DAVAO RESEARCH JOURNAL
https://davaoresearchjournal.ph

ORIGINAL RESEARCH REVIEW

A Scoping Review of Generative AI Usage and Human Cognition in Education and Professional Practice: Dual-Edged Cognitive Impacts and a Governance Framework

Kaneeka Vidanage[1], Manith Marapperuma[1], Shakya Dissanayake[1], Faiz Mohideen Mohamed Thassim Marikar[2]

[1]*Faculty of Computing, General Sir John Kotelawala Defense University, Sri Lanka*
[2]*Staff Development Centre, General Sir John Kotelawala Defense University, Sri Lanka*

*Corresponding author: *faiz@kdu.ac.lk*

ABSTRACT

The use of Generative Artificial Intelligence (Gen-AI) across education, healthcare, ethics, and professional practice is rapidly increasing. This growth has sparked a polarized debate, with Gen-AI viewed either as a powerful cognitive augmenter or as a potential threat to critical thinking, creativity, and independent reasoning. To examine this issue, the review scope was defined using the PRISMA-ScR guidelines, Joanna Briggs Institute (JBI) methodology, and the Population–Concept–Context (PCC) framework. A systematic literature search was conducted across PubMed, IEEE Xplore, ACM Digital Library, Springer, and Wiley Online Library. Only English-language publications published between 2020 and 2025 were considered. Following multi-stage screening, duplicate removal, eligibility assessment, and human verification, 107 peer-reviewed articles were included in the final analysis. Among the selected studies, 42% focused on university education, 23% on school education, 16% on medical education, 11% on ethics and moral responsibilities, and 8% on professional training. Synthesis of the findings led to two major conceptual contributions. First, the Cognitive Impact Taxonomy (CIT) provides a structured approach for assessing Gen-AI's influence on fluid and crystallized intelligence, key cognitive processes, and the trajectory of cognitive impacts leading to severity assessment. Second, the Integrated Cognitive Symbiosis Framework (ICSF) introduces a three-layer governance model to support responsible and cognitively healthy Gen-AI adoption. Together, the CIT–ICSF pipeline offers educators, institutional leaders, and policymakers a practical mechanism to maximize the benefits of Gen-AI while mitigating potential long-term cognitive risks.

Keywords: *Generative Artificial Intelligence, Governance Framework, Higher Education, Human Cognition, Scoping Review*

Submitted: 29 Apr 2026
Revised: 02 Jun 2026
Accepted: 30 Jul 2026
Published: 08 Sep 2026

OPEN ACCESS

How to cite: Vidanage, K., Marapperuma, M., Dissanayake, S., and Marikar, F. M. M. T. (2026). A Scoping Review of Generative AI Usage and Human Cognition in Education and Professional Practice: Dual-Edged Cognitive Impacts and a Governance Framework. *Davao Research Journal*, 17(3), 45-58. https://doi.org/10.59120/drj.v17i3.615

INTRODUCTION

Generative AI (Gen-AI) is an emerging concept within Artificial Intelligence that generates novel content from learnt patterns in exposed datasets (Qian, 2025). Gen-AI content can range from text and images to audio and other media (Shi et al., 2025; Yao et al., 2025). Tools such as OpenAI's ChatGPT, Google's Bard, and DALL·E have become game changers in industries such as education and creative businesses (Al-Abri, 2025; Chandrasekaran and Girijakumari Sreekantan Nair, 2024; Kohen-Vacs et al., 2025). The exponential growth in the use of these applications triggered a debate about their role relative to human intelligence and creativity (Luo et al., 2025; Liu et al., 2025; Ji et al., 2025). This paper explores this argument by conducting a comprehensive scoping review of the latest literature published from 2020 to 2025. This paper proposes a novel conceptual taxonomy and framework for governance to ensure healthier use of Gen-AI without causing adverse effects on human intelligence. This could be used as a benchmark across numerous industries to draw the proper boundary line and emphasize the insightful use of Gen-AI.

Since 2020, Gen-AI has been adopted exponentially in forms such as intelligent search engines, writing assistants, customer service bots, and educational platforms (Kohnke et al., 2025; Tophel et al., 2025; Hewedy and Abdelhady, 2025). This has reshaped how individuals interact with information (Linares-Pellicer et al., 2025; Chu et al., 2025). This revolutionary distinction has triggered long-term impacts across cognitive, societal, and cultural domains (Uludağ et al., 2025; Langner et al., 2025). Human intelligence comprises a range of cognitive abilities including memory, reasoning, problem solving, creativity and emotional awareness (Speicher and Becker, 2025; Zhang and Wang, 2025). However, debates argue that excessive use of Gen-AI leads to intellectual laziness, reduced critical thinking, and overdependence on automated systems (Adnin et al., 2025; Karayianni et al., 2025). Likewise, counterarguments emphasize that the use of Gen-AI augments human intelligence by offloading routine tasks (Schicchi and Taibi, 2025; Karafil and Uyar, 2025). Further, it allows humans to concentrate more deeply on more complex problems with proper attention to detail (El Fathi et al., 2025; Chang & Lee, 2025). Gen-AI resolves the bottlenecks associated with quick access towards novel information, democratizing access to knowledge (Lin et al., 2025; Tolstykh and Oshchepkova, 2024). Hence, as discussed, the debate over using Gen-AI appropriately is polarized.

Furthermore, educational institutions have raised concerns that Gen-AI challenges academic integrity and erodes genuine thought articulation (Park et al., 2024; Fokides and Peristeraki, 2024). Hence, this dichotomy emphasizes the need for a balanced, evidence-based analysis (Ko et al., 2024; Parra Pennefather, 2024). This evolving discourse is consequential (Boumalek et al., 2024; Yan et al., 2024). Recognizing the correct boundary is vital to ensuring responsible use of Gen-AI (Ding and Zou, 2024; Krushinskaia et al., 2024). Appropriate governing workflows should be in place to support pedagogical use without complete restrictions (Crosthwaite et al., 2024; Darban, 2024). This review synthesizes findings from multiple domains, including education, professionalism, and ethics, to derive a multidimensional understanding of the matter. Hence, by appropriately amalgamating these insights, the focus is on constructing a novel conceptual framework to govern and educate on the proper balance in the use of Gen-AI. This could be recognized as a novel conceptual contribution from this scoping review.

This review is undertaken with the primary objective of developing a novel conceptual framework that explains the cognitive implications of generative artificial intelligence (GenAI). To achieve this, the study examines both the positive and negative cognitive outcomes associated with GenAI use (Weerasinghe et al., 2024; Inie et al., 2023), analyses its influence on different forms of intelligence, particularly fluid and crystallized intelligence (Liang et al., 2023; Jimenez et al., 2025), and investigates how varying contexts such as educational and professional settings mediate these cognitive effects (Jackson, 2025). In addition, the review explores the ethical and societal concerns arising from GenAI's cognitive influence (Naeem et al., 2025; Zhang, 2025) and evaluates the potential long-term cognitive consequences associated with habitual use of such technologies (Oiva-Cordova et al., 2025; Shao and Tang, 2025). The paper is structured accordingly, with the methodology outlining the criteria for source selection, followed by a literature review that critically synthesizes perspectives addressing these objectives, a discussion that integrates key insights to inform the proposed framework as the main contribution of the study, and a conclusion that summarizes the findings while highlighting avenues for future research.

MATERIALS AND METHODS

The PRISMA-ScR (Preferred Reporting Items for Scoping Reviews and Meta-Analyses extension for Scoping Reviews) framework and JBI methodology have been used (Offor, 2025; Alibar et al., 2025). PRISMA-ScR is recognized as a globally accepted reporting framework (Alaswad et al., 2025). Its main attributes are transparency and reproducibility. Hence, PRISMA-ScR has been chosen as a suitable tool for the continuation of this research. Secondly, the JBI methodology introduced by the Joanna Briggs Institute is recognized as the gold standard for conducting scoping reviews (Amos et al., 2025; Puttajanyawong et al., 2025). This uses the PCC framework internally to define the scope of the literature selection. PCC framework encompasses population, concept and context paradigms to ensure a solid rational basis for the scope aligned with the problem of concern (Calderón-Oliver, 2025; Elizondo-García et al., 2025). Table 1 reflects the adoption of the JBI methodology for the problem under investigation.

Table 1. Application of PCC framework.

Paradigm	Justification
Population	Emphasis is given to human population clusters, who mainly interact with Gen-AI application bases. i.e., Students, Healthcare workers, Knowledge workers, General public (Gong et al., 2025). Comprehending the impact of Gen-AI across multiple potent populations allows us to capture a more holistic view about both the positive and negative impacts (Luo et al., 2025; Lukhmanov et al., 2025).
Concept	Phenomenon of how Gen-AI impacts cognitive processes such as creativity, decision making, problem solving, memory and attention (Alli et al., 2025; Shaner et al., 2025). Deeper investigations allow to decide on dual edged transformations of human cognition due to Gen-AI (Sanchez-Rodriguez et al., 2025; Pham and Pham, 2025).
Context	Circumstantial impact of Gen-AI applications across domains such as educational, workplace and routine life (Liu et al., 2025; Chan, 2025).

