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Pedagogical Uses of Generative AI in Education: A Structured Literature Review

Research Report

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1. Summary

Recent advances in generative artificial intelligence (GenAI), especially large language models such as ChatGPT, together with the rapid growth in the number of these tools, are reshaping education. These changes raise important questions about how GenAI is used and its effects on learning specifically:

- What pedagogical roles does GenAI play for learners and teachers?
- What instructional approaches are associated with the integration of GenAI in teaching and learning?
- What GenAI tools are used?
- What positive learning outcomes are associated with the use of GenAI in education?
- What risks, challenges, and barriers are identified in relation to GenAI use in education?

To explore these questions, we carried out a structured literature review. A structured review follows clear steps to make the findings strong and reliable. First, we defined the scope of the research. Next, we searched bibliographic databases, such as Scopus, for relevant peer-reviewed systematic reviews. This helped ensure the evidence was robust. We then read the titles, abstracts, and full texts to check if they met criteria linked to the research questions. For example, studies had to focus on GenAI in educational settings for learners aged 3 to 19. We kept only the studies that met these criteria. After this, we recorded key information, such as study results, using clear and consistent categories. In total, we identified 14 reviews and brought their findings together in this report.

Our findings show that:

- Learners use GenAI to support their learning.
- Teachers use it for teaching tasks and for administrative work.
- GenAI supports a range of teaching approaches. These include giving information, helping with tasks, supporting interaction, and enabling one-to-one learning. However, these approaches represent only a small part of all instructional approaches used in schools including offline work. GenAI may also lead to new approaches or changes to existing ones.
- Many different GenAI tools are used in education. This is expected, as the number of such tools continues to grow rapidly.
- When used well, GenAI can support cognitive, social, and emotional learning outcomes. However, there are challenges. These include teacher readiness, technical issues, ethical concerns, data use, and possible negative effects on learning or wellbeing. It is therefore important to teach pupils how to use GenAI well and how to work without it.

This research provides a valuable overview of key educational elements, but effective learning design requires understanding how these and additional elements interact within specific contexts. Further research is needed to identify effective combinations of AI use, pedagogy, tools, a diversity of learners, a range of domains and subjects, and the conditions in which the learning takes place and so on. Given AI's rapid evolution, decisions must combine the best available evidence with professional judgement.

A key next step may be to consider how AI can support learning and promote fairness. Some frameworks already exist. While this review does not evaluate them, we recommend that future work assesses these frameworks to decide whether to adopt an existing one or develop a new approach.

2. Introduction

Recent advances in generative artificial intelligence (GenAI), particularly large language models such as ChatGPT, have significantly reshaped educational discourse and practice. Unlike earlier applications of artificial intelligence in education, which primarily focused on adaptive systems, intelligent tutoring, and learning analytics, GenAI tools are interactive, generative, and widely accessible to learners and teachers (Kasneci et al., 2023; Zawacki-Richter, Marín, Bond, & Gouverneur, 2019). Intelligent tutoring uses GenAI to give each learner personalised help, feedback, and guidance (Ma, Adesope, Nesbit, & Liu, 2014).

This shift has expanded both the potential and the complexity of AI integration in education. GenAI systems are now capable of generating explanations, solving problems, providing feedback, supporting writing, creative production, and facilitating idea generation, while positioning such systems not only as tools but also as active participants of the learning process. These developments raise important questions about pedagogy, assessment, and the role of human agency in learning (Holmes & Miao, 2023).

Alongside these developments, there has been a rapid increase in systematic literature reviews examining GenAI in education. These reviews address a wide range of topics, including pedagogical applications, ethical considerations, and emerging competencies such as AI literacy (Holmes, Bialik, & Fadel, 2019). However, despite this growing body of work, key gaps in research about AI in school level education persist (Yusuf, Pervin, Román-González, & Noor, 2024). To address this gap, we undertook a structured literature review to synthesise findings from existing systematic literature reviews on GenAI in school level education. Our work focuses on how GenAI is pedagogically integrated across teaching and learning contexts, examining its roles, associated instructional approaches, and reported outcomes, as well as the risks and limitations identified in the literature.

2.1. Why is it important? Implications for the future of learning and assessment

The rapid integration of GenAI into educational contexts raises fundamental questions about the nature of learning, knowledge, and assessment. While GenAI offers significant opportunities to enhance access to information, personalise learning, and support complex tasks, it also challenges long-standing assumptions about what it means to know, understand, and demonstrate competence.

From a learning perspective, GenAI is not simply a new educational tool but a transformative cognitive partner. Learners can now, for example, generate explanations, solve problems, and produce extended pieces of work with AI support. This shifts the locus of cognitive activity from the individual to a distributed system that includes both human and technological components. Such developments align with theories of distributed and extended cognition, which suggest that thinking can be supported and partially externalised through interaction with tools and environments (Clark & Chalmers, 1998; Kirsh, 2010). Such literature considers GenAI to be a tool to think with.

At the same time, this externalisation of cognitive processes introduces important tensions. On the one hand, delegating routine or lower-level cognitive tasks to GenAI may free up mental resources for higher-order thinking, reflection, and creativity. On the other hand, excessive reliance on AI tools may reduce opportunities for deep processing, critical

thinking, and independent problem-solving. Research on cognitive offloading highlights this trade-off, showing that while external tools can increase efficiency, they may also alter how knowledge is encoded, retained, and applied (Risko & Gilbert, 2016; Sparrow, Liu, & Wegner, 2011).

These shifts have significant implications for curriculum design. If learners can reliably access or generate information through AI systems, educational priorities may need to move beyond knowledge reproduction towards skills such as evaluation, interpretation, and epistemic judgement. This aligns with broader educational perspectives that conceptualise learning as an active process of meaning-making rather than passive information acquisition (Salomon, 1990).

The implications for assessment are particularly profound. Traditional assessment models often assume that performance reflects an individual's internal knowledge and abilities. However, in AI-mediated environments, performance may increasingly reflect the ability to effectively interact with and leverage external systems. This raises critical questions about construct validity: what exactly is being measured when learners complete tasks with AI support?

Distinguishing between unaided performance and AI-supported performance becomes essential. Rather than viewing AI use solely as a threat to academic integrity, it may be more productive to conceptualise it as part of the assessment context. This shift reframes the challenge from one of control to one of design: determining which cognitive processes should be supported, which should be assessed independently, and how evidence of learning should be interpreted.

At a system level, these developments call for a re-evaluation of long-standing assumptions about knowledge, progression, and readiness. As GenAI becomes embedded in educational practice, institutions must consider not only how to integrate these technologies, but also how to redefine educational goals in ways that remain meaningful in an AI-rich world.

In this context, synthesising evidence on how GenAI is used pedagogically, and what outcomes it supports or undermines is critical. Without a coherent understanding of these patterns, there is a risk that adoption will be driven by technological possibility rather than educational purpose. This report therefore contributes to a more structured and evidence-informed foundation for navigating the future of learning and assessment.

2.2. Research aim and research questions

The aim of this study is to synthesise existing systematic literature reviews on GenAI in education in order to develop a comprehensive and pedagogically grounded understanding of how these technologies are used across teaching and learning contexts. Specifically, the study seeks to map the pedagogical roles of GenAI for both learners and teachers, examine the instructional approaches through which it is integrated, and analyse the reported learning outcomes, risks, and challenges. By doing so, the study aims to identify overarching patterns and key gaps in the evidence base, and to provide a structured foundation for informing future research, policy, and practice. This study addresses the following research question:

"How is generative artificial intelligence (GenAI) used and integrated pedagogically in education, and what patterns emerge across systematic literature reviews in relation to its roles, instructional approaches, learning outcomes, risks, and evidence gaps?"

The overarching question is explored through the following sub questions:

1. What pedagogical roles does GenAI play for learners and teachers?
2. What instructional approaches are associated with the integration of GenAI in teaching and learning?
3. What GenAI tools are used?
4. What positive learning outcomes are associated with the use of GenAI in education?
5. What risks, challenges, and barriers are identified in relation to GenAI use in education?

3. Method

3.1. Search strategy and inclusion/exclusion criteria

This study drew from the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) guidelines. A structured literature review was conducted. This review followed a systematic, step-by-step approach and used a predefined protocol to determine which studies were included in the review (Figure 1). Each stage of the process was carefully documented to ensure transparency and consistency. However, a structured literature review does not involve a formal assessment of the quality of the included studies. Instead, it relies on the peer-review process involved in academic publishing as an indicator of research quality.

The review targeted publications between 2022 and 2025, reflecting the emergence and rapid development of GenAI in educational contexts.

A literature search was performed using three major bibliographic databases: Scopus, Web of Science (WoS), and Google Scholar. Search strings combined terms related to generative AI technologies (e.g., *"generative AI", "ChatGPT", "large language models"*), cognitive constructs (e.g., *"cognitive offloading", "critical thinking", "memory", "learning outcomes"*), educational contexts (e.g., *"student", "school", "K-12"*) and methodological terms (e.g., "experiment", "survey", "case study"). Searches were limited to English-language publications within education, psychology and related social science disciplines. Comparable Boolean logic was applied across databases. An example search string used in a database is provided in Appendix 1.

