 2025), (Trindade et al., 2025), (Truong & Nguyen, 2025). This was then followed by two papers, published early in 2026, (Habeeb & Dashti, 2026), and (Yao & González-Vélez, 2025), that indicated a relatively consistent shift into much more structured, empirical, multi-agent work.

Limitation and Recommendations

One of the chief methodological limitations of this scoping review is that it includes only those empirical articles that were identified by Web of Science and Scopus database indices. This limited range of databases opens avenues for research and reflection on the importance of including wider databases to establish a more holistic view of the role of generative AI in education (Abbas et al., 2024). A broader scope of pertinent academic literature will be found through a search across additional databases (Lee & Otani, 2025). This is particularly important as research on generative AI has surged in recent years, especially among researchers examining the multifaceted psychological and practical challenges of developing adaptive tutoring systems, which strive to deliver personalized education and support to students at every stage of learning (Al Taqataq et al., 2025). The future holds great promise in enriching search collections with other databases such as those provided by Springer and ProQuest (Nguyen et al., 2025). These are very broad searches that would produce organised and thorough data sets (Yao & González-Vélez, 2025). Second, statistically oriented designs provide a vital access point to understanding and reporting AI-cognitive outcomes in a more fine-grained and precise manner (Tracy & Spantidi, 2025). Also, remember that literature reviews must be continually and thoroughly assessed. AI in higher education R&D has a strong focus on the immediate timeframe. The current research context implies the need for future research to be systematically conducted in a meta-analytical way. These could facilitate the systematic extraction, combination, and full assessment of quantitative and qualitative evidence from diverse populations of students (Trindade et al., 2025). The shift to these grander approaches is needed to validate the conclusions drawn from existing practices and provide a valid basis for future designs and ethically considerate integration of educational technology.

Conclusion

The findings from this scoping review clearly establish that the future of tertiary education is rapidly transforming with the influence of Gen AI. The material supplied, however, is sufficient; although not complete. This scoping review investigates a wider spectrum of research areas and the growing number of studies involving generative AI amongst universities. These are key findings: Pedagogy, scaffolding, and the management of cognitive loading and of human-in-the-loop validation is very important. Given the results, unguided technology use may lead to cognitive offloading, while guided integrations may lead to authentic cognitive engagement. This discussion offers a general overview; however, more research is required to clearly outline the cognitive and psychological effects of an AI mediated environment upon students in the long term. Moreover, other variables that might be factors influencing the learner's autonomy and language retention in digital education should be further explored, which calls for longitudinal and empirical studies to establish agreement. Among the assessment's findings is a research lacuna and calls for the development of more extensive databases to extensively examine the impact of generative AI with respect to objective academic achievement. Overall, this study comprehensively summarizes the scope of research, the current status, and the directions for future research.

Acknowledgements:	The authors would like to express their sincere gratitude to Universiti Teknikal Malaysia Melaka, Malaysia for providing the necessary resources and support throughout the course of this research. Special appreciation is extended to colleagues and peers who contributed valuable insights and constructive feedback, which greatly enhanced the quality of this paper.
Funding Statement:	No Funding
Conflict of Interest Statement:	The authors declare that there is no conflict of interest regarding the publication of this paper. All authors have contributed to this work and approved the final version of the manuscript for submission to the International Journal of Modern Education (IJMOE).
Ethics Statement:	This study did not involve any human participants, animals, or sensitive data requiring ethical approval. The authors confirm that the research was conducted in accordance with accepted academic integrity and ethical publishing standards.
Author Contribution Statement:	All authors contributed significantly to the development of this manuscript. Khadijah Wan Mohd Ghazali was responsible for the conceptualization, methodology, overall supervision of the study and drafting the article. Norazlin Mohammed handled data collection, Ariff Idris ran analysis and interpretation of results. Aslina Saad contributed critical revision of the manuscript. All authors read and approved the final version of the manuscript prior to submission.

References

Abbas, M., Jam, F. A., & Khan, T. I. (2024). Is it harmful or helpful? Examining the causes and consequences of generative AI usage among university students. *International Journal of Educational Technology in Higher Education, 21*(1), 10. https://doi.org/10.1186/s41239-024-00444-7

Al Taqataq, F. A. S., Hazaymeh, W. A., Ismail, S. M., Abu-Alghayth, K., & Khan, A. S. (2025). Personalized AI-driven language learning in Saudi Arabia: An experimental study on perceived adaptability, learner autonomy, and language retention. *Computer-Assisted Language Learning Electronic Journal, 2*6(7), 230-255.