As depicted in Table 1, incorporating the PCC framework for the problem discourse narrows the scope to be investigated, along with a rational basis (Ping et al., 2025; La Scala et al., 2025). This, in turn, helps govern the direction of the study more methodically, avoiding information overload (Wang et al., 2025; Ji et al., 2025). Once the scope is properly tuned, the amalgamation of PRISMA-ScR aids in rational reporting of the findings (Guo et al., 2025; Matobobo et al., 2025). Table 2 represents the practical application of the PCC framework for the domain of concern.

Table 2. Application of PCC framework - detailed criteria.

PCC element	Inclusion criteria	Exclusion criteria	Example search terms
Population	People using Gen-AI along with cognitive impacts (Liu et al., 2025; Charalambous et al., 2025)	Studies with non-human subjects along with non-Gen-AI and non-cognitive interactions (Le and Taherdoost, 2025)	"Human cognition" OR "thinking skills" OR "decision making" OR "creativity" OR "memory" OR "critical thinking"
Concept	Research with dual-edged transformation on cognition, due to Gen-AI. Include both pros and cons (Sanchez-Lopez et al., 2025; Haugsbaken ans Hagelia, 2024)	Studies that do not investigate cognitive impacts caused by Gen-AI (Frenzke-Shim et al., 2024)	"Cognitive overload" OR "intellectual laziness" OR "creativity enhancement" OR "cognitive impact"
Context	Research which uses Gen-AI applications in educational, workplaces or routine life settings (Castillo et al., 2024; Noenthaisong and Thanwisai, 2024)	Studies out of the bounds of education, workplaces or routine life settings (Khangkhan et al., 2024)	"Knowledge work" OR "learning", "education", "daily work"

As depicted in Table 2, utilization of the PCC framework ensures keeping the scope of literature investigations manageable without hindering the comprehensive realizations associated with Gen-AI-influenced cognitive impacts (Chandrasekaran and Girijakumari Sreekantan Nair, 2024; Maro et al., 2025). Once the contents have been extracted as per the PCC framework's enforcement, the next step is interpretation of the collated information. As conversed earlier, PRISMA-ScR will be utilized in this context.

As per the PRISMA-ScR guidelines, the applied workflow is as follows:

1. Literature identification

Reliable literature databases such as PubMed, IEEE Xplorer, ACM Digital Library, SpringerLink, and Wiley Online Library have been used to identify relevant research articles, adhering to the aforementioned PCC framework constraints.

This discovery of information resulted in the following statistics:

- PubMed → 3,144 Articles
- IEEE Xplorer → 8,436 Articles
- ACM Digital Library → 114 Articles
- Springer Link → 2,727 Articles
- Wiley Online Library → 47 Articles

As per the exploration conducted across five reliable repositories, a total of 14,468 articles were yielded. The search criteria utilised are described in Table 1 and adhere to the PCC framework guidelines (Tseng and Chang, 2025; MacArthur, 2025). Apart from the aforementioned search criteria, additional filtering has been imposed to restrict articles published in English only within the time span of 2020-2025.

2. Article screening and eligibility assessment

As per the workflow utilized in step-01, this resulted in a total of 14,468 articles adhering to the enforced search criteria. This is quite a large number for manual review. Hence, the search criteria were further refined. Under article types, clinical trials, randomized controlled studies, clinical protocols, newspaper articles, educational handouts, portraits, preprints, interviews and webcasts were eliminated.

Clinical trials, protocols, and randomized controlled studies were excluded as they focus primarily on interventional outcomes rather than thematic synthesis. Preprints, newspaper articles, and educational handouts were also disregarded, as they are not peer-reviewed and are non-scholarly. Likewise, anecdotal items such as interviews and webcasts were also removed as they are not systematic and could be overly subjective. With these additional constraints in place, the total paper count was reduced from 14,468 to 2,701.

3. Full-text review and study selection

In this step, two main tasks were carried out.

3.1. Duplicate removal

The filtered search results were downloaded as CSV files, and with the assistance of a reference manager (i.e. Zotero), all duplicates were resolved. Hence, certain articles appeared in multiple repositories.

3.2. Relevance assessment

The main goal of this research is to evaluate cognition impacts caused by Gen-AI interventions, but not due to ailments or other factors. When this aspect was introduced to the refined solution set, it was identified that papers published in 2025 have the most aligned significance. Some articles discussed excessive engagement with computer gaming and the cognitive impairments imposed by digital infrastructure. However, these were eliminated; hence, the focus of this scoping review is the influence of Gen-AI on cognitive comportments.

Hence, the refined paper count was also quite high, and manual screening still seemed exhaustive. Therefore, a combination of Large Language Models (LLMs) and their semantic search capabilities, combined with agent functionalities, was used to filter the derived solution set against the opinionated lexicons systematically.

The pool of opinionated lexicons was derived according to the PCC framework guidelines as depicted in Table 2. These lexicons functioned as the filtering criteria for the LLMs, confirming the systematic alignment of the scoping review's objectives. LLMs were prompted to evaluate article abstracts against the opinionated lexicon pools as well as the stipulated inclusion criteria. Articles were directly verified for explicit mention of Gen-AI's impact on cognition, contextual alignment with numerous usage scenarios, and facts about both pros and cons aligned with Gen-AI usage.

The output retrieved from this process was manually verified with extensive human involvement. Two independent human reviewers were appointed to verify the suitability of the screened articles against the domain of discourse. Discrepancies were discussed and resolved between the two reviewers. This yielded the most impactful 107 articles for the in-depth meta-analysis. During this step, LLMs were used for computational efficiency with rigorous human oversight. This hybrid workflow ensures transparency without sacrificing scalability.

4. AI-Augmented screening protocol (Gemini API integration)

This review aims to develop a novel conceptual framework that explains the cognitive implications of generative artificial intelligence (GenAI). It examines both the positive and negative cognitive outcomes associated with GenAI use, analyses its influence on different forms of intelligence, and explores how contextual factors such as educational and professional environments mediate these effects. The study further considers the ethical and societal concerns linked to GenAI's cognitive impact and evaluates the potential long-term consequences of sustained use. Methodologically, a key innovation of this research is the integration of a human-verified, AI-augmented filtering workflow, through which an initial corpus of 2,701 articles was reduced to a final set of 107 sources. This process incorporates Large Language Models via the Gemini API, utilising semantic search and agentic capabilities across two phases guided by PCC-based inclusion and exclusion criteria, with human checks ensuring accuracy and rigour throughout.

Phase 1: Lexicon and keyword filtering

This phase was dedicated to eliminating irrelevant records while maximizing recall by applying border semantic filtering.

- Mechanism: The LLM performed vector-based semantic proximity matching against article abstracts with predefined opinionated lexicon pools.
- Lexicon Criteria: The opinionated lexicons were derived as per the PCC framework's operational dimensions. The model

scanned abstracts for the specified lexicons aligned against the PCC paradigms.

- Purpose: This step is dedicated to eliminating articles aligned with Gen-AI and non-cognitive contexts. For instance, using Gen-AI to optimize server loads.
- Outcome: This phase successfully reduced the number of papers not addressing cognitive or psychological parameters. The remaining articles were thematically consistent with the goal of the research conducted.

Phase 2: Low-level exact match and contextual evaluation

This step ensures more fine-grained filtering beyond keyword search by considering logical and contextual fit.

- Mechanism: By utilizing Gemini API's Agentic features, agents were instructed to interrogate the filtered abstracts about their underlying logic and contextual framing.
- Exact Matching Criteria:

1. Contextual Alignment: The agent verified that the refined study contexts were linked across universities, schools, healthcare, ethics, or professional training. This ensures adherence to the PCC framework parameters.
2. Biased Nature: Articles without a condensed discussion of the pros and cons of Gen-AI usage across the aforementioned domains were deprioritized. Hence, the review focuses on the dual-edged impact of Gen-AI on the cognitive patterns of human stakeholders.
3. Exclusion of Non-GenAI Cognitive "Ailments": Cognitive impairments triggered via other means apart from the Gen-AI influence have been excluded

- Attrition: As a result of stricter AI-augmented refinements, only 107 articles have been pruned and finalized. This is a firm selection, representing 3.9% of 2701 articles. The upcoming conceptual contributions of Cognitive Impact Taxonomy (CIT) and Integrated Cognitive Systems Framework (ICSF) from this review paper have been derived from the enriched insights yielded from the pruned articles. Figure 1 presents the workflow followed in the AI-augmented filtering process.

Figure 1. AI augmented filtering protocol.

5. Data extraction, synthesis, and interpretation

Although the investigation spanned 2020 to 2025, almost all the articles selected after the pruning process belonged to 2025. This is mainly because the Gen-AI concept became much more popular in the latter segment of 2023. There were not many significantly impactful articles identified before 2023, which aligned with our topic of concern. The chosen 107 articles represented a balanced distribution across the contexts of education, the workplace, and general cognitive impacts triggered by the use of Gen-AI. The process up to this stage is depicted in Figure 2.