Studies were included if the title and abstract met these following inclusion criteria:

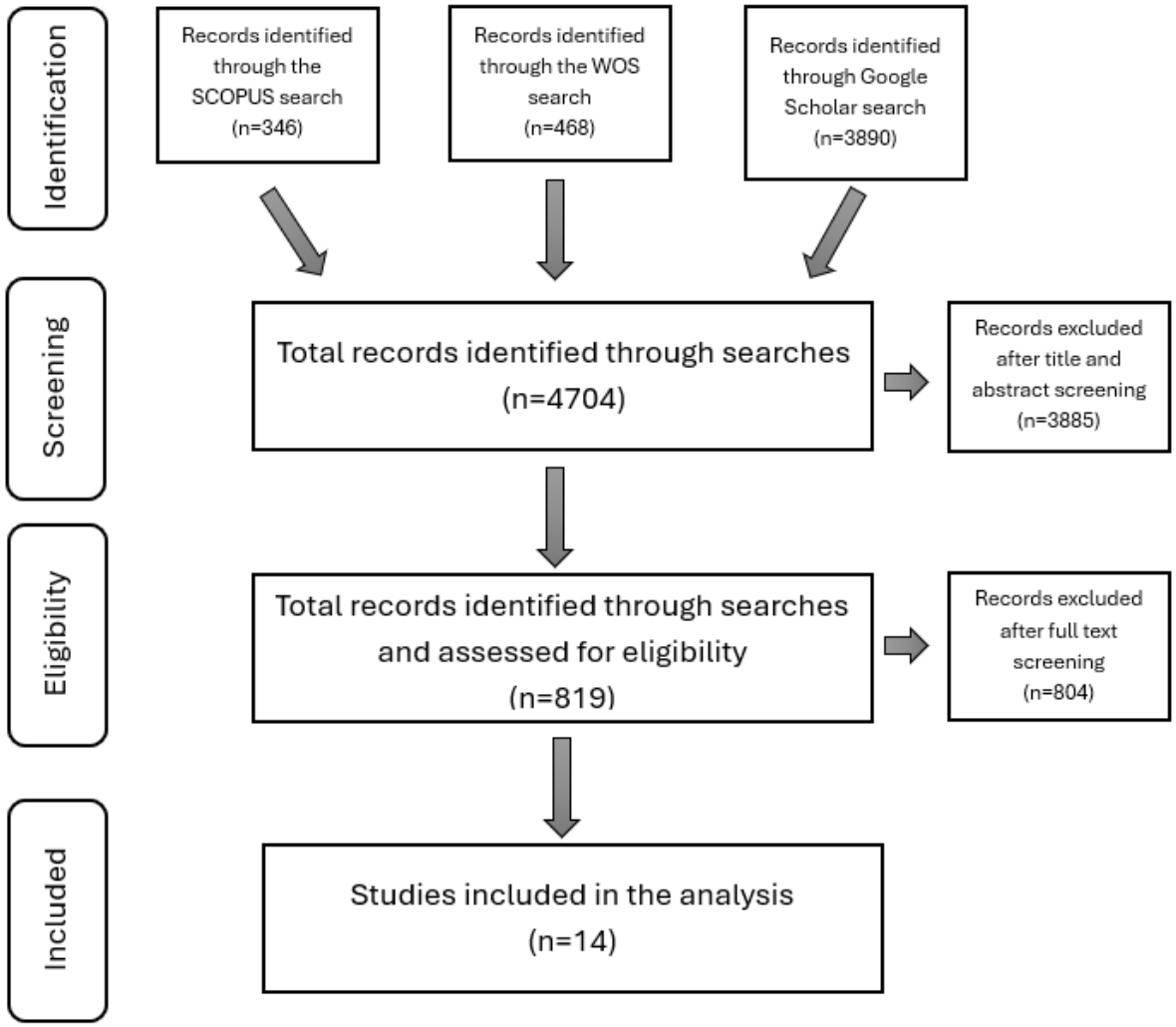
- peer-reviewed systematic literature review
- focus on AI or GenAI in educational contexts
- participants are aged between 3 and 19 years, reflecting the internationally recognised trajectory from early childhood through upper secondary education (UNESCO, 2012)
- published in English

Studies were excluded if they:

- focused on higher education or teacher training contexts
- were book reviews, or editorials
- did not address learning or cognitive outcomes

The initial search yielded 146 records from Scopus, 428 from Web of Science, and 3,890 from Google Scholar. Following screening and eligibility checks, the corpus was refined to systematic literature reviews meeting the age and context criteria. Fourteen systematic reviews were retained and categorised into three conceptual clusters for synthesis.

Figure 1 PRISMA flow diagram of the study

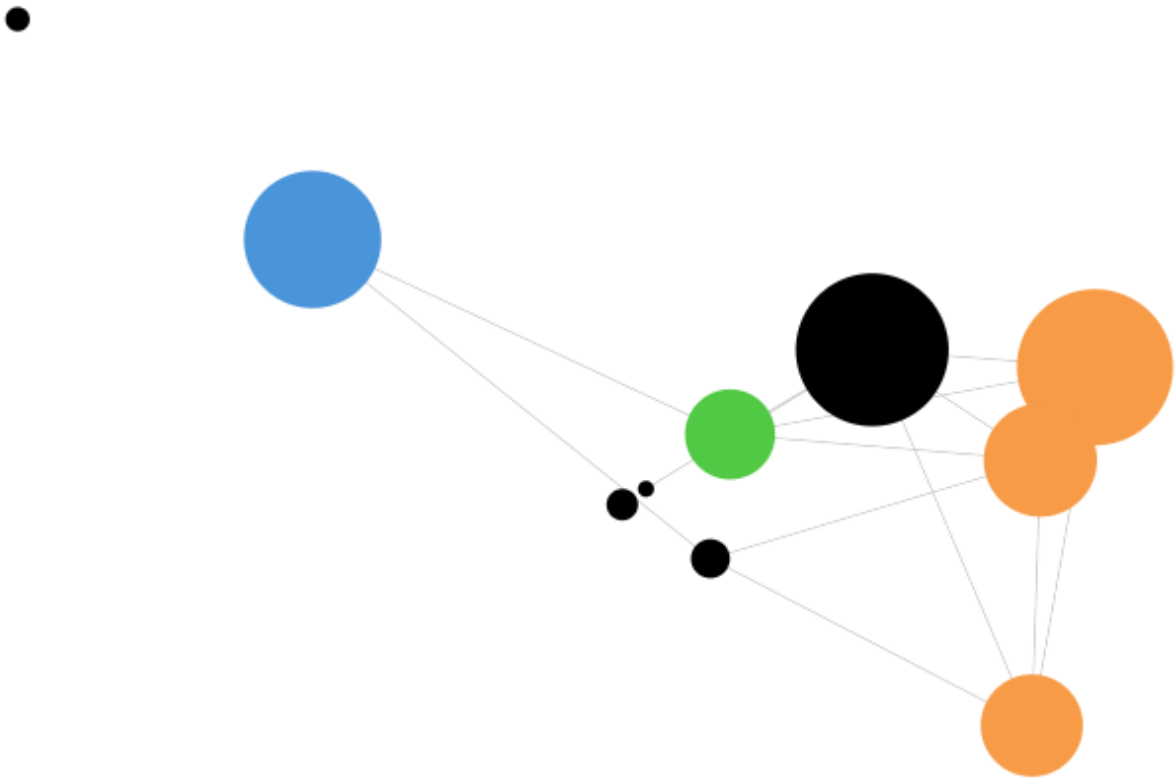


3.2. Data extraction, generating categories and coding procedure

Based on the research questions and the inclusion criteria applied during screening, a set of preliminary coding categories was developed to guide the data extraction process. Data extraction was piloted independently by two researchers using three included articles to test the clarity and applicability of the coding framework. The researchers then compared results and discussed any discrepancies to harmonise interpretations and ensure a shared understanding of the coding categories. Following this calibration exercise, the coding framework was refined and finalised. Data extraction for the remaining studies was subsequently conducted in accordance with the agreed framework.

In the citation graph (Figure 2), each node represents an article and each edge shows a citation link between two articles. Black nodes represent the reviews retained for data extraction, while the coloured nodes indicate works that appear in the reference lists of more than one of these reviews. Reading from left to right, the black dots represent Zhang & Tur (2023), Aravantinos et al. (2024), Song et al. (2024), Lee & Kwon (2024) and Casal Otero et al. (2023). The coloured nodes indicate Zawacki-Richter et al. (2019), Ng et al. (2023), Tedre et al. (2021), Touretzky, Gardner-McCune, Martin, and Seehorn (2019), and Long and Magerko (2020).

Figure 2 Citation graph illustrating five of the fourteen systematic reviews included in the study



The graph includes only papers for which a DOI was recognised by the software, corresponding to five of the fourteen reviews analysed. This limitation should be noted. Nevertheless, the graph shows that two of the five reviews share no citations with the remaining three. Among the three that do share citations, only five common papers were identified.

These findings suggest minimal overlap across the fourteen reviews, indicating that their evidence bases are largely distinct.

Table 1 Characteristics of the reviewed studies

	Year of publication	Title of the study	Studies in the systematic review
Al-Kamzari & Alias	2026	A systematic literature review of artificial intelligence (AI) in secondary school physics: applications, benefits, and challenges	29
Lee & Kwon	2024	A systematic review of AI education in K-12 classrooms from 2018 to 2023: Topics, strategies, and learning outcomes	25
Aravantinos et al.,	2024	Educational approaches with AI in primary school settings: A systematic review of the literature available in Scopus	35
Lin & Tan	2025	A systematic review of generative AI in K-12: mapping goals, activities, roles, and outcomes via the 3P Model	84
Alfarwan	2025	Generative AI use in K-12 education: a systematic review	30
Li & Wilson	2025	AI-integrated scaffolding to enhance agency and creativity in K-12 English language learners: A systematic review	14
Iftitah, Chaeruman & Khaerudin	2025	Generative artificial intelligence in teacher-driven personalized learning for K-12 education: A systematic literature review	34
Saputra, Murdiono, Tohani & Ibda	2024	AIEd in elementary school nationalism education: A systematic literature review	50
Boulhrir & Hamash	2025	Unpacking artificial intelligence in elementary education: A comprehensive thematic analysis systematic review	80
Lee, Kim & Yan	2025	Promoting inclusive AI and technology in K-12 education: A review of context, instructional strategies, and learning outcomes	17
Song et al	2024	A framework for inclusive AI learning design for diverse learners	10
Zhang & Tur	2023	A systematic review of ChatGPT use in K-12 education	13
Zhang, Lai & Yu	2026	Generative artificial intelligence in K-12 education: A systematic review	45
Casal-Otero et al.,	2023	AI literacy in K-12: a systematic literature review	179

4. Results

In this section we summarise the data extracted from the systematic reviews.

4.1. Learners' pedagogical uses of GenAI

We considered how learners use GenAI in their learning. Reflecting on the systematic reviews we identified three main categories of ways in which it is applied:

- **GenAI as a writing assistant**
- **GenAI as a creative partner**
- **GenAI as a tutor**

First, learners employ **GenAI as a writing assistant**. This encompasses two related uses. The first is **writing support**, where GenAI is used to draft text or contribute to the drafting process (Alfarwan, 2025; Boulhrir & Hamash, 2025; Iftitah, Chaeruman, & Khaerudin, 2025; Li & Wilson, 2025; Lin & Tan, 2025; Zhang & Tur, 2024; Zhang, Lai, & Yu, 2026). The second is **content summarisation**, where GenAI is used to shorten existing text (Boulhrir & Hamash, 2025; Iftitah et al., 2025; Zhang et al., 2026). Boulhrir and Hamash (2025) note that, in elementary schools, learners use GenAI to draft or summarise text, and they emphasise the importance of selecting appropriate tools judiciously.