Arksey, H., & O'Malley, L. (2005). Scoping studies: Towards a methodological framework. *International Journal of Social Research Methodology, 8*(1), 19-32. https://doi.org/10.1080/1364557032000119616

Bachiri, Y. A., Mouncif, H., & Bouikhalene, B. (2025). Harnessing generative AI to boost active retrieval and retention in MOOCs with spaced repetition. *Knowledge Management & E-Learning, 17*(3), 391-408. https://doi.org/10.34105/j.kmel.2025.17.018

Habeeb, K. M., & Dashti, F. A. (2026). Evaluating the effectiveness of AI-generated animated films for first aid instruction in early childhood. *Computers in the Schools, 43*(1), 105-128. https://doi.org/10.1080/07380569.2025.2589502

Hodgkinson, G. P., & Ford, J. K. (2014). Narrative, meta-analytic, and systematic reviews: what are the differences and why do they matter?. *Journal of Organizational Behavior, 35*(S1), S1-S5. https://doi.org/10.1002/job.1918

Johnson, R. B., & Christensen, L. (2020). *Educational research: Quantitative, qualitative, and mixed approaches* (7th ed.). United States: Sage publications.

Lee, Y. J., & Otani, M. (2025). EFL university students' motivation, cognitive load, and satisfaction with using GenAI for English learning. *LLT Journal: A Journal on Language and Language Teaching, 28*(2), 572-586.

Nguyen, M., Agarwal, R., Malik, A., & Pandey, R. (2025). Generative AI: Elevating knowledge acquisition and retention and recall through autonomy, interactivity and engagement. *Journal of Enterprise Information Management, 38*(6), 1692-1719. https://doi.org/10.1108/JEIM-08-2024-0433

Ramdan, M. R., Yin, K. Y., Ab Wahab, N. Y., Samsudin, N., Abdullah, N. L., Abd Aziz, N. A., ... & Rambeli, N. (2024). The impact of applying the servant leadership style among educators in educational institutes: A scoping review. *TEM Journal, 13*(2), 1068.

Ryan, R. M., & Deci, E. L. (2000). Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. *American Psychologist, 55*(1), 68-78. https://doi.org/10.1037/0003-066X.55.1.68

Sánchez, A. D., de la Cruz Del Río Rama, M., & García, J. Á. (2017). Bibliometric analysis of publications on wine tourism in the databases Scopus and WoS. *European Research on Management and Business Economics, 23*(1), 8-15. https://doi.org/10.1016/j.iedeen.2016.02.001

Sussman, S. W., & Siegal, W. S. (2003). Informational influence in organizations: An integrated approach to knowledge adoption. *Information Systems Research, 14*(1), 47-65. https://doi.org/10.1287/isre.14.1.47.14767

Sweller, J. (1988). Cognitive load during problem solving: Effects on learning. *Cognitive Science, 12*(2), 257-285. https://doi.org/10.1207/s15516709cog1202_4

International Journal of Modern Education
EISSN: 2637-0905
IJMOE
Volume: 8 Issue: 31 (September 2026) PP. 387-402
Tracy, K., & Spantidi, O. (2025). Impact of GPT-driven teaching assistants in VR learning environments. *IEEE Transactions on Learning Technologies, 18*, 192-205. https://doi.org/10.1109/TLT.2025.3539179

Trindade, M. A. M., Edirisinghe, G. S., & Luo, L. (2025). Teaching mathematical concepts in management with generative artificial intelligence: The power of human oversight in AI-driven learning. *The International Journal of Management Education, 23*(2), 101104. https://doi.org/10.1016/j.ijme.2024.101104

Truong, V. L., & Nguyen, T. H. T. (2025). Enhancing STEM learning through AI-driven mind mapping: A study on the educational impact of Napkin AI on student outcomes and knowledge retention. *Computer Applications in Engineering Education, 33*(6), e70106. https://doi.org/10.1002/cae.70106

Venkatesh, V., Thong, J. Y., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly, 36*(1), 157-178. https://doi.org/10.2307/41410412

Yao, Y., & González-Vélez, H. (2025). AI-powered system to facilitate personalized adaptive learning in digital transformation. *Applied Sciences, 15*(9), 4989. https://doi.org/10.3390/app15094