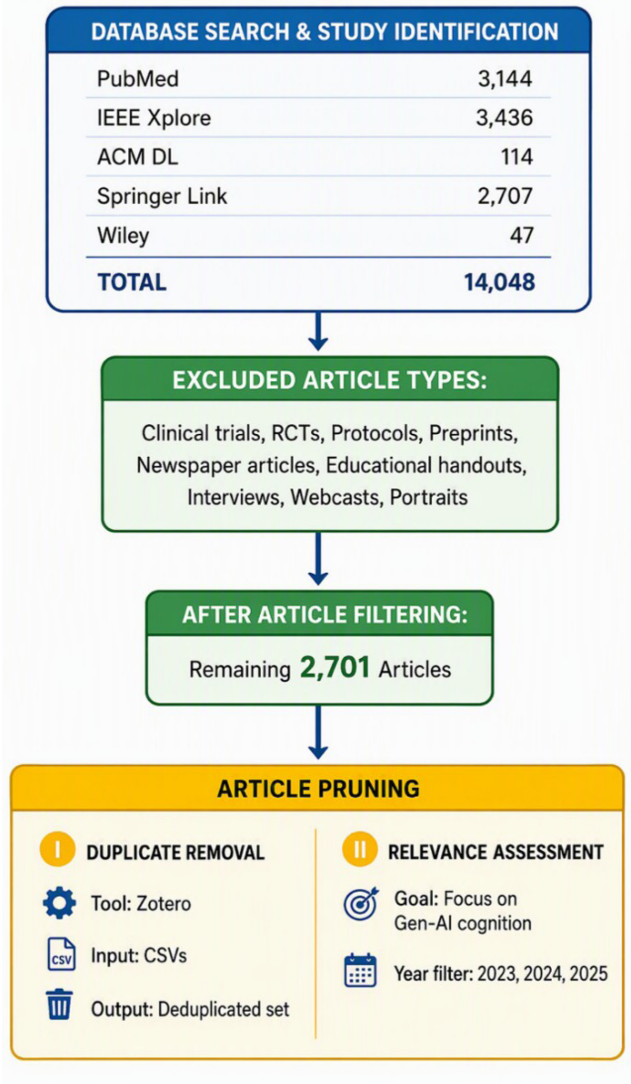

Figure 2. Workflow

RESULTS

Summary statistics of included studies

Table 3 presents summarized statistics on the composition of the 107 papers. The scoping review synthesized reflections from 107 screened articles. The summarized statistics derived from the investigations conducted were tabulated in Table 3. Of the included studies, 79% were published in 2025, 19% in 2024, and 2% in 2023. The identified domains included university education (42%), school education (23%), healthcare/medical (16%), ethics (11%), and professional training (8%).

Table 3. Summary Statistics of Included Studies.

Metric	Count	Percentage (%)
Total studies included	107	100
Publication Years		
- 2025	84	79
- 2024	21	19
- 2023	2	2
Domains Identified		
- University Education	45	42
- School Education	25	23
- Healthcare / Medical	17	16
- Ethics	12	11
- Professional Training	8	8

The domain-wise distribution revealed that university education accounted for the largest proportion of studies (42%), followed by school education (23%), healthcare/medical (16%), ethics (11%), and training and development (8%).

Table 4. Domain-wise Impact Analysis.

Domain	Percent of articles	Primary enhancement	Primary concern	Dual-edged impact
University education	42	Critical thinking and metacognition	Academic integrity and over reliance	High
School education	23	Creativity and problem solving	Hindering cognitive development appropriately	Moderate
Health / Medical	16	Knowledge acquisition enhancement	Clinical reasoning dependency	Very High
Ethics	11	Reasoning transparency	Ethical autonomy erosion	High
Training & development	8	Skills synthesis augmentation	Skill atrophy	High

Table 4 summarizes the primary enhancements, concerns, and dual-edged impacts identified across the five domains. University education was associated with critical thinking and metacognition enhancement, whereas school education was linked to concerns regarding cognitive development. Healthcare/medical studies highlighted enhanced knowledge acquisition alongside increased dependence on clinical reasoning. Ethics-related studies emphasized reasoning transparency and the erosion of ethical autonomy, while training and development studies identified skill synthesis augmentation and skill atrophy.

Domain-wise impact assessment

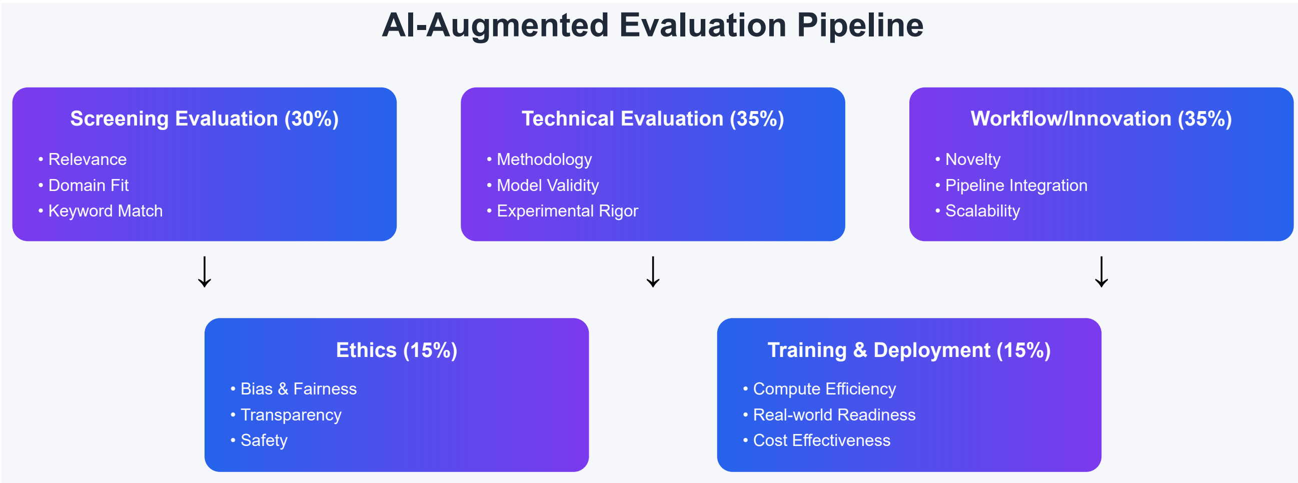

Figure 3. Domain-wise impact assessment.

The visual assessment demonstrated positive contributions towards critical thinking and metacognition in university education. School education exhibited predominantly negative impacts. In the healthcare/medical domain, benefits outweighed the identified challenges. The ethics domain displayed nearly equal positive and negative influences, while training and development showed an overall positive contribution (Figure 3). These findings are consistent with emerging empirical evidence showing that Gen-AI can enhance higher education when integrated as a cognitive partner rather than a replacement for human reasoning. Studies have reported that AI-assisted learning environments can promote reflection, feedback-driven learning, and metacognitive awareness among university students when guided by appropriate pedagogical strategies (Kasneci et al., 2023; Lo, 2023).

Conversely, research in school education highlights concerns regarding excessive dependence on AI-generated responses, reduced cognitive effort, weakened knowledge construction, and challenges in developing independent reasoning skills among younger learners (UNESCO, 2023; Cotton et al., 2024). In healthcare and medical education, empirical studies indicate that AI technologies can improve diagnostic support, clinical reasoning, simulation-based learning, and access to medical knowledge; however, issues related to explainability, bias, accountability, and professional judgement remain significant challenges (Rajpurkar et al., 2022; Topol, 2019). The near-equilibrium observed in the ethics domain reflects ongoing evidence that AI provides opportunities for fairness, transparency, and responsible decision-making while simultaneously introducing risks associated with privacy, algorithmic bias, misinformation, and human oversight (Jobin et al., 2019; UNESCO, 2021). Furthermore, positive impacts observed in training and development align with evidence that AI-enabled adaptive learning systems support personalised professional development, skill acquisition, and continuous learning pathways (Chen et al., 2020).

Collated representation of net impacts

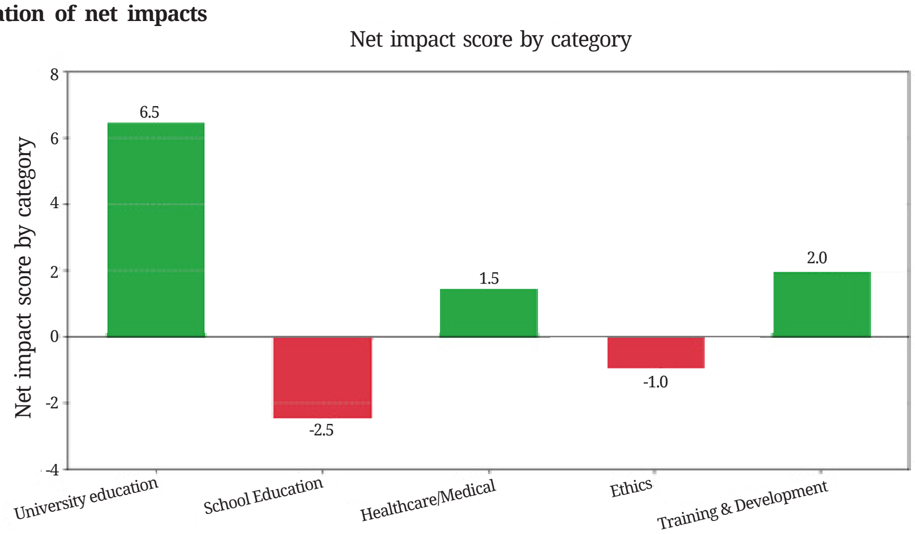

Figure 4. Collated representation of net impacts.