In the second category, learners utilise **GenAI as a creative partner**, typically either for **creative production** (such as generating images, text, music, or other artefacts) or for **idea generation** to support brainstorming and concept development (Aravantinos et al., 2024; Boulhrir & Hamash, 2025; Casal-Otero et al., 2023; Iftitah et al., 2025; Lee & Kwon, 2024; Saputra, Murdiono, Tohani, & Ibda, 2024; Song et al., 2024; Zhang & Tur, 2024; Zhang et al., 2026). Illustrative examples include using GenAI to create music compositions (Aravantinos et al., 2024), experimenting with machine learning to classify self-captured images using a coding platform (Casal-Otero et al., 2023), and using Midjourney to design illustrations of fairy tales, combined with ChatGPT to create interactive children's books (Zhang et al., 2026).

The third category is learners using **GenAI as a tutor**. In the studies reviewed, this tutoring function is divided into four main uses: GenAI used as a learning assistant or companion; GenAI used to enable adaptive learning; GenAI used to support personalised and self-regulated learning; and GenAI used to provide personalised feedback.

Within this third category, some literature notes learners use GenAI as a **learning assistant/companion** (Alfarwan, 2025; Boulhrir & Hamash, 2025; Casal-Otero et al., 2023; Iftitah et al., 2025; Lee, Kim, & Yan, 2025; Lee & Kwon, 2024; Li & Wilson, 2025; Saputra et al., 2024; Song et al., 2024; Zhang et al., 2026). For instance, this includes using GenAI to explain content (Li & Wilson, 2025; Zhang & Tur, 2024), to act as a language-learning partner, and to provide guidance for solving problems (Zhang & Tur, 2024). There is also evidence of learners using GenAI for **adaptive learning** (Al-Kamzari & Alias, 2026; Boulhrir & Hamash, 2025; Casal-Otero et al., 2023; Iftitah et al., 2025; Song et al., 2024). For example, learners' dialogue and modelling are used to tailor complex conceptual physics content to the needs of the individual student (Al-Kamzari & Alias, 2026).

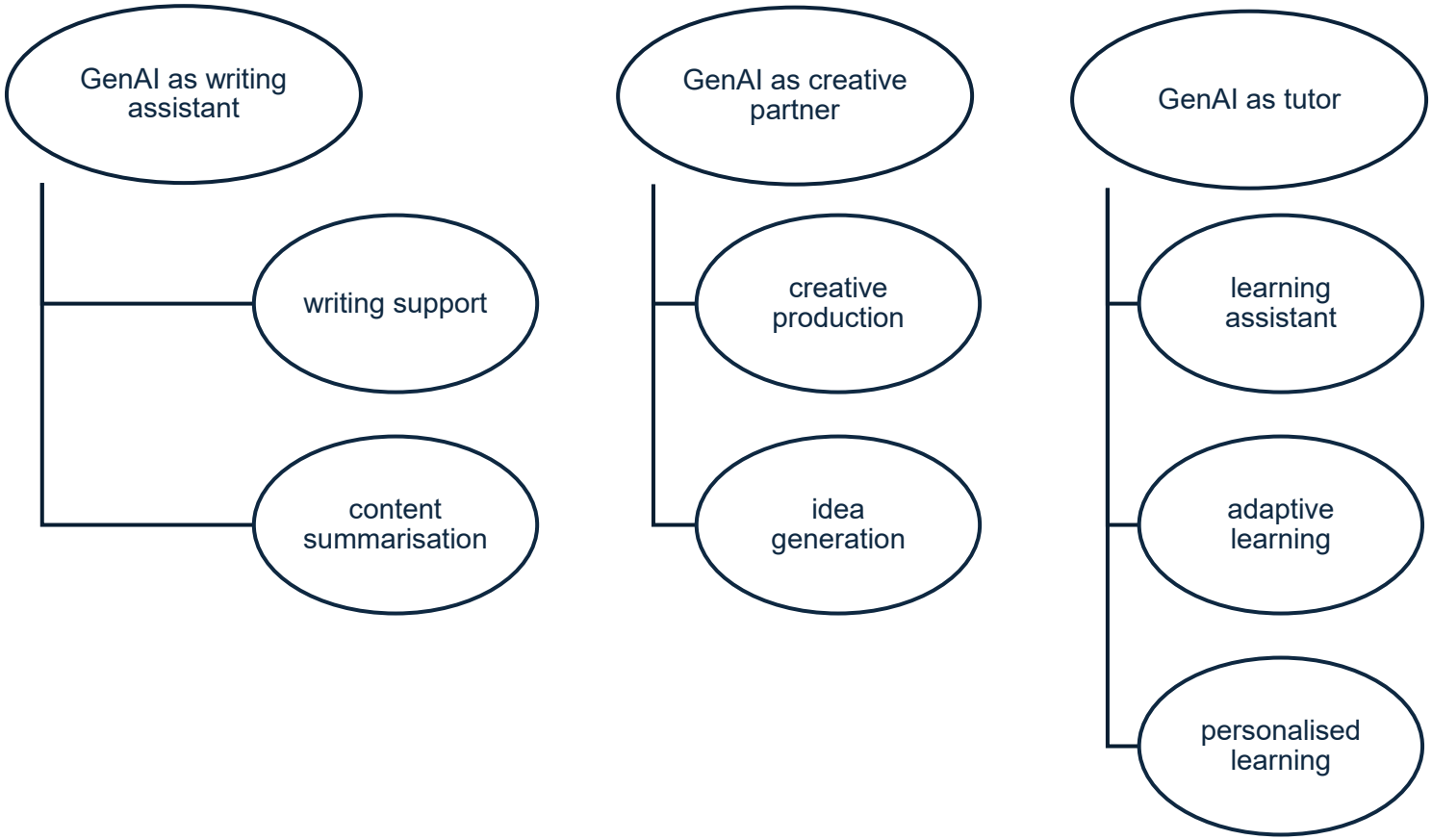
In addition, several studies discuss GenAI as part of **personalised learning/self-regulated learning** (Al-Kamzari & Alias, 2026; Alfarwan, 2025; Boulhrir & Hamash, 2025; Iftitah et al., 2025; Lee et al., 2025; Lee & Kwon, 2024; Li & Wilson, 2025; Lin & Tan, 2025; Saputra et al.,

2024; Song et al., 2024; Zhang & Tur, 2024; Zhang et al., 2026). For example, within a self-regulated learning process, learners use an SRLbot: a personalised interactive tool that provides targeted suggestions about content, while taking account of the learner's individual learning preferences (Zhang et al., 2026).

Finally, within the third category, literature indicates that learners use GenAI to obtain **personalised feedback** (Boulhrir & Hamash, 2025; Iftitah et al., 2025; Song et al., 2024; Zhang & Tur, 2024; Zhang et al., 2026). In mathematics and other domains, for example, learners use conversational agents, that is software that uses GenAI to interact with learners using natural language (Aktaş & Akbıyık, 2025; Boulhrir & Hamash, 2025). Some conversational agents give immediate personalised feedback on the learners task performance, which is particularly useful for learners with diverse learning profiles (Boulhrir & Hamash, 2025).

Figure 3 represents learners pedagogical uses of GenAI.

Figure 3 Learners' pedagogical uses of GenAI



4.2. Teachers' pedagogical uses of GenAI.

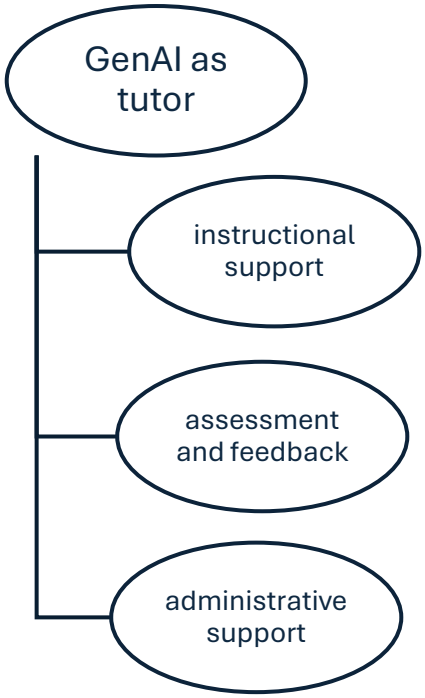
We consider how teachers use GenAI in teaching and learning. A portion of the literature identifies one way it is employed: **GenAI as a tutor.**

This incorporates three related uses (Figure 4). The first is **instructional support**, including lesson planning, content generation, and learning material development. The literature frequently notes teachers using GenAI for instructional support (Alfarwan, 2025; Aravantinos et al., 2024; Boulhrir & Hamash, 2025; Casal-Otero et al., 2023; Iftitah, Chaeruman, & Khaerudin, 2025; Lee, Kim, & Yan, 2025; Lee & Kwon, 2024; Lin & Tan, 2025; Saputra, Murdiono, Tohani, & Ibda, 2024; Zhang & Tur, 2024; Zhang, Lai, & Yu, 2026). Specifically teachers use it for resource design (Casal-Otero et al., 2023).

Secondly, teachers use GenAI as an **assessment and feedback tool**, for instance to generate questions and answers. The literature often notes teachers using GenAI in this way (Zhang et al., 2026). For instance, to tailor assessment to students' needs (Iftitah et al., 2025), to generate writing tasks (Li & Wilson, 2025), to generate questions and feedback (Song et al., 2024).

Thirdly, teachers use GenAI as **administrative support**. The studies repeatedly highlights teachers using GenAI in this way (Zhang et al., 2026). For instance, teachers use it to help with student reports and emails to parents (Zhang et al., 2026).

Figure 4 Teachers' pedagogical uses of GenAI



4.3. Instructional approaches for/in teaching GenAI

We investigate whether the reviews discuss the methods or strategies used in GenAI education. This includes ways of teaching GenAI concepts or using GenAI in learning activities.

We use a framework to see how these instructional approaches fit together into categories. This framework is based on learning theories (Majewska et al., 2025). It shows key ideas from learning theories and the teaching practices that mainly come from them. The instructional approaches found in the reviews are shown in blue text. Their place in the framework is shown in Table 2. From this analysis we create five main categories (which are four learning theories and an "other" category) and sixteen instructional approaches:

- behaviourism
  - gamification
- cognitivism
  - self-reflected learning
- constructivism
  - problem-based learning
  - (hybrid human-GenAI) collaborative learning
  - scaffolding
  - project-based learning
  - experiential learning
- constructionism
  - designed based learning
  - hands on activities
- other
  - GenAI assisted instruction
  - teacher guided GenAI integration
  - student-directed GenAI exploration
  - active learning
  - student centred activities
  - personalised learning
  - self-directed learning

The categories and instructional approaches are also represented in Figure 5.