The collated analysis showed that university education, healthcare/medical, and training and development domains recorded positive net impacts. Conversely, school education was identified as the most adversely affected domain (Figure 4). This finding is consistent with empirical evidence indicating that AI-assisted tools can enhance higher education through personalised learning, improved academic productivity, research support, and adaptive feedback mechanisms when implemented with appropriate pedagogical oversight (Kasneci et al., 2023; Tlili et al., 2023). In healthcare and medical education, AI applications have demonstrated potential benefits in clinical decision support, diagnostic accuracy, knowledge acquisition, and simulation-based training by augmenting human expertise rather than replacing professional judgement (Topol, 2019; Rajpurkar et al., 2022). Similarly, workplace training and professional development studies suggest that AI-enabled adaptive learning systems improve accessibility, individualised learning pathways, and continuous skill development (Chen et al., 2020).

In contrast, school education has been identified as a higher -risk environment due to concerns related to overdependence on AI-generated answers, reduced development of foundational cognitive skills, academic integrity challenges, and unequal access to AI technologies among learners (UNESCO, 2023; Kasneci et al., 2023). Younger learners may be more vulnerable to cognitive offloading because critical reasoning, metacognitive regulation, and independent knowledge construction are still developing. Therefore, the differential impacts observed across educational domains may reflect variations in learner maturity, instructional design, AI literacy, and governance mechanisms.

Cognitive Impact Taxonomy (CIT)

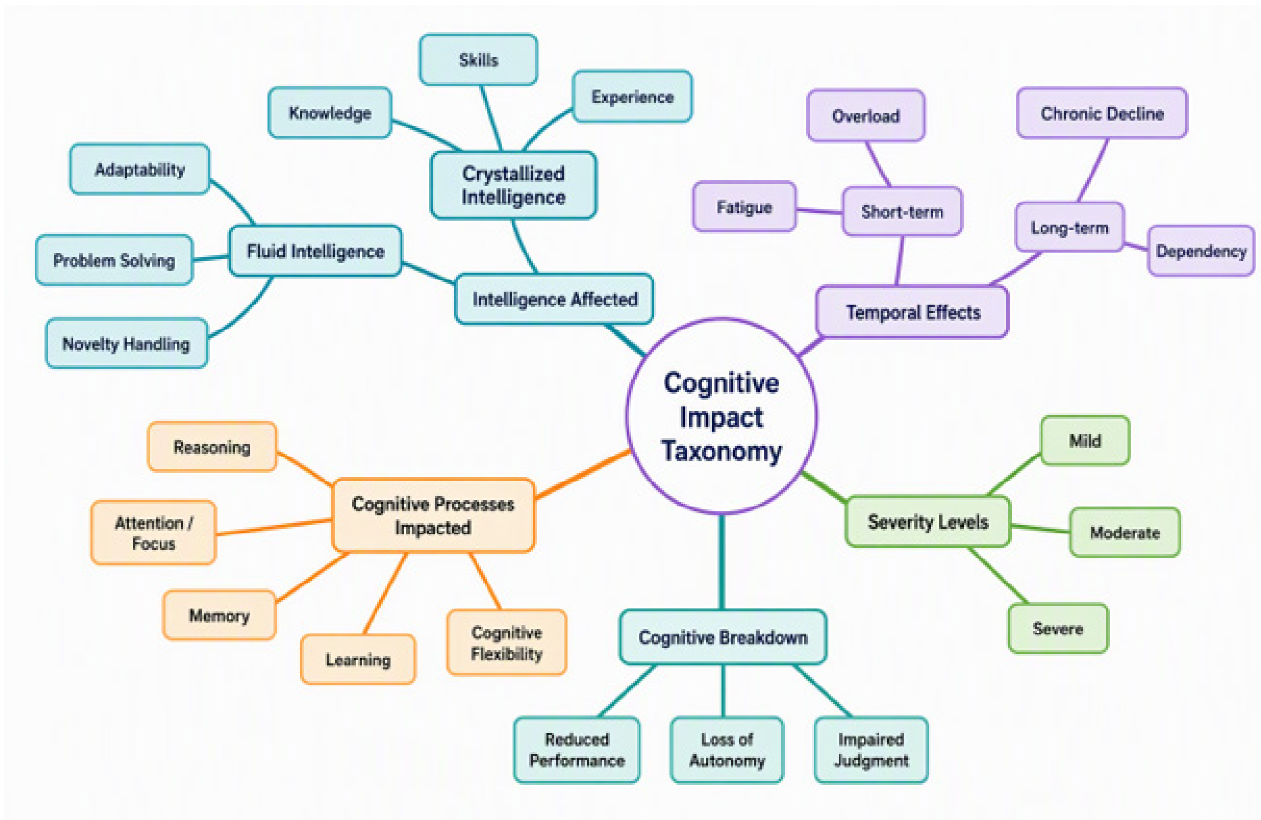

Figure 5. Cognitive Impact Taxonomy (CIT).

The Cognitive Impact Taxonomy (CIT) was developed from the screened literature and identified four key dimensions of cognitive impact: intelligence, cognitive processes, temporal effects, and severity levels (Figure 5). The structure of CIT is supported by empirical evidence from cognitive psychology and human–technology interaction research, which demonstrates that emerging technologies influence cognition through multiple pathways, including changes in information processing, decision-making, problem-solving, memory utilisation, and higher-order thinking. Research on cognitive offloading has shown that external technological aids can enhance performance while simultaneously altering memory and cognitive strategies, depending on the level and duration of reliance on these tools (Risko and Gilbert, 2016). Furthermore, studies on automation and artificial intelligence indicate that AI systems can produce both beneficial cognitive augmentation and adverse effects, including reduced critical engagement and automation bias, depending on task complexity, user expertise, and system transparency (Parasuraman & Riley, 1997; Parasuraman & Manzey, 2010). The inclusion of temporal effects and severity levels is consistent with evidence that technology-mediated cognitive changes may vary from immediate performance improvements to long-term adaptations in cognitive behaviour and skill development (Carr, 2010; Sparrow et al., 2011).

Integrated Cognitive Symbiosis Framework (ICSF)

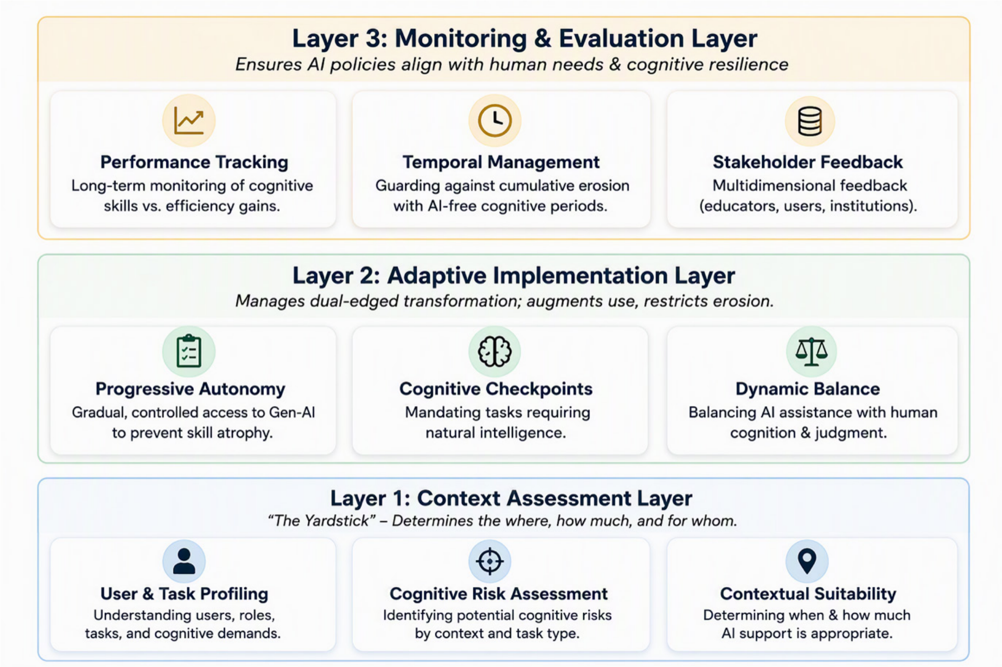

Figure 6. Integrated Cognitive Symbiosis Framework (ICSF).

The synthesis of evidence resulted in the development of the Integrated Cognitive Symbiosis Framework (ICSF), comprising three layers: Context Assessment, Adaptive Implementation, and Monitoring and Evaluation. The framework was designed to govern the dual-edged impacts of Gen-AI usage (Figure 6). The three-layer architecture is supported by empirical evidence from implementation science, which demonstrates that interventions are more effective and sustainable when they begin with systematic context assessment, are adapted to local conditions during implementation, and incorporate continuous monitoring and iterative evaluation. Similarly, research on trustworthy AI and educational technology has shown that ongoing evaluation and human oversight are essential for ensuring safe, ethical, and effective AI integration in learning environments (Damschroder et al., 2022; Graham et al., 2006; Skivington et al., 2021; UNESCO, 2023; OECD, 2024).