Focusing on the instructional approaches, the literature does not always distinguish between teaching GenAI concepts and integrating GenAI into learning. The literature highlights a wide variety of instructional approaches. These approaches are not always mutually exclusive. We aim to give an illustrative example of each approach in the classroom. The literature often summarises these approaches instead of showing clear examples. Because of this, we use other sources to give clear examples.

Table 2 Framework of theories and associated teaching practices from Majewska et al (2025)

Learning theory	Deriving Learning Theory	Teaching practices / strategies
Behaviourism	Classical conditioning	Sensory cues
	Operant conditioning	Positive reinforcement
		Negative reinforcement
		Positive punishment
		Negative punishment
		Gamification elements
Cognitivism	Cognitive Load Theory	Worked examples
Self reflected		Scaffolding, guidance and schema-based instruction
learning		Collaborative problem-solving
		Spaced learning
		Interleaving
	Information processing theory	Retrieval practice
		Repetition
		Advance organisers and cues
	Distributed Cognition Theory	Using external resources to aid cognitive tasks
	Dual coding theory	Providing visual and verbal information
	Cognitive theory of multimedia	Diagrams
	learning	Multiple modes: spatial, visual and stimulus approaches
		Embodied learning and physical approaches
		Managing cognitive processing demands
		Putting words into a conversational style
	Schema theory	Working with schemas through mapping
		Building on prior knowledge
		Analogies and metaphors
	Generative Learning Theory	Summarising
		Drawing
		Imagining
		Self-testing
		Self-explaining
		Learners teaching other learners
		Enacting (e.g., gesturing, manipulating objects)
		Note taking
Constructivism	Constructivism	(Guided) discovery learning
		Problem-based learning
		Case-based learning
		Experiments
		Inquiry teaching

Learning theory	Deriving Learning Theory	Teaching practices / strategies
		Games, tournaments
	Social constructivism/	Group discussions
	sociocultural theory	Peer collaboration / collaborative learning hybrid human-GenAI collaboration
		Peer-assisted learning (peer tutoring and instruction)
		Apprenticeships
		Instructional scaffolding
		Reciprocal teaching
		Project-based learning (group projects, group investigations)
		Jigsaw
		Think-pair-share
		Tutoring and mentoring
	Social learning/ social	Modelling and imitation
	cognitive theory	Learning from videos
	Situated learning/cognition	Cooperative learning experiences
	Experiential Learning Theory	Simulations
		Laboratory work
Constructionism	Distributed constructionism	Sharing constructions
Design based learning Hands on activities		Using social technologies to work together and build artifacts
Humanism	Humanism	Activities relevant to learners
		Self-assessment
		Encouraging critical thinking
		Place-based learning
	Flow theory	Activities that match the level of demand with learners' existing skills

The first main category is behaviourism. An instructional approach broadly based on behaviourism is **gamification**. A number of reviews document gamification (Aravantinos et al., 2024; Casal-Otero et al., 2023; Lee & Kwon, 2024; Lin & Tan, 2025; Song et al., 2024; Zhang et al., 2026). Gamification is using game design elements (like entertainment and interaction) in non-game situations to change learning processes (Deterding, Dixon, Khaled, & Nacke, 2011). For example, learners use GenAI tools in language learning activities where tasks are framed as games. In vocabulary learning, learners earn points for fluency or accuracy, and the GenAI provides corrective feedback to support improvement (Lee & Kwon, 2024).

The learning theory of cognitivism suggests that humans learn by thinking about information, storing it in their memory, and using it to understand new ideas. This is the main theory behind self reflected learning. **Self reflected learning** appears in several papers (Song et al., 2024; Zhang et al., 2026). In general, self-reflected learning involves learners thinking about their own learning, what they understand, and how they learn (Schön, 1983). Learners reflect on what they do well and what they find difficult, and decide what works and what does not. They use these reflections to adapt and improve how they learn in the future. In relation to self-reflected learning with GenAI, learners create a GenAI artefact, such as a chatbot, and evaluate both the artefact they produce and those created by others (Song et al., 2024). Learners then reflect on what they have learned and use this reflection to set new learning goals.

Constructivism, the third main category, is noted in several articles (Aravantinos et al., 2024; Boulhrir & Hamash, 2025; Iftitah et al., 2025; Lin & Tan, 2025; Zhang et al., 2026). Many GenAI applications align with constructivist learning, where students actively construct knowledge through interaction with their environment (Boulhrir & Hamash, 2025). GenAI-powered tools such as intelligent tutoring systems and conversational agents provide interactive environments that allow students to experiment, receive feedback, and construct meaning, all key principles of constructivist learning (Boulhrir & Hamash, 2025). Five of the instructional approaches found in the literature are broadly based on constructivism; problem-based learning, (hybrid human-GenAI) collaborative learning, scaffolding, project-based learning, experiential learning.

Studies highlight **problem based learning** (PBL) (Alfarwan, 2025; Aravantinos et al., 2024; Iftitah et al., 2025; Lee et al., 2025; Lin & Tan, 2025; Song et al., 2024; Zhang & Tur, 2024). PBL involves immersing learners in a problem drawn from the real world (Erdem, 2022). Learners define a problem and develop a solution by drawing on their existing knowledge, gathering new information, and working in groups under the guidance of an instructor. Learners are responsible for their own learning. Through cognitive activity and group work, learners integrate new learning with their existing knowledge. Key characteristics of PBL include learner-centred learning, small-group work, the teacher acting as a guide, and social interaction. When GenAI is integrated into the process, it provides adaptive feedback, personalised learning pathways, and intelligent scaffolding (Ayanwale & Omeh, 2026).

Inquiry based learning emerges in the literature (Aravantinos et al., 2024; Casal-Otero et al., 2023; Iftitah et al., 2025; Lee & Kwon, 2024; Lin & Tan, 2025; Song et al., 2024; Zhang & Tur, 2024; Zhang et al., 2026). This approach guides learners through the investigation of complex topics and the formulation of research questions. In some cases, GenAI acts as the guide (Zhang & Tur, 2024). One example of GenAI-supported inquiry based learning aims to help language learners appreciate traditional music skills (Nurmalinda, 2025). Learners

engage with traditional music, ask questions, test ideas, and use the outcomes to construct their own knowledge and improve their performance. As part of this process, GenAI technology observes and evaluates students' musical performances, including conceptual understanding, and provides instant feedback in the form of developmental suggestions. Learners can record this feedback, review their performance, and experiment with their own ideas for improvement, alongside those suggested by the GenAI. They can also ask further questions of the GenAI. This inquiry-based process enables learners to construct their own knowledge.

One example comes from a computer robotics programme in which students tackle a real-world brief: programming a robot to support visually impaired people in navigating indoor spaces (Ayanwale & Omeh, 2026). The project combines human–robot interaction, voice-command recognition, and obstacle avoidance. Learners consider accessibility and usability, applying computational thinking to manage unpredictable environments. GenAI simulations model interaction flows, allowing students to test responses to different commands and environmental/physical conditions. Real-time chatbot feedback flags sensor–response errors. ChatGPT supports troubleshooting, helps refine voice-command logic, and assists with iteratively improving algorithms, enabling safe experimentation and continuous improvement.

A selection of articles reference **hybrid human-GenAI collaboration (collaborative learning)** (Alfarwan, 2025; Aravantinos et al., 2024; Iftitah et al., 2025; Li & Wilson, 2025; Lin & Tan, 2025; Song et al., 2024; Zhang & Tur, 2024; Zhang et al., 2026). In this context, human–GenAI collaboration refers to learners and GenAI systems working together in thinking and learning processes. In a science learning task, for example, the GenAI explains ideas or poses questions, while the learner determines what makes sense and what does not (Zhang et al., 2026). The learner and GenAI jointly guide and regulate the learning process (Zhang et al., 2026).

Scaffolding is observed in a selection of the articles (Aravantinos et al., 2024; Iftitah et al., 2025; Lee & Kwon, 2024; Li & Wilson, 2025; Lin & Tan, 2025; Song et al., 2024; Zhang et al., 2026). Scaffolding is when learners are offered guidance, resources and or structured assistance at an appropriate level until they can complete a specific task independently. GenAI tools are used to offer such support by providing cognitive assistance, such as prompts or resources, while learners are engaged in a task (Li & Wilson, 2025).

The literature also highlights **project-based learning** (Aravantinos et al., 2024; Iftitah et al., 2025; Lee & Kwon, 2024; Lin & Tan, 2025; Song et al., 2024; Zhang et al., 2026). Lee and Kwon (2024) note this as a major instructional strategy in GenAI education. An example includes learners designing GenAI models or applications by identifying a problem, such as how to classify images, and then training a simple GenAI system to perform this task. This process involves testing and refining solutions.

Multiple articles point to **experiential learning** (Aravantinos et al., 2024; Casal-Otero et al., 2023; Iftitah et al., 2025). Broadly, this refers to learning as situated participation and meaning making (Lin & Tan, 2025). For example, secondary school students learn humanities and science through a digital modality (Hmoud, Daher, & Ayyoub, 2025). This digital system includes extended reality environments supported by virtual and augmented reality headsets, allowing learners to engage with curriculum-relevant, problem-based scenarios in immersive contexts. The modality also incorporates intelligent tutoring systems that provide adaptive learning pathways, real-time feedback, and analytics powered by

machine learning to personalise instruction. This approach aligns with Kolb's experiential learning cycle by supporting learning through experience, reflection, and real-time feedback within extended reality environments (almost in situ).

Constructionism is mentioned across a range of articles (Casal-Otero et al., 2023; Lee & Kwon, 2024; Song et al., 2024), and is the fourth main category. For example, to help learners understand artificial intelligence concepts in a more concrete way, educators use unplugged activities in which students build or simulate systems that reflect how GenAI algorithms work (Casal-Otero et al., 2023). These activities make abstract ideas tangible by allowing learners to experience GenAI processes through games and hands on tasks rather than through code alone. For example, games such as *Mystery Hunt* support learning about graph traversal (systematically visiting connected nodes), as learners search step by step without seeing the full structure. This approach helps learners understand blind search in GenAI; searches where decisions are made using only local information rather than a complete view of the problem space (Kandlhofer, Steinbauer, Hirschmugl-Gaisch, & Huber, 2016). Two instructional approaches are broadly based on this theory; design based learning and hands on activities.

Some of the literature reviewed includes **design-based learning** (Aravantinos et al., 2024; Casal-Otero et al., 2023; Lee et al., 2025). Design-based learning is characterised by students engaging in authentic problem-solving through the iterative creation and refinement of designs, applying subject knowledge in practical contexts, and developing understanding through reflection, and continuous evaluation of their work (Doppelt, 2009). In one example, students use ChatGPT and MidJourney to create digital stories in a design-based learning activity (Saritepeci & Durak, 2024). After learning how to use the GenAI tools, students select a topic and research it, sometimes by asking ChatGPT questions. Students create their stories within defined parameters. First, ChatGPT is asked three questions during the story set-up, with each question contributing to the development of the narrative. Second, the story is created by organising ChatGPT's responses. Third, between 20% and 50% of the story is written by the student. Learners then create scenes using MidJourney based on their storyboards and ensure that the scenes connect clearly. Students record voice narration for each scene and combine the images, script, and audio using digital storytelling tools.

Hands on activities are identified in the literature (Al-Kamzari & Alias, 2026; Aravantinos et al., 2024; Casal-Otero et al., 2023; Lee & Kwon, 2024; Song et al., 2024). For instance, students learn by using GenAI orientated tools (Casal-Otero et al., 2023). Students may use Scratch a platform for creating interactive stories and games. Scratch is a block-based coding platform, to make GenAI-based coding more child-friendly. Block-based coding involves using pre-built blocks of code rather than writing code from nothing. Learners can experiment with machine learning by classifying self-captured images using a block-based coding platform.

The literature review highlights several instructional approaches that do not appear in Majewska et al. (2025), even though their study has broad coverage. This is not surprising for some instructional approaches, as they focus specifically on using GenAI, while Majewska et al. (2025) takes a more general view. These instructional approaches include GenAI-assisted instruction, teacher guided GenAI integration, and student-directed GenAI exploration. For the remaining approaches—active learning, student-centred activities, personalised learning, and self-directed learning—it is less clear why they are not included in

Majewska et al. (2025). One possible reason is that these are broad, umbrella terms. Some of the specific approaches within these terms may already be included in the earlier research.

GenAI assisted instruction is reported in some studies (Alfarwan, 2025; Aravantinos et al., 2024; Iftitah et al., 2025; Lin & Tan, 2025; Saputra et al., 2024; Zhang & Tur, 2024; Zhang et al., 2026). GenAI-assisted learning is often used as an umbrella term to describe teaching and learning processes in which artificial intelligence systems support, guide, provide feedback on, or enhance students' learning (Wan, Li, Li, & Du, 2025). For example, GenAI-facilitated dialogic tutoring and formative feedback are particularly common in science and technology domains (Lin & Tan, 2025). The dialogic tutoring would be back and forth questioning, multiple perspectives shared as explanations, challenge and reflection.

Certain articles describe **teacher guided GenAI integration** (Alfarwan, 2025; Iftitah et al., 2025; Li & Wilson, 2025; Lin & Tan, 2025; Zhang & Tur, 2024; Zhang et al., 2026). Teacher guided GenAI integration frequently means teachers plan and control how GenAI tools are used in lessons, making sure they support learning, feedback, and student progress while the teacher stays in charge of the teaching decisions (Shi, 2024). One example involves teachers using GenAI to generate differentiated tasks. The teacher selects appropriate tasks for each student, edits and aligns the AI-generated outputs with wider curriculum goals, and then uses them in the classroom. Learners complete the tasks, while the teacher monitors learning and regulates GenAI use (Zhang et al., 2026).

Student-directed GenAI exploration emerges in parts of the literature (Alfarwan, 2025; Lin & Tan, 2025; Zhang & Tur, 2024; Zhang et al., 2026). Student-directed GenAI exploration refers to learning situations in which students actively manage their own interactions with GenAI tools. Students use GenAI to investigate ideas, test solutions, and generate feedback, while making decisions about what to explore and how to respond to outputs. For example, students co-create learning objectives with ChatGPT (Zhang & Tur, 2024).

Active learning is evident in parts of the literature (Aravantinos et al., 2024; Casal-Otero et al., 2023; Iftitah et al., 2025; Lin & Tan, 2025; Saputra et al., 2024; Song et al., 2024; Zhang et al., 2026). Here active learning involves learners engaging in activities—typically entailing interaction and/or feedback—through which they think about what they are learning, connect new ideas to their prior knowledge, and construct their own understanding. In essence, it emphasises active meaning-making rather than the passive receipt of information. Active learning approaches support students' understanding of GenAI and technology while introducing new knowledge (Williams, 2023). In one example, students learn about neural networks. Quickdraw is an online game where you draw an object in 20 seconds, and an AI system tries to guess what it is. Then the learners explore a Quickdraw dataset and create image-recognition models using Google's Teachable Machine (Williams, 2023). Through trial-and-error experimentation, students learn how neural networks use features to classify images, with many able to identify how the system distinguishes between different playing-card suit shapes.

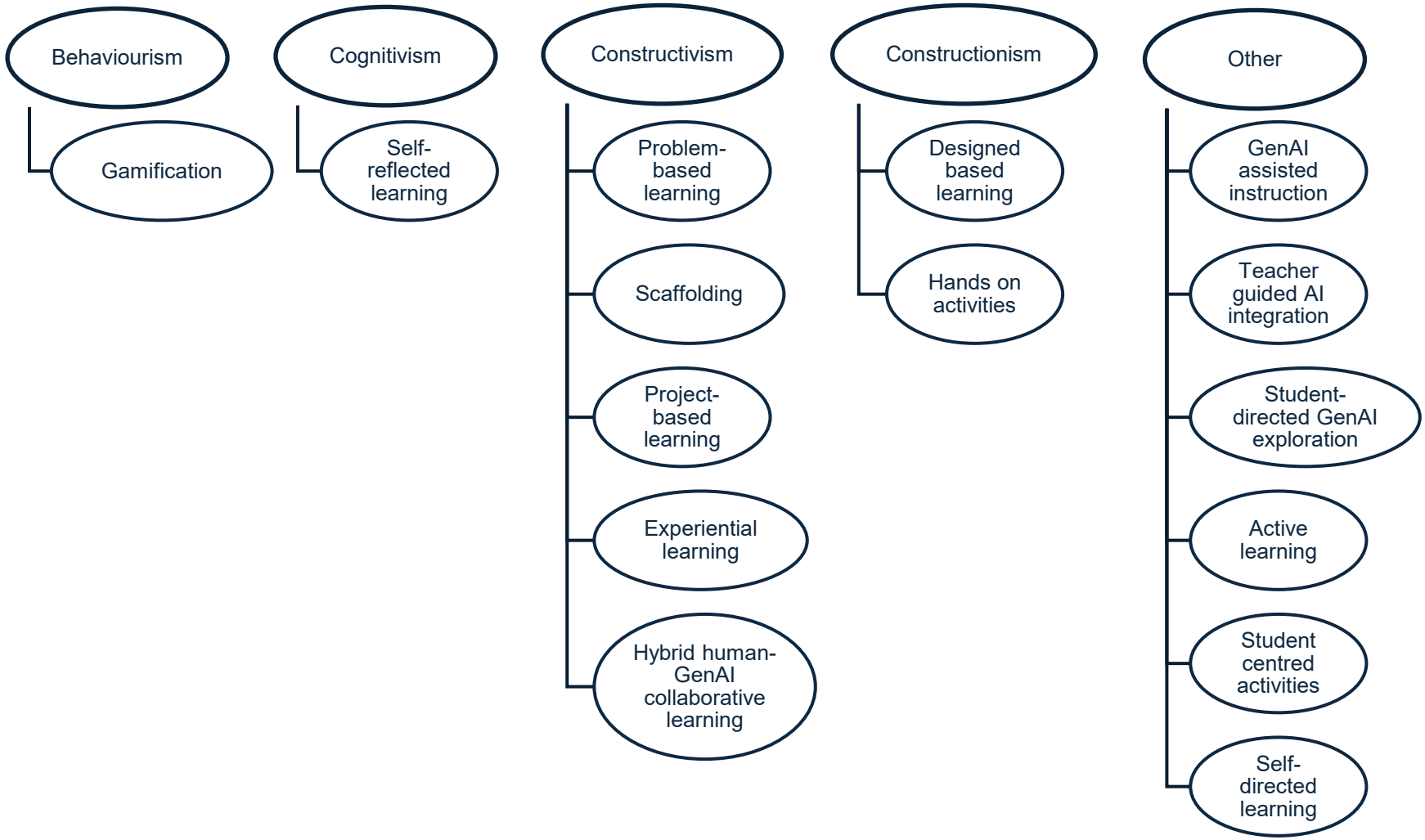
Personalised learning features in part of the evidence (Al-Kamzari & Alias, 2026; Alfarwan, 2025; Aravantinos et al., 2024; Casal-Otero et al., 2023; Iftitah et al., 2025; Lee et al., 2025; Lee & Kwon, 2024; Lin & Tan, 2025; Saputra et al., 2024; Song et al., 2024; Zhang & Tur, 2024; Zhang et al., 2026). Broadly, personalised learning refers to adapting education to meet each learner's needs, rather than expecting learners to fit into a standardised system.

Learners progress at their own pace, engage in different learning activities, and make choices about how they learn based on their interests and needs (Ferdig & Kennedy., 2014). One example involves students setting learning goals and schedules based on their prior knowledge in theoretical physics. A GenAI-enhanced learning system then allocates appropriate e-books, tasks, or resources, and uses task outcomes to track individual progress (Al-Kamzari & Alias, 2026; Ingkavara, Panjaburee, Srisawasdi, & Sajjapanroj, 2022). In this process, learners begin with a self-regulated diagnostic stage, which enables the system to identify weak concepts and misconceptions (Ingkavara et al., 2022). GenAI uses data analytics and machine learning algorithms to analyse learner data and determine appropriate resources, tasks, and learning pathways for each individual, thereby supporting personalised learning.

A subset of the reviewed articles discuss **student-centred activities** (Aravantinos et al., 2024; Iftitah et al., 2025; Lee et al., 2025; Lin & Tan, 2025; Song et al., 2024; Zhang et al., 2026). Student-centred activities using GenAI platforms are generally interactive, personalised, and tailored to children's needs and learning pace, by adapting to the individual regardless of socio-economic background they may create equal opportunities (Tarakli, 2025). One form of such platforms is social robots, which interact directly with children. An example involves learning French vocabulary by teaching it to a social robot. The performance of both the robot and the learner improves through the child's evaluative feedback on the robot's responses.