Combined workflow system

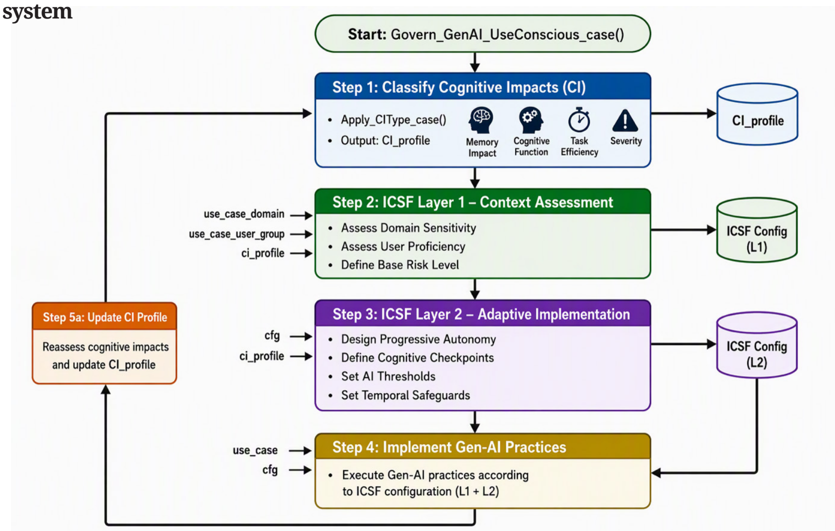

Figure 7. Combined workflow system for governing GenAI Use cases.

The proposed workflow integrated the Cognitive Impact Taxonomy (CIT) and the Integrated Cognitive Symbiosis Framework (ICSF) into a diagnosis–intervention–evaluation chain. The workflow incorporated cognitive impact classification, context assessment, adaptive implementation, practical execution, and ongoing monitoring and evaluation (Figure 7). This sequential process aligns with established implementation science frameworks, which have consistently shown that systematic assessment, context-sensitive implementation, and iterative evaluation improve intervention effectiveness, fidelity, and sustainability (Graham et al., 2006; Damschroder et al., 2022; Skivington et al., 2021). Furthermore, educational research demonstrates that structured cognitive classification enhances instructional design and learning assessment, while continuous feedback enables refinement of interventions and supports sustained improvements in educational outcomes (Anderson andKrathwohl, 2001; Kirkpatrick and Kirkpatrick, 2016).

DISCUSSION

The findings demonstrate the rapid progression of Gen-AI research and its bidirectional impacts. The dominance of studies published in 2025 (79%) highlights substantial scholarly interest and reflects the increasing integration of Gen-AI applications across a range of user contexts. The exponential growth of publications further suggests broader acceptance and adoption of Gen-AI technologies. University education emerged as the most represented domain. The reviewed literature consistently emphasized improvements in critical thinking, metacognition, and complex problem-solving capabilities (Sanchez-Lopez et al., 2025). However, the evidence also highlighted concerns regarding excessive dependency and academic integrity. Collectively, the findings suggest that intentional and regulated utilization contributes positively to higher-order thinking skills (Chen et al., 2024). The school education domain presented mixed findings. While some studies suggested that Gen-AI may facilitate the gradual development of future-oriented skills, including prompt engineering, other studies emphasized concerns regarding foundational cognitive development, creativity, and authenticity. The overall evidence reflected considerable opposition towards extensive use of Gen-AI in school-level academic activities because of potential long-term impacts on essential cognitive skills.

Within healthcare and medical education, Gen-AI demonstrated substantial benefits through educational enhancement, clinical decision support, and AI-assisted medical training (Buess et al., 2025). Nevertheless, concerns were identified regarding overdependence, diminished analytical reasoning, and reduced opportunities for developing human-centred care and empathetic patient interactions. These findings reinforce the dual-edged nature of Gen-AI integration within healthcare environments. Ethics-related studies revealed contrasting perspectives. Several studies reported strong alignment between GPT-4 outputs and human ethical judgments (Wu et al., 2025; Hoke, 2025) and highlighted sophisticated moral reasoning capabilities (Chung et al., 2025; Jiang et al., 2025; Bhasuran et al., 2025; Alabsi et al., 2025). Conversely, concerns regarding moral outsourcing, bias amplification, and erosion of autonomous ethical decision-making were repeatedly emphasized (Sinnappan et al., 2025; Chen et al., 2025; Rachmat et al., 2025; Park et al., 2025). The training and development domain similarly reflected both benefits and challenges. Gen-AI enhanced analytical capability, technical information synthesis, and articulation of complex concepts (Ma et al., 2025). However, excessive reliance was associated with skill atrophy and concerns regarding academic integrity (Rachmat et al., 2025; Park et al., 2025; Loo et al., 2025; Chen et al., 2025).

The Cognitive Impact Taxonomy (CIT) provided a structured synthesis of how Gen-AI affects intelligence, cognitive processes, temporal development, and severity of outcomes. The taxonomy suggests that Gen-AI can simultaneously function as a cognitive augmenter and a cognitive stressor depending on the context and intensity of use. Furthermore, the Integrated Cognitive Symbiosis Framework (ICSF) offers a structured governance model that balances augmentation benefits with risks such as overreliance, skill atrophy, and cognitive erosion. Through its layered architecture and associated modules, the framework enables context-sensitive and adaptive implementation strategies while ensuring continuous monitoring and multidisciplinary governance.

CONCLUSION

This scoping review synthesizes evidence from 107 peer-reviewed studies and highlights the dual nature of Generative Artificial Intelligence (Gen-AI). The findings show that while Gen-AI can enhance productivity, creativity, learning, and decision-making, it may also contribute to cognitive dependency, reduced critical thinking, and diminished cognitive autonomy when used without appropriate oversight. These outcomes suggest that the technology itself does not determine the impact of Gen-AI, but rather by how it is designed, adopted, and governed. To address this challenge, the review introduces two key contributions: the Cognitive Impact Taxonomy and the Integrated Cognitive Symbiosis Framework. The Cognitive Impact Taxonomy offers a structured approach for understanding, assessing, and monitoring the diverse cognitive effects of Gen-AI across contexts. It enables stakeholders to identify both benefits and risks and supports more informed research, practice, and policy development. The Integrated Cognitive Symbiosis Framework complements this taxonomy by outlining a balanced model of human–AI collaboration. Rather than replacing human cognition, it emphasizes the responsible use of Gen-AI to enhance cognitive capabilities through conscious engagement, continuous evaluation, and adaptive governance. Overall, this review underscores the need for human-centred and evidence-based approaches to Gen-AI adoption, ensuring that technological progress strengthens rather than erodes the cognitive capacities essential for long-term individual and societal well-being.

LIMITATIONS

- This review is limited to evidence reported in the 107 studies included in the final sample, making its conclusions dependent on the scope, quality, and methodologies of the existing literature.
- As a scoping review, the study aimed to map and synthesize current knowledge rather than establish causal relationships between Gen-AI use and cognitive outcomes.
- Variations in research settings, participant groups, and measurement approaches across studies may limit the comparability and generalizability of findings.
- The rapidly evolving nature of Gen-AI technologies means that some findings may become outdated as new tools, capabilities, and patterns of use emerge.
- Empirical evidence on the long-term cognitive effects of Gen-AI remains limited, highlighting the need for more longitudinal research.

RECOMMENDATIONS

- Develop context-sensitive implementation strategies: Organizations and institutions should adopt guided Gen-AI usage frameworks that maximize cognitive and productivity benefits while mitigating risks such as cognitive dependency and erosion of critical thinking.

- Validate and operationalize the Cognitive Impact Taxonomy: Future research should empirically test the taxonomy across disciplines and contexts, develop measurable indicators, and support comparative and predictive risk assessment studies.
- Apply the Integrated Cognitive Symbiosis Framework in practice: Educators and professional practitioners should integrate the framework into teaching, learning, and workplace processes to promote mindful and balanced human–AI collaboration.
- Strengthen policy and governance mechanisms: Policymakers should use the proposed frameworks to develop evidence-based regulations emphasizing ethical use, cognitive accountability, transparency, and ongoing monitoring.
- Prioritize longitudinal and experimental research: Future studies should investigate the long-term cognitive impacts of Gen-AI use and refine both the Cognitive Impact Taxonomy and the Integrated Cognitive Symbiosis Framework based on emerging evidence.

FUNDING SOURCE

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

AUTHOR CONTRIBUTIONS

K. V: Conceptualized and designed the study, developed the research framework, and led the methodology, data analysis, and manuscript writing, supervised the entire research process and finalized the Integrated Cognitive Symbiosis Framework (ICSF) and Cognitive Impact Taxonomy (CIT). M. M: Data collection, database screening, initial analysis under the PRISMA-ScR and JBI frameworks and assisted in structuring the results and discussion sections, provided critical feedback on data interpretation and refinement of tables and visual models. S. D: Literature synthesis, referencing validation, and contributed to descriptive summaries and the graphical visualizations, reviewed and edited the manuscript for coherence, clarity, and alignment with Scientific Reports style and. F. M. M. T. M: supervised and finalized the document. All authors reviewed and approved the final version of the manuscript for submission.

DECLARATION

Informed consent statement
Not Applicable.

Conflict of interest

The authors do not have any non-financial or financial gains that might have biased the work reported in this paper.

AI Disclosure

Artificial intelligence (AI)-assisted image generation and enhancement tools were used solely to improve the visual quality and layout of figures presented in this manuscript. The AI tools were not used to generate, analyze, manipulate, or interpret the research data. All figures were reviewed, verified, and approved by the authors to ensure they accurately represent the original findings.