There is also a mention of **self-directed learning** (Alfarwan, 2025). Self-directed learning is when learners taking responsibility for their own learning process, including setting goals, choosing strategies, practising independently, and evaluating their progress (Sung, 2024). One example involves learners in a language classroom using a GenAI chatbot to practise conversation, receive instant feedback, and improve their responses. Learners reflect on mistakes and adjust their practice independently (Sung, 2024). In this process learners take responsibility for many aspects of their learning.

Figure 5 Instructional approaches for/in teaching GenAI



4.4. Tools used in GenAI education and teaching GenAI

We note what appear to be GenAI tools based on how it is framed in the literature. Most tools (n=152) are mentioned in only one of the reviews. Fourteen tools, including Micro:bit and Social Robots, are each cited in two reviews. Chatbots, Midjourney and Nao humanoid robots are each referred to in three reviews, while DALL-E and Scratch are each stated in two reviews. LLM are referred to in five reviews. ChatGPT and Teachable Machine are each mentioned in seven of the 14 reviews. For full details see Appendix 2.

However, these counts should be interpreted with caution, as the frequency of articles that mention a tool does not necessarily reflect its prevalence in practice. In addition, the descriptions of tools are not standardised: some reviews describe broad categories (e.g. “robots”) rather than a single tool (e.g. “BERT”), while others refer to specific versions (e.g. “ChatGPT-3”) or to concepts (e.g. “artificial neural networks”). Furthermore, individual reviews often mention tools as examples rather than listing all the tools identified in the studies they synthesise.

What is very clear is that the systematic reviews indicate a wide variety of GenAI tools in use, as well as tools used to teach about GenAI. For further details of key GenAI tools see Strobel, Banh, Möller, and Schoormann (2024) or Gozalo-Brizuela and Garrido-Merchán (2023).

4.5. Student outcome variables (positive)

We noted the positive learning outcomes reported for students as a result of GenAI use. There are 13 categories of outcomes which were reported across the reviews (Figure 6). It is noteworthy that the learning outcomes will have been derived from particular GenAI use, it is not that every and any GenAI use will lead to these outcomes.

Improvements in **academic achievement** are highlighted in some of the literature (Al-Kamzari & Alias, 2026; Aravantinos et al., 2024; Boulhrir & Hamash, 2025; Iftitah et al., 2025; Lee et al., 2025; Lee & Kwon, 2024; Li & Wilson, 2025; Song et al., 2024; Zhang & Tur, 2024; Zhang et al., 2026). For example, using GenAI supports improvements in students’ writing quality (Alfarwan, 2025).

Deeper understanding also emerges as a notable positive outcome in several studies (Al-Kamzari & Alias, 2026; Aravantinos et al., 2024; Boulhrir & Hamash, 2025; Iftitah et al., 2025; Lee et al., 2025; Lee & Kwon, 2024; Lin & Tan, 2025; Zhang & Tur, 2024; Zhang et al., 2026). In one case, 12-year-old students construct a machine learning–based artefact, which supports a deeper understanding of GenAI concepts and the machine learning process (Aravantinos et al., 2024; Shamir & Levin, 2021).

Evidence from portions of the literature indicate students experience **cognitive development** (Aravantinos et al., 2024; Li & Wilson, 2025; Lin & Tan, 2025; Zhang et al., 2026). For instance, students use a GenAI-based music program, Doodle Bach, to assist and inspire their music composition creation process (Aravantinos et al., 2024; Choi, 2023).

As a result, students show improvements in music-related cognitive abilities, including rhythm, harmony, and melody.

A selection of studies emphasise student improvements in **problem solving abilities** (Alfarwan, 2025; Aravantinos et al., 2024; Boulhrir & Hamash, 2025; Casal-Otero et al., 2023; Iftitah et al., 2025; Lee et al., 2025; Lee & Kwon, 2024; Li & Wilson, 2025; Lin & Tan, 2025; Song et al., 2024; Zhang & Tur, 2024; Zhang et al., 2026). In one example, school students participate in a GenAI education programme that covers topics such as the basics of artificial intelligence, machine learning, automation, the history of AI, and its social impact (Lee & Kwon, 2024; Park & Kwon, 2024). The programme includes problem-solving activities using AI experiments, AI drawing, AI music, and related applications. Through participation, students develop their problem-solving abilities.

Enhanced **critical thinking** is noted by some literature (Alfarwan, 2025; Aravantinos et al., 2024; Boulhrir & Hamash, 2025; Casal-Otero et al., 2023; Iftitah et al., 2025; Lee & Kwon, 2024; Li & Wilson, 2025; Lin & Tan, 2025; Song et al., 2024; Zhang & Tur, 2024; Zhang et al., 2026). For example, middle school students attend a workshop in which they learn how GenAI recognises images and how web scraping is used to collect image–text pairs to create datasets for training image recognition systems and text-to-image tools (Vartiainen, Tedre, & Jormanainen, 2023; Zhang et al., 2026). Web scraping is automated garnering of data online, that captures data intended to be used on a web page or app (Brown et al., 2025). Midjourney is used as an illustrative example. Students are also taught the basics of writing prompts and how text inputs guide the images generated by the tools. Students then work in twos or threes to explore and experiment with Midjourney collaboratively. The teachers and or facilitators deliberately foster critical reflection in the session. This process prompts critical reflection, on issues like traditional creative processes in art and how they differ from GenAI supported creation and the creators' agency in art-making.

Gains in **computational thinking skills** feature in several sources (Alfarwan, 2025; Aravantinos et al., 2024; Casal-Otero et al., 2023; Lee et al., 2025; Lee & Kwon, 2024; Lin & Tan, 2025; Saputra et al., 2024). In GenAI-based lessons on topics, South Korean primary school pupils identify problems and use GenAI tools to support solutions, recognise a problem and used GenAI to solve it (Aravantinos et al., 2024; Joo & Park, 2022). This tends to develop their computational thinking ability.

Boosts in **creativity** are referenced in sections of the literature (Alfarwan, 2025; Aravantinos et al., 2024; Boulhrir & Hamash, 2025; Casal-Otero et al., 2023; Iftitah et al., 2025; Lee & Kwon, 2024; Li & Wilson, 2025; Lin & Tan, 2025; Saputra et al., 2024; Song et al., 2024; Zhang et al., 2026). For example, secondary school students studying English as a Foreign Language write original stories of up to 500 words (Li & Wilson, 2025; Woo, Wang, Susanto, & Guo, 2023). They combine their own writing with AI-generated text produced through prompts entered into natural language generation tools. Students are able to experiment freely with prompting customised GenAI systems. This approach is associated with high levels of creative output and overall gains in creativity.

Heightened **self-regulation** is recognised as a positive learning outcome across several reviews (Alfarwan, 2025; Aravantinos et al., 2024; Lee et al., 2025; Li & Wilson, 2025; Lin & Tan, 2025; Song et al., 2024; Zhang et al., 2026). Although Lee et al. (2025) do not provide a specific classroom example, they offer a useful synthesis linking instructional approaches to learning outcomes. In particular, they find that GenAI-based personalisation and

student-centred project work tend to lead to learning gains, including improvements in self-regulation.

Greater **digital literacy** (GenAI literacy) is discussed in a number of the reviewed studies (Aravantinos et al., 2024; Boulhrir & Hamash, 2025; Casal-Otero et al., 2023; Lee et al., 2025; Lin & Tan, 2025; Saputra et al., 2024; Zhang & Tur, 2024; Zhang et al., 2026). For example, young children (aged five) interact with intelligent agents in classroom settings, which supports their understanding of basic GenAI principles (Boulhrir & Hamash, 2025; Yang, 2023). Intelligent agents are systems that can understand what is happening around them, think about different options, and choose and carry out actions on their own (Qu et al., 2025).

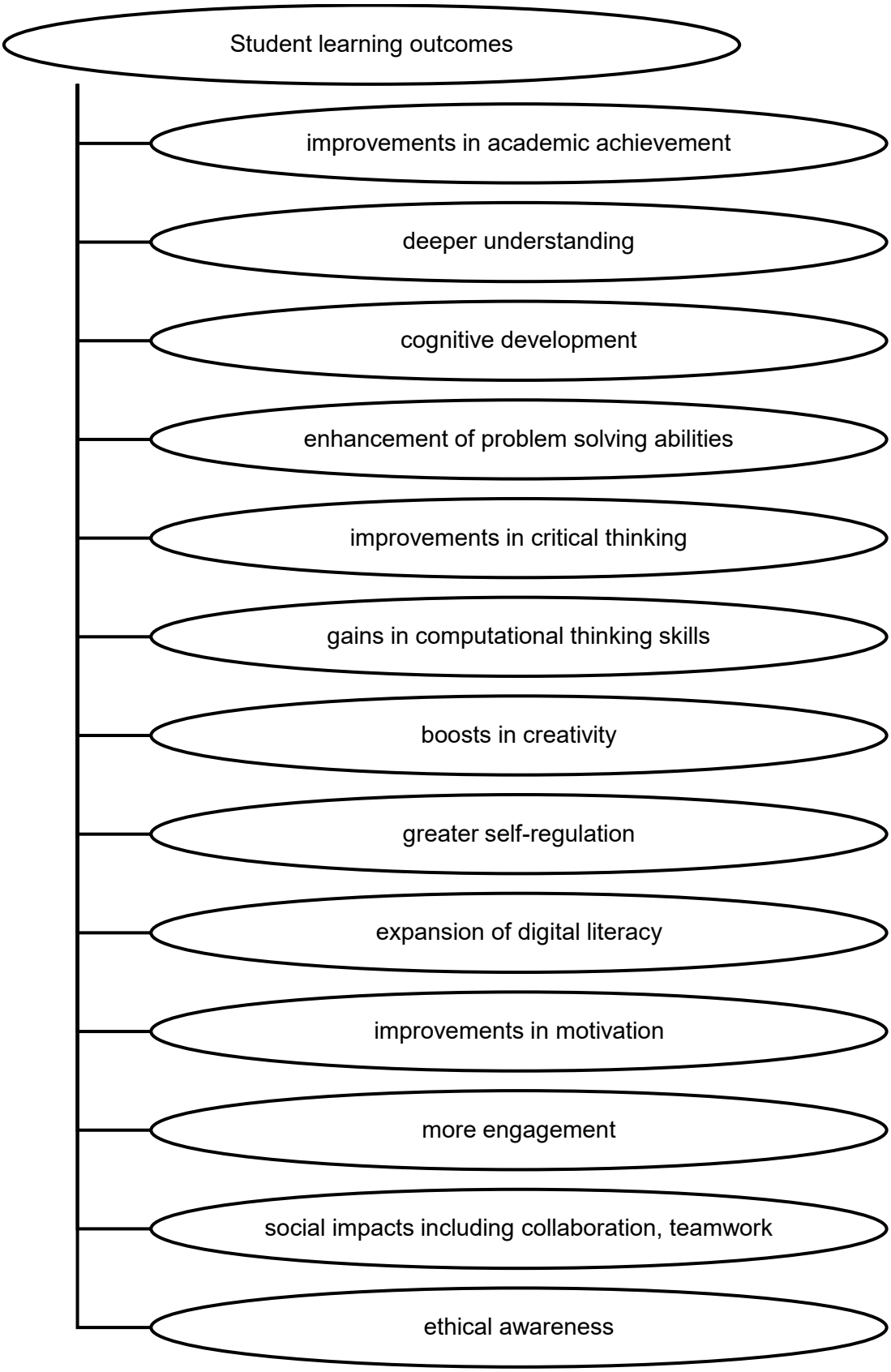
Motivation is improved according to much of the literature (Alfarwan, 2025; Aravantinos et al., 2024; Boulhrir & Hamash, 2025; Casal-Otero et al., 2023; Iftitah et al., 2025; Lee et al., 2025; Lee & Kwon, 2024; Lin & Tan, 2025; Song et al., 2024; Zhang & Tur, 2024; Zhang et al., 2026). As already mentioned Lee et al. (2025) highlight links between instructional strategies and outcomes. Their synthesis indicates that collaborative design tasks and culturally relevant activities often increase motivation.

Increased **engagement** is evident in many of the studies (Alfarwan, 2025; Aravantinos et al., 2024; Boulhrir & Hamash, 2025; Casal-Otero et al., 2023; Iftitah et al., 2025; Lee et al., 2025; Lee & Kwon, 2024; Li & Wilson, 2025; Lin & Tan, 2025; Song et al., 2024; Zhang & Tur, 2024; Zhang et al., 2026). In a blended learning mathematics context secondary school students use CILA, a system that combines ChatGPT with other GenAI tools and provides real-time responses to learners' queries (Wu, Lee, Li, Huang, & Huang, 2024; Zhang et al., 2026). CILA tends to return convergent information, rather than the more divergent responses often associated with web searches and general GenAI chat tools. The system also records students' questions and responses. In such contexts using CILA generally results in enhanced behavioural engagement.

Several reviews note positive **social impacts including collaboration, teamwork** (Aravantinos et al., 2024; Boulhrir & Hamash, 2025; Casal-Otero et al., 2023; Iftitah et al., 2025; Lee et al., 2025; Lee & Kwon, 2024; Li & Wilson, 2025; Lin & Tan, 2025; Saputra et al., 2024; Song et al., 2024; Zhang & Tur, 2024; Zhang et al., 2026). For example, primary school pupils are presented with a complex real-world problem that is adapted by GenAI to match their individual levels of attainment across subjects (Aravantinos et al., 2024; Shi, 2024). Pupils work in groups to solve the problem. Usually, one of the learning outcomes is enhanced communication skills.

Often **ethical awareness** is flagged as a positive learning outcome (Aravantinos et al., 2024; Boulhrir & Hamash, 2025; Casal-Otero et al., 2023; Lee & Kwon, 2024; Lin & Tan, 2025; Song et al., 2024; Zhang & Tur, 2024; Zhang et al., 2026). Here's an example, primary school children use augmented reality to experience situations involving moral dilemmas (Aravantinos et al., 2024; Lin et al., 2023). Children adopt roles within these scenarios and participate in discussions through role-play. This process supports their understanding of complex ethical issues related to GenAI.

Figure 6 Student learning outcome variables (positive)



4.6. Challenges

In our research, we note that GenAI education or using GenAI in education can face challenges (including risks or barriers). Eight categories of challenges are reported across the reviews. It is noteworthy that; this does not mean that every use of GenAI leads to such challenges (Figure 7).

Sections of the literature highlight issues of **teacher readiness** (Aravantinos et al., 2024; Boulhrir & Hamash, 2025).

Teachers lack, and need, specialised knowledge in a cluster of GenAI areas (Al-Kamzari & Alias, 2026; Badrani, Marouan, Kannouf, & Chetouani, 2024; Ramli et al., 2024). For example, complex data processing requires specialized knowledge of GenAI model (Al-Kamzari & Alias, 2026; Badrani et al., 2024). Relatedly, teachers show a lack of awareness of GenAI's potential (Zhang & Tur, 2024). Research also shows that teachers GenAI literacy is limited (Bekeš & Galzina, 2023; Boulhrir & Hamash, 2025; Fan & Zhong, 2022; Han, 2021; Zhang et al., 2026). In addition, teachers can lack expertise in delivering GenAI-based curricula (Boulhrir & Hamash, 2025; Han, 2021; Ramli et al., 2024). For instance, sometimes teachers cannot explain how GenAI meets student needs, such as identifying and explaining that there are potential biases in AI systems or generations (Meyer et al., 2024; Zhang et al., 2026).

The challenge of teachers' limited (specialized) knowledge or skills is further compounded by the lack of teacher training available in these areas (Al-Kamzari & Alias, 2026; Badrani et al., 2024; Ramli et al., 2024).

Teachers' limited knowledge, together with the lack of teacher training, indicate the need for structured professional development and training (Boulhrir & Hamash, 2025; Wang, Li, Tan, Yang, & Lei, 2023).

Technical issues relate to the technical aspects of technology (hardware, software and connectivity) and take several forms. First, there is uneven access to devices in schools, which means that students are not always able to use them (Lee et al., 2025; Manikutty, Frey, Natarajan, Chilakapati, & Rao R, 2019). Second, there is unequal access to devices for homework, meaning that some students cannot use a device to complete their work (Al-Kamzari & Alias, 2026; Lee et al., 2025; Manikutty et al., 2019; Salas-Rueda, De-La-Cruz-Martínez, Alvarado-Zamorano, & Prieto-Larios, 2022).

Relatedly, there are limitations in hardware and connectivity at school (Al-Kamzari & Alias, 2026; Ingkavara et al., 2022; Sanchez & Ponce, 2020), as well as for homework or other forms of remote learning (Al-Kamzari & Alias, 2026; Ingkavara et al., 2022; Sanchez & Ponce, 2020). Once students have access to hardware and connectivity to use GenAI, the challenges shift to issues such as uneven feedback quality (Burner, Lindvig, & Wærness, 2025; Lin & Tan, 2025), the limited reasoning abilities of GenAI, and difficulties in recognising particular accents when learners talk (Liu et al., 2023; Zhang & Tur, 2024). There are also user-related issues with software interfaces, such as students finding the number of options overwhelming (Williams et al., 2024; Zhang et al., 2026).

Furthermore, sometimes students need teachers to use the GenAI and interpret its content (Zhang et al., 2026). For instance, students can struggle to understand complex explanations in ChatGPT-generated content (Murgia, Soledad Pera, Landoni, & Huibers, 2023).

There are **practical issues** associated with GenAI (in) education (Al-Kamzari & Alias, 2026). There are a variety of costs involved, and so generally there is a high cost of implementation (Al-Kamzari & Alias, 2026; Angara, Stege, MacLean, Müller, & Markham, 2021). There are also affordability issues regarding using GenAI in early childhood education (Boulhrir & Hamash, 2025; Luo et al., 2023). There are examples of how cost is address by using more affordable or even free alternatives. For example, robotics equipment can be expensive, like wg so some educators use BBC Micro:bit which is cheaper (Lee et al., 2025; Manikutty et al., 2019). If affordability remains a barrier and cannot be addressed, this raises a social justice issue regarding whether GenAI education is available to all (Boulhrir & Hamash, 2025; Luo et al., 2023).

Ethical concerns are highlighted in a proportion of the literature (Al-Kamzari & Alias, 2026; Boulhrir & Hamash, 2025). GenAI exhibits inconsistent accuracy, a tendency to overfit narrow datasets, and opaque decision-making processes that are rarely transparent to end users (Boulhrir & Hamash, 2025). There is also potential for academic dishonesty and issues of plagiarism (Zhang & Tur, 2024). In addition, there are also examples of bias/inaccuracy in automated grading and marking (Al-Kamzari & Alias, 2026; Çınar, Ince, Gezer , & Yılmaz 2020).

A section of the literature point to **data privacy concerns** associated with the use of GenAI (Al-Kamzari & Alias, 2026; Pasic, Vatres, Ferizbegovic, Bajric, & Pasic, 2023; Zhang & Tur, 2024; Zhang et al., 2026).

AI generating or sharing **misinformation** arises across a range of reviews. Misinformation arises through inaccuracy (Zhang & Tur, 2024; Zhang et al., 2026) and or hallucination (Al-Kamzari & Alias, 2026). Incorrect information can lead to impeding learners' knowledge construction (Lee & Kwon, 2024; Lin & Tan, 2025; Shao et al., 2025). Misinformation can also manifest in the form of potential bias and or harmful stereotypes (Zhang & Tur, 2024; Zhang et al., 2026). In addition, inaccuracies can also result in copyright infringements (Monteiro et al., 2024; Zhang et al., 2026).

Literature provides some evidence linking GenAI (in) education with **lower quality learning**. Learning based solely on GenAI can lead to oversimplified conceptual understanding (Lee & Kwon, 2024; Zhang & Tur, 2024). Another challenge is that learners may appear to complete tasks while treating GenAI as an answer generator, failing to internalize the practice skills of the community (Lin & Tan, 2025). In one study using GenAI rather than conventional methods did have advantages but not in terms of knowledge (Lin & Tan, 2025; Zhu et al., 2025).

Over-reliance on GenAI leads to impeded learning. Dependence on GenAI for brainstorming or direct reuse can dampen originality and depth of creativity (Alammar & Amin, 2023; Kim, Ravi, Williams, & Yoo, 2024; Li & Wilson, 2025; Lin & Tan, 2025). Over-reliance on GenAI can also reduce productivity (Zhang & Tur, 2024) and limits critical thinking about AI generated content (Chen, Zhu, & Díaz del Castillo H., 2023; Zhang et al., 2026).

There are also challenges around cognitively accessing GenAI (in) education. Levels of digital literacy vary among students, so their access to GenAI learning experiences varies (Lee et al., 2025). These challenges include output quality difficulties (Zhang & Tur, 2024). For instance, AI generated content is often pitched above students' knowledge levels, which leads to difficulties in understanding (Kim & Park, 2023; Zhang et al., 2026). Interaction design can also induce excessive cognitive load, which leaves no spare cognitive capacity

for learning (Lin & Tan, 2025; Woo, Wang, Guo, & Susanto, 2024). Students may also lack the cognitive skills needed to transfer learning from conversations with GenAI to other contexts (Elim, 2026; Zhang et al., 2026). In addition, using GenAI to teach programming, rather than conventional methods, results in lower levels of flow and reduced learning achievement (Lin & Tan, 2025; Yang, Hsu, & Wu, 2025).