REFERENCES

Adnin, R., Pandkar, A., Yao, B., Wang, D., and Das, M. (2025) Examining student and teacher perspectives on undisclosed use of generative AI in academic work. In: *Proceedings of the 2025 CHI Conference on Human Factors in Computing Systems*, pp 1–17. ACM, New York, NY, USA. https://doi.org/10.1145/3706598.3713393

Al-Abri, A. (2025). Exploring ChatGPT as a virtual tutor: A multi-dimensional analysis of large language models in academic support. *Education and Information Technologies*, 30(12), 17447-17482.https://doi.org/10.1007/s10639-025-13484-x

Alabsi, H., Almotairi, M., Alyami, M., Alqahtani, Y., Obeidat, R., and Almansour, F. (2025) Can ChatGPT serve as a cognitive stimulus? A proposed model for assessing the impact on graduate students' perceptions of cognitive and developmental skills. In: *Advances in Intelligent Systems and Computing*, 461–468. Springer Nature Switzerland, Cham

Alaswad, S., Kalganova, T., and Awad, W. (2025). Developing a Framework for Using Large Language Models for Viva Assessments in Higher Education. In *2024 International Conference on IT Innovation and Knowledge Discovery* (ITIKD) (pp. 1-7). IEEE. https://doi.org/10.1109/ITIKD63574.2025.11005250.

Amos, J.P., Amodu, O.A., Mahmood, R.A.R., Abdulqudus, A.B., Zakaria, A.F., Iyanda, A.R., Bukar, U.A. and Hanapi, Z.M. (2025). A bibliometric exposition and review on leveraging LLMs for programming education. *IEEE Access*. https://doi.org/10.1109/ACCESS.2025.3554627

Bhasuran, B., Jin, Q., Xie, Y., Yang, C., Hanna, K., Costa, J., Shavor, C., Han, W., Lu, Z. and He, Z. (2025). Preliminary analysis of the impact of lab results on large language model generated differential diagnoses. npj *Digital Medicine*, 8(1), 166.

Boumalek, K., El Mezouary, A., Hmedna, B., and Bakki, A. (2024). Transforming microlearning with generative AI: Current advances and future challenges. *General Aspects of Applying Generative AI in Higher Education: Opportunities and Challenges*, 241-262.

Calderón-Oliver, M. (2025) ChatGPT as a support and search tool for research-based learning. In: 2025 Institute for the Future of Education Conference (IFE), pp 1–6. *IEEE, Monterrey, Mexico.* https://doi.org/10.1109/IFE63672.2025.11025058.

Carr, N. (2020). The shallows: What the Internet is doing to our brains. W. W. Norton & Company.

Castillo, K. C., Hernández, X. M. Z., Herrera, L. A. G., and Bernabe, J. G. (2024). Study of perception on the use of generative artificial intelligence in higher-level students. In *2024 IEEE International Conference on Engineering Veracruz* (*ICEV*) (pp. 1-5). IEEE. https://doi.org/10.1109/ICEV63254.2024.10765939.

Chan, Y. H. C. (2025). Exploring Language, Society, and Culture with AI Video Creation: A Hands-On Case Study. In *2025 6th International Conference on Information Technology and Education Technology* (*ITET*) (pp. 6-10). IEEE. https://doi.org/10.1109/ITET65804.2025.11100767.

Chandrasekaran, B., and Nair, S. G. S. (2024). Unleashing the potential of ChatGPT in education: Revolutionizing learning and collaboration. *IEEE Potentials*, 43(6), 13-22. https://doi.org/10.1109/MPOT.2024.3449257.

Chang, K. Y., and Lee, C. F. (2025). Enhancing virtual restorative environment with generative AI: personalized immersive stress-relief experiences. In *International Conference on Human-Computer Interaction* (pp. 132-144). Cham: Springer Nature Switzerland.

Chen, W., Yin, X., and Xie, Y. (2024). The construction and application of prompt framework for improving college students' human-machine synergy learning ability with generative AI. *In 2024 International Symposium on Educational Technology* (*ISET*) (pp. 109-113). IEEE. https://doi.org/10.1109/ISET61814.2024.00030.

Chen, X., Li, N., Bajaj, N., and Fan, P. (2025). Enhancing competition-based big data analytics learning through ai-driven distributed scaffolding. In *2025 IEEE Global Engineering Education Conference* (*EDUCON*) (pp. 1-5). IEEE. https://doi.org/10.1109/EDUCON62633.2025.11016504,

Chen, L., Chen, P., and Lin, Z. (2020). Artificial intelligence in education: A review. *IEEE access*, 8,75264-75278. https://doi.org/10.1109/ACCESS.2020.2988510.

Chu, X., Wang, M., Spector, J. M., Chen, N. S., Chai, C. S., Hwang, G. J., and Zhai, X. (2025). Enhancing the flipped classroom model with generative AI and Metaverse technologies: insights from lag sequential and epistemic network analysis. *Educational technology research and development,* 73(3), 1539-1567. https://doi.org/10.1007/s11423-025-10457-2

Chung, S., Giuffrè, M., Rajashekar, N., Pu, Y., Shin, Y.E., Kresevic, S., Chan, C., Nakamura-Sakai, S., You, K., Saarinen, T. and Hsiao, A. (2025). Usability and adoption in a randomized trial of GutGPT a GenAI tool for gastrointestinal bleeding. *NPJ Digital Medicine,* 8(1), p.527.https://doi.org/10.1038/s41746-025-01896-5.

Cotton, D. R., Cotton, P. A., and Shipway, J. R. (2024). Chatting and cheating: Ensuring academic integrity in the era of ChatGPT. *Innovations in education and teaching international,* 61(2), 228-239. https://doi.org/10.1080/14703297.2023.2190148

Crosthwaite, P., Smala, S., and Spinelli, F. (2025). Prompting for pedagogy? Australian F-10 teachers' generative AI prompting use cases. *The Australian Educational Researcher,* 52(3), 1795-1825.

Damschroder, L. J., Reardon, C. M., Widerquist, M. A. O., and Lowery, J. (2022). The updated Consolidated Framework for Implementation Research based on user feedback. *Implementation science,* 17(1), 75. https://doi.org/10.1186/s13012-022-01245-0

Darban, M. (2024). Navigating virtual teams in generative AI-led learning: The moderation of team perceived virtuality. *Education and Information Technologies,* 29(17), 23225-23248. https://doi.org/10.1007/s10639-024-12681-4.

Ding, L., and Zou, D. (2024). Automated writing evaluation systems: A systematic review of Grammarly, Pigai, and Criterion with a perspective on future directions in the age of generative artificial intelligence. *Education and Information Technologies*, 29(11), 14151-14203. https://doi.org/10.1007/s10639-023-12402-3.

El Fathi, T., Saad, A., Larhzil, H., Lamri, D., and Al Ibrahmi, E. M. (2025). Integrating generative AI into STEM education: Enhancing conceptual understanding, addressing misconceptions, and assessing student acceptance. *Disciplinary and Interdisciplinary Science Education Research,* 7(1), 6. https://doi.org/10.1186/s43031-025-00125-z.

Elizondo-García, M. E., Lara-Prieto, V., García-García, R., Benavides-García, I. G., and Membrillo-Hernández, J. (2025). AI and Challenge-Based Learning: The Case of Biotechnology Engineering Understanding the Role of the Microbiota. In *2025 IEEE Global Engineering Education Conference* (*EDUCON*) (pp. 1-5). IEEE. https://doi.org/10.1109/EDUCON62633.2025.11016569.

Fokides, E., and Peristeraki, E. (2025). Comparing ChatGPT's correction and feedback comments with that of educators in the context of primary students' short essays written in English and Greek. *Education and Information Technologies,* 30(2), 2577-2621. https://doi.org/10.1007/s10639-024-12912-8.

Frenzke–Shim, A., Kohl–Dietrich, D., Standl, B., Langner, M., Maedche, A., and Kerber, U. (2024). The evolving role of generative AI in text literacies: exploring the potential of cognition-adaptive assistance. In *2024 IEEE Global Engineering Education Conference* (*EDUCON*) (pp. 01-03). IEEE.. https://doi.org/10.1109/EDUCON60312.2024.10578629.

Graham, I. D., Logan, J., Harrison, M. B., Straus, S. E., Tetroe, J., Caswell, W., and Robinson, N. (2006). Lost in knowledge translation: Time for a map? *Journal of Continuing Education in the Health Professions*, 26(1), 13–24. https://doi.org/10.1002/chp.47

Guo, R., Li, G., Miao, H., Huang, X., and Wang, Z. (2025). Construction and Application Effectiveness of a Project-Based Learning Model Based on Generative Artificial Intelligence. In *2025 7th International Conference on Computer Science and Technologies in Education* (*CSTE*) (pp. 515-521). IEEE. https://doi.org/10.1109/CSTE64638.2025.11092069.

Haugsbaken, H., and Hagelia, M. (2024). A New AI Literacy For The Algorithmic Age: Prompt Engineering Or Eductional Promptization? In *2024 4th international conference on applied artificial intelligence* (*ICAPAI*) (pp. 1-8). IEEE. https://doi.org/10.1109/ICAPAI61893.2024.10541229.

Helal, M. Y., Elgendy, I. A., Albashrawi, M. A., Dwivedi, Y. K., Al-Ahmadi, M. S., and Jeon, I. (2025). The impact of generative AI on critical thinking skills: a systematic review, conceptual framework and future research directions. Information Discovery and Delivery.

Hewedy, D. W., and Abdelhady, A. S. (2025). PETRA: A personalized educational tutoring tool for recursive assistance leveraging multi-model LLMs for dynamic programming learning. In *2025 15th International Conference on Electrical Engineering* (*ICEENG*) (pp. 1-6). IEEE. https://doi.org/10.1109/ICEENG64546.2025.11031311.

Hoke, T. (2025). Beyond Fear: Unleashing the Power of AI in Ethical and Psychological Growth. In *2025 Eighth International Women in Data Science Conference at Prince Sultan University* (*WiDS PSU*) (pp. 140-144). IEEE. https://doi.org/10.1109/WiDS-PSU64963.2025.00038.

Inie, N., Falk, J., and Tanimoto, S. (2023). Designing participatory ai: Creative professionals' worries and expectations about generative ai. In *Extended Abstracts of the 2023 CHI Conference on Human Factors in Computing Systems* (pp. 1-8). https://doi.org/10.1145/3544549.3585657.

Jackson, J. (2025). "Who's Doing the Thinking Here?": A Pedagogy-First Approach to Integrating Large Language Models in Higher Education. In *2025 IEEE Global Engineering Education Conference* (*EDUCON*) (pp. 1-3). IEEE. https://doi.org/10.1109/EDUCON62633.2025.11016560.

Ji, Y., Zhan, Z., Li, T., Zou, X., and Lyu, S. (2025). Human-machine co-creation: the effects of ChatGPT on students' learning performance, AI awareness, critical thinking, and cognitive load in a STEM course towards entrepreneurship. *IEEE Transactions on Learning Technologies.* https://doi.org/10.1109/TLT.2025.3554584.

Jiang, Y. H., Tang, K., Chen, Z. W., Wei, Y., Liu, T. Y., and Wu, J. (2025). MAS-KCL: Knowledge component graph structure learning with large language model-based agentic workflow. *The Visual Computer*, 41(9), 6453-6464. https://doi.org/10.1007/s00371-025-03946-1.

Jobin, A., Ienca, M., and Vayena, E. (2019). The global landscape of AI ethics guidelines. *Nature Machine Intelligence*, 1, 389–399. https://doi.org/10.1038/s42256-019-0088-2

Karafil, B., and Uyar, A. (2025). Exploring knowledge, attitudes, and practices of academics in the field of educational sciences towards using ChatGPT. *Education and Information Technologies,* 30(9), 11649-11692. https://doi.org/10.1007/s10639-024-13291-w.

Karayianni, I., Klidas, A., and Karakitsou, C. (2025). Between a Bot and a Hard Place: Student Engagement, Technology Anxiety and ChatGPT Trust in Higher Education. *TechTrends*, 1-18. https://doi.org/10.1007/s11528-025-01124-7.

Kasneci, E., Sessler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., Gasser, U., Groh, G., Günnemann, S., Hüllermeier, E., Kasneci, G., Koller, B., Krieg-Brückner, B., Kutyniok, G., Michaeli, T., Nerdel, C., Pfeffer, J., Poquet, O., Sailer, M., Schmidt, A., Seidel, T., Weller, J., Kuhn, J., and Kasneci, E. (2023). ChatGPT for good? On opportunities and challenges of large language models for education. Learning and Individual Differences, 103, Article 102274. https://doi.org/10.1016/j.lindif.2023.102274

Ko, H. T., Liu, Y. K., Tsai, Y. C., and Suen, S. (2024). Enhancing python learning through retrieval-augmented generation: A theoretical and applied innovation in generative ai education. In *International Conference on Innovative Technologies and Learning* (pp. 164-173). Cham: Springer Nature Switzerland.

Kohen-Vacs, D., Usher, M., and Jansen, M. (2025). Integrating generative AI into programming education: Student perceptions and the challenge of correcting AI errors. *International Journal of Artificial Intelligence in Education*, 1-19. https://doi.org/10.1007/s40593-025-00496-4.

Kohnke, L., Zou, D., and Xie, H. (2025). Microlearning and generative AI for pre-service teacher education: A qualitative case study. *Education and Information Technologies*, 30(15), 21221-21248. https://doi.org/10.1007/s10639-025-13606-5.

Krushinskaia, K., Elen, J., and Raes, A. (2024). Effects of generative artificial intelligence on instructional design outcomes and the mediating role of pre-service teachers' prior knowledge of different types of instructional design tasks. In *International Conference on Artificial Intelligence in Education* (pp. 395-400). Cham: Springer Nature Switzerland.

Kwon, H., Kim, J., Lim, H. H., Kim, J. M., Kim, Y., Sunwoo, C., and Hwang, D. (2025). Automated business decision-making using generative AI in online A/B testing: Comparative analysis with human decision-making. *IEEE Access*, 13, 124530-124542.

Le, N., and Taherdoost, H. (2025). Pervasive AI and IoT in STEAM Education: Advancing Future Learning Through Intelligent Systems and Computational Technologies. In 2025 *International Conference on Pervasive Computational Technologies* (*ICPCT*) (pp. 736-741). IEEE. https://doi.org/10.1109/ICPCT64145.2025.10940569.

Liang, Y., Zou, D., Xie, H., and Wang, F. L. (2023). Exploring the potential of using ChatGPT in physics education. *Smart Learning Environments*, 10(1), 52. https://doi.org/10.1186/s40561-023-00273-7.

Lin, H. C. K., Feng, C. H., and Liu, Y. L. E. (2026). Generative AI-enhanced UX storyboarding: transforming novice designers' engagement and reflective thinking for IoMT product design: Lin et al. *International Journal of Technology and Design Education*, 36(1), 223-248. https://doi.org/10.1007/s10798-025-09993-y.

Linares-Pellicer, J., Izquierdo-Domenech, J., Ferri-Molla, I., and Aliaga-Torro, C., (2024). Breaking the bottleneck: Generative AI as the solution for XR content creation in education. In Advanced Technologies and the University of the Future (pp. 9-30). Cham: Springer Nature Switzerland.

Liu, C., Chai, K. K., and Chen, Y. (2025). The Transformative Role of Generative AI in Higher Education: Perspectives from Academia and Industry. In *2025 IEEE Global Engineering Education Conference* (*EDUCON*) (pp. 1-6). IEEE. https://doi.org/10.1109/EDUCON62633.2025.11016643.

Lo, C. K. (2023). What is the impact of ChatGPT on education? A rapid review of the literature. *Education Sciences*, 13(4), 410. https://doi.org/10.3390/educsci13040410

Loo, J., Chen, Y., and Chai, K. K. (2025). Transforming embedded systems design course: GenAI-empowered CDIO-based authentic assessment with challenge-based learning. In *2025 6th International Conference on Information Technology and Education Technology* (*ITET*), 30-35. IEEE. https://doi.org/10.1109/ITET65804.2025.11100409.

Lukhmanov, Y., Perveen, A., and Tsakalerou, M. (2025). ChatGPT in engineering teaching & learning: student and faculty perspective. *In 2025 IEEE Global Engineering Education Conference* (*EDUCON*), 1-5. https://doi.org/10.1109/EDUCON62633.2025.11016423.

Luo, G., Niu, C., Lu, L., Wu, L., and Huang, L. (2025). Empirical study on the double-edged effects of generative artificial intelligence on team creativity among university students. *Education and Information Technologies*, 30(13), 18853-18878. https://doi.org/10.1007/s10639-025-13527-3.

Ma, L., Pan, M., Siu, V., Chang, X., Holopainen, J., Li, J., and LC, R. (2025). Follow My Logic: Generative AI Workflows in Designing for Serious Table-Top Games. In *International Conference on Human-Computer Interaction* (pp. 153-172). Cham: Springer Nature Switzerland.

MacArthur, M. (2025). Large language models and the problem of rhetorical debt. *AI & SOCIETY*, 1-14. https://doi.org/10.1007/s00146-025-02403-w.

Matobobo, C., Ncube, P. D. N., Ngesimani, N. L., Dzvapatsva, G. P., and Chinhamo, E. (2025). Enhancing computational thinking and problemsolving in programming education through generative AI: A scoped review. In *2025 IEEE global engineering education conference* (*EDUCON*), 1-9. https://doi.org/10.1109/EDUCON62633.2025.11016317.

Naeem, U., Styve, A., and Virkki, O. T. (2025). Stimulating Critical Thinking in a Web Programming Module with Generative AI Tools. In *2025 IEEE Global Engineering Education Conference* (*EDUCON*) (pp. 1-7). IEEE. https://doi.org/10.1109/EDUCON62633.2025.11016298.

Noenthaisong, K., and Thanwisai, S. (2024). Impact of ChatGPT and the Capability to Critically Use Technological Creativity on English Proficiency of High School Student. In *2024 5th International Conference on Information Technology and Education Technology* (*ITET*) (pp. 7-11). IEEE. https://doi.org/10.1109/ITET64267.2024.00011.

Offor, K. J. (2025). Leveraging Generative AI to simulate stakeholder involvement in the engineering design process: a case study of MSc Team-Based Projects. In *2025 IEEE Global Engineering Education Conference* (*EDUCON*) (pp. 1-3). IEEE. https://doi.org/10.1109/EDUCON62633.2025.11016557.

Oiva-Córdova, L. M., Alvarez-Icaza, I., and George-Reyes, C. E. (2025). Evaluation of generative AI use to foster critical thinking in higher education. *IEEE Revista Iberoamericana de Tecnologias Del Aprendizaje.* https://doi.org/10.1109/RITA.2025.3597848.

Organisation for Economic Co-operation and Development (OECD). (2024). OECD digital education outlook 2024: Towards an effective digital education ecosystem. OECD Publishing.

Parasuraman, R., and Manzey, D. H. (2010). Complacency and bias in human use of automation: An attentional integration. Human Factors, 52(3), 381–410. https://doi.org/10.1177/0018720810376055

Parasuraman, R., and Riley, V. (1997). Humans and automation: Use, misuse, disuse, abuse. Human Factors, 39(2), 230–253. https://doi.org/10.1518/001872097778543886

Park, S. M., Ho, M., Lin, M. P. C., and Ryoo, J. (2025). Evaluating the impact of assistive ai tools on learning outcomes and ethical considerations in programming education. In *2025 IEEE Global Engineering Education Conference* (*EDUCON*) (pp. 1-10). IEEE. https://doi.org/10.1109/EDUCON62633.2025.11016517.

Park, Y., Kim, H., Choi, C., Kim, J., and Sohn, J. Y. (2024). Can separators improve chain-of-thought prompting?. In *2024 2nd International Conference on Foundation and Large Language Models* (*FLLM*) (pp. 493-500). IEEE. https://doi.org/10.1109/FLLM63129.2024.10852507.

Parra Pennefather, P. (2025). Reconcile Using Generative AI. In Regenerating Learning: Transforming How You Learn with Generative AI (pp. 211-289). Berkeley, CA: Apress.

Pérez, M. M. G., Figarola, A. F., and Villegas, E. R. (2025). Leveraging Emerging Digital Technologies in Climate Change Education: A National-Level Case Study. In 2*025 IEEE Global Engineering Education Conference* (*EDUCON*) (pp. 1-8). IEEE. https://doi.org/10.1109/EDUCON62633.2025.11016608

Pham, V. T. T., and Pham, A. T. (2025). Investigating EFL Students' Attitudes Towards AI-Powered Tools in English Language Learning,". In *2025 13th International Conference on Information and Education Technology (ICIET*) (pp. 192-196). IEEE.

Ping, H., Wang, W., Xie, Y., Lv, S., Li, J., and Weng, L. (2025). Generative AI Dependency in Higher Education: Investigating Continuance Intention, Cognitive Response, and Creativity. In *2025 7th International Conference on Computer Science and Technologies in Education* (*CSTE*) (pp. 615-621). IEEE. https://doi.org/10.1109/CSTE64638.2025.11092242.

Puttajanyawong, N., Suamuang, W., and Chomsuwan, K. (2025). Utilizing generative AI to develop programming skill through self-directed and interactive learning. In *2025 IEEE Global Engineering Education Conference* (*EDUCON*) (pp. 1-9). IEEE. https://doi.org/10.1109/EDUCON62633.2025.11016488.

Qian, Y. (2025). Pedagogical applications of generative AI in higher education: A systematic review of the field. *TechTrends*, 1-16. https://doi.org/10.1007/s11528-025-01100-1.

Rajpurkar, P., Chen, E., Banerjee, O., and Topol, E. J. (2022). AI in health and medicine. Nature Medicine, 28, 31–38. https://doi.org/10.1038/s41591-021-01614-0

Sanchez-Lopez, A. L., Jimenez-Perez, M. I., Perfecto-Avalos, Y., Navarro-Lopez, D. E., Esparza-Sanchez, J., and Mena, E. R. L. (2025). Integration of Artificial Intelligence as a Tool to Enhance Critical Thinking Skills and Foster Learning in Bioengineering Education. In *2025 IEEE Global Engineering Education Conference* (*EDUCON*) (pp. 1-5). IEEE. https://doi.org/10.1109/EDUCON62633.2025.11016586.

Segura-Azuara, N. D. L. A., Garza-Arriaga, F. D. J., and Guzman-Segura, J. G. (2025). Enhanced Learning with Artificial Intelligence: A Comparative Study in Medical Students. In 2025 Institute for the Future of Education Conference (IFE) (pp. 1-8). IEEE.

Schicchi, D., and Taibi, D. (2025) Enhancing active learning in education through ChatGPT and concept maps: A case study. In: Communications in Computer and Information Science, pp 3–16. Springer Nature Switzerland, Cham

Shao, H., and Tang, G. (2025). Empowering mathematical problem-posing pedagogy with generative AI: A theoretical framework and case study. In *2025 14th International Conference on Educational and Information Technology* (*ICEIT*) (pp. 111-115). IEEE. https://doi.org/10.1109/ICEIT64364.2025.10975950.

Shi, Y., Gao, Y., Lai, Y., Wang, H., Feng, J., He, L., Wan, J., Chen, C., Yu, Z. and Cao, X., (2025). Shield: An evaluation benchmark for face spoofing and forgery detection with multimodal large language models. *Visual Intelligence*, 3(1), p.9. https://doi.org/10.1007/s44267-025-00079-w.

Skivington, K., Matthews, L., Simpson, S. A., Craig, P., Baird, J., Blazeby, J. M., Boyd, K. A., Craig, N., French, D. P., McIntosh, E., Petticrew, M., Rycroft-Malone, J., White, M., and Moore, L. (2021). A new framework for developing and evaluating complex interventions: Update of Medical Research Council guidance. BMJ, 374, Article n2061. https://doi.org/10.1136/bmj.n2061

Sparrow, B., Liu, J., and Wegner, D. M. (2011). Google effects on memory: Cognitive consequences of having information at our fingertips. *science*, 333(6043), 776-778. https://doi.org/10.1126/science.1207745.

Speicher P., and Becker L. (2025) LLMs as your second brain - how AI will affect the way we solve problems. In: Digital Management and Artificial Intelligence, pp 456–475. Springer Nature Switzerland, Cham

Tlili, A., Shehata, B., Burgos, D., and Jemni, M. (2023). What if the devil is my guardian angel: ChatGPT as a case study of using chatbots in education. Smart Learning Environments, 10, Article 15. https://doi.org/10.1186/s40561-023-00237-x

Tophel, A., Chen, L., Hettiyadura, U., and Kodikara, J. (2025). Towards an AI tutor for undergraduate geotechnical engineering: a comparative study of evaluating the efficiency of large language model application programming interfaces. *Discover Computing*, 28(1), 76. https://doi.org/10.1007/s10791-025-09580-8.

Topol, E. J. (2019). Deep medicine: How artificial intelligence can make healthcare human again. Basic Books.

Tseng, Y. C., and Chang, Y. Y. (2025). Interdisciplinary Co-design with LLM-Based Multi-agents: A Human-AI Platform for Complex Design Challenges. In *International Conference on Human-Computer Interaction* (pp. 396-410). Cham: Springer Nature Switzerland.

Uludağ, F., Kılıç, E., and Çelik, H. E. (2025). Artificial intelligence, social influence, and AI anxiety: analyzing the intentions of science doctoral students to use ChatGPT with PLS-SEM. *Humanities and Social Sciences Communications*, 12(1), 1-17. https://doi.org/10.1057/s41599-025-05641-x.

United Nations Educational, Scientific and Cultural Organization (UNESCO) (2021). Recommendation on the ethics of artificial intelligence. United Nations Educational, Scientific and Cultural Organization.

United Nations Educational, Scientific and Cultural Organization (UNESCO) (2023). Guidance for generative AI in education and research. United Nations Educational, Scientific and Cultural Organization.

Wang, Y., Luo, Z., Guo, D., Zhou, Z., and Paas, F. (2025). Impacts of a progressive feedback prompt-based text-generative AI approach on Chinese poetry learning. In *2025 7th International Conference on Computer Science and Technologies in Education* (*CSTE*) (pp. 533-537). IEEE. https://doi.org/10.1109/CSTE64638.2025.11092104.

Weerasinghe, K., Janapati, S., Ge, X., Kim, S., Iyer, S., Stankovic, J. A., and Alemzadeh, H. (2024). Real-time multimodal cognitive assistant for emergency medical services. *arXivPreprintar Xiv:*2403.06734. https://doi.org/10.48550/arXiv.2403.06734

Wu, Y., Zhang, W., and Lin, C. (2025). Generative Artificial Intelligence in University Education. *IT Professional*, 27(2), 69-74. https://doi.org/10.1109/MITP.2025.3545629.

Yan, L., Zhao, L., Echeverria, V., Jin, Y., Alfredo, R., Li, X., Gaševi'c, D. and Martinez-Maldonado, R. (2024). VizChat: enhancing learning analytics dashboards with contextualised explanations using multimodal generative AI chatbots. In International conference on artificial intelligence in education (pp. 180-193). Cham: Springer Nature Switzerland.

Yao, X., Zhong, Y., and Cao, W. (2025). The analysis of generative artificial intelligence technology for innovative thinking and strategies in animation teaching. *Scientific Reports*, 15(1), 18618. https://doi.org/10.1038/s41598-025-03805-y.

Zhang, X. (2025). Course Design for Fostering Critical Use of Chatgpt in Academic Writing. In *2025 International Symposium on Educational Technology* (*ISET*) (pp. 1-5). IEEE.

Zhang, R., and Wang, J. (2025). Perceptions, adoption intentions, and impacts of generative AI among Chinese university students. *Current Psychology*, 44(11), 11276-11295.

Print-ISSN 2244-4432 Online-ISSN 2984-7125