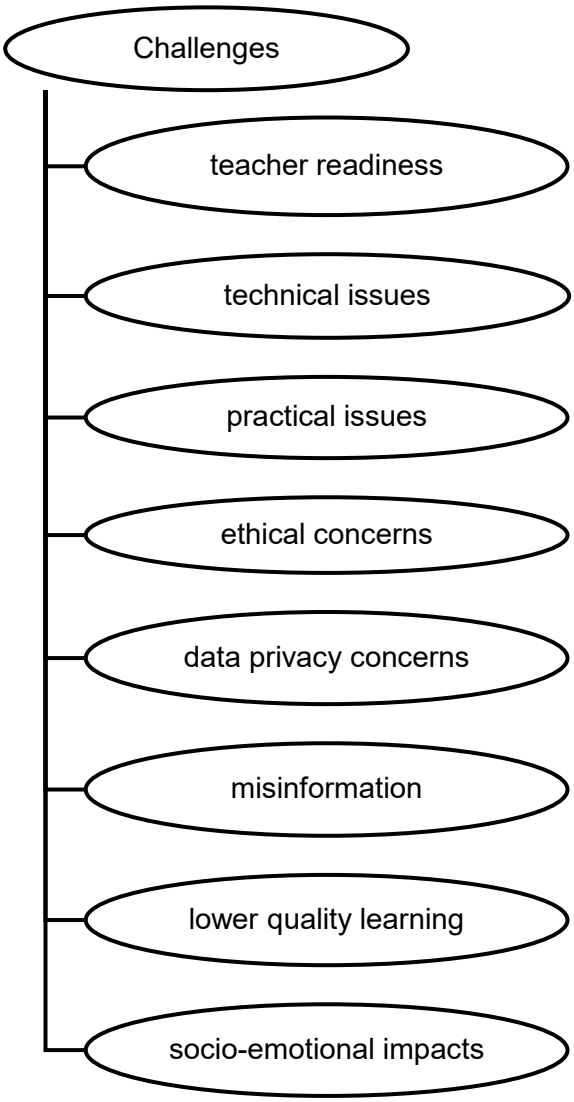
One of the reoccurring challenges of GenAI (in) education are negative **socio-emotional impacts**. Intrapersonal impacts include:

- declines in self-efficacy (Lin & Tan, 2025; Yang et al., 2025; Zhang & Tur, 2024)
- diminished sense of autonomy (Zhang & Tur, 2024)
- deduction in engagement (Zhang & Tur, 2024)
- too much procrastination (Zhang & Tur, 2024)
- gains in motivation are not guaranteed (Lin & Tan, 2025; Zhu et al., 2025)
- tension and anxiety (Kim & Park, 2023; Zhang et al., 2026)
- confusion, frustration, and other negative emotions (Khor, Leta, Elizabeth, & Peter, 2024; Lin & Tan, 2025)

Interpersonal impacts include:

- diminished interaction between learners and educators (Zhang & Tur, 2024)
- reduced social skills (Zhang & Tur, 2024)

Figure 7 Challenges



5. Discussion

5.1. What pedagogical roles does GenAI play for learners and teachers?

A high-level understanding of the pedagogical roles of GenAI for learners is evident in the literature. GenAI is used in several ways. It acts as a **writing assistant**, supporting drafting and summarisation. It also functions as a **creative partner**, helping with idea generation and creative production. In addition, it operates as a **tutor** and a **learning assistant**, for example by explaining concepts or offering guidance when solving problems. It also contributes to **personalised learning**, where it provides tailored suggestions about content and offers personalised feedback.

Collectively, these roles suggest that GenAI extends beyond the functionality of many earlier educational technologies. Rather than supporting a single aspect of learning, it appears capable of multiple functions. This versatility may help explain its rapid adoption across a wide range of educational contexts. Although of course these functionalities tend not to be part of the same tool or platform. A similarly broad picture emerges for teachers. GenAI is used for **instructional support**, such as lesson planning and the preparation of teaching materials. It is also used for **assessment and feedback**, for example by generating questions or providing feedback on student work. In addition, it supports **administrative tasks**, including the drafting of student reports. Arguably AI is contributing to a range of activities in the teaching domain in addition to supporting learning.

However, the literature does not always make clear whether these uses are intended or emergent. It is likely that many uses do align with intended purposes, but this is not always stated explicitly. As a result, the current evidence may describe what is achieved in practice, rather than what is formally intended, what policy postulated or envisioned for future development.

5.2. What instructional approaches are associated with the integration of GenAI in teaching and learning?

We found eighteen instructional approaches which for teaching GenAI concepts or integrating GenAI into learning;

- gamification
- self-reflected learning
- constructivism (problem-based learning, hybrid human-GenAI collaborative learning, scaffolding, project-based learning, experiential learning)
- constructionism (designed based learning, hands on activities)
- other (GenAI assisted instruction, teacher guided GenAI integration, student-directed GenAI exploration, active learning, student centred activities, personalised learning and self-directed learning).

Therefore, GenAI is pedagogically flexible rather than being associated with a single instructional perspective. This range shows that the use of GenAI can be led by the teacher, the student, or through collaboration between the student and the technology. In short a wide range of instructional approaches are being used, there is no one size fits all approach.

The breadth of instructional approaches identified also suggests that there is no single best-practice model for using GenAI in education. Instead, educators appear to be adapting GenAI to existing pedagogical approaches rather than fundamentally restructuring learning around the technology itself.

Comparison with Majewska et al.'s comprehensive framework of instructional approaches, highlights the relatively limited range of pedagogical applications of AI currently reported in the literature. While the reviewed studies encompass eighteen approaches, these represent only a small subset of the approaches practised in primary and secondary education (with or without AI). For example, well-established approaches such as **interleaving** and **spaced learning** are not identified in the studies we reviewed. This suggests that there is considerable scope for GenAI to be used in a wider variety of instructional contexts than currently reported.

The review also identifies several approaches that do not occur in Majewska et al. (2025). These include **GenAI-assisted instruction, teacher-guided GenAI integration, and student-directed GenAI exploration**. This is not surprising, as these approaches are developed in response to the unique capabilities of AI, whereas Majewska et al. take a broader view of instructional design. Their appearance may indicate an emerging distinct body of GenAI-related pedagogical practice. Indeed the emergence of new technologies is likely to be accompanied with an associated paradigm shift in teaching and learning (Creely & Carabott, 2025). For other approaches, such as **active learning, student-centred learning, personalised learning, and self-directed learning**, the reason for their absence from Majewska et al. is less clear. One possible explanation is that these are broad umbrella terms, and some of their underlying strategies may already be included within existing frameworks.

5.3. What GenAI tools are used?

The review identifies a wide range of GenAI tools and related concepts. These include items that are described in different ways across the literature. Some studies refer to broad groupings, such as "robots", while others refer to specific systems, such as "ChatGPT-3" or "BERT". In addition, some references are conceptual rather than tool-based, for example "artificial neural networks". This variety reflects the rapidly evolving nature of the field and the absence of consistent terminology within the literature.

All of these are included in the review, resulting in a very large and diverse list. Comparing studies is difficult because researchers describe AI tools in different ways. Some focus on the underlying technology or AI model, while others focus on specific applications or educational products. As a result, it is often unclear whether the reported outcomes are linked to a particular tool, a specific feature of a tool, or a broader type of AI technology.

The large number and wide variety of tools also make detailed classification difficult. It is not practical to check and categorise every tool accurately. Therefore, this review provides an overview of the AI tools mentioned in the literature, but it cannot fully specify which tools were used, how they were used, or how they differ from one another in practice.

5.4. What positive learning outcomes are associated with the use of GenAI in education?

Across the literature we found 13 categories of positive student learning outcomes;

- improvements in academic achievement
- deeper understanding
- cognitive development
- increases in problem solving abilities
- enhanced critical thinking
- gains in computational thinking skills
- boosts in creativity
- heightened self-regulation
- greater digital literacy
- improved motivation
- increased engagement
- positive social impacts including collaboration, teamwork
- ethical awareness

The breadth of these reported outcomes suggests that the educational potential of GenAI extends beyond improving academic performance alone. Rather, GenAI appears capable of supporting multiple dimensions of learning simultaneously, including the development of higher-order thinking skills, learner motivation, self-regulation, and social interaction. This may reflect the diverse pedagogical roles identified earlier.

These findings appear highly promising. However, the evidence also shows that simply using GenAI does not guarantee these outcomes. For example, while some studies report increased creativity, others report reduced creativity. In particular, dependence on AI is identified as a factor that may limit creative thinking. Such findings indicate that the relationship between GenAI use and learning outcomes is neither straightforward nor deterministic.

This suggests that the impact of GenAI depends on how it is used. It is therefore important to understand which conditions, combinations of activities, instructional approaches, and tools lead to particular learning or social outcomes. In other words, there is a need for more detailed, evidence-based understanding of what constitutes effective use of GenAI in specific educational contexts.

5.5. What risks, challenges, and barriers are identified in relation to GenAI use in education?

The findings indicate that GenAI use in education is accompanied by a diverse set of challenges. The review identifies eight main categories of challenges associated with GenAI use. These include:

- teacher readiness
- technical issues (e.g. hardware, software, connectivity)
- practical constraints (e.g. cost)
- ethical concerns, including opaque decision-making processes
- data privacy risks
- misinformation (e.g. inaccurate or biased outputs)
- lower quality learning
- socio-emotional impacts (both interpersonal and intrapersonal)

The breadth of these challenges suggests that effective implementation of GenAI is not simply a technological issue, but requires consideration of organisational, pedagogical, ethical and other factors. It is important to note that these challenges do not occur in every instance of GenAI use. Rather, their occurrence may depend on how AI is used, the context in which it is used and whether the risks have been considered and mitigated. It is useful to consider these challenges as highlighting potential risks.

Addressing these challenges requires careful implementation. For example:

- teacher readiness may be improved through specialist training
- cost issues may be reduced by using low-cost or free tools
- data privacy may be addressed through appropriate systems and anonymisation
- misinformation may be mitigated through the use of trusted tools and strong critical evaluation skills

These findings suggest that successful implementation requires not only access to GenAI technologies but also the development of the human capabilities needed to use them effectively and responsibly.

A key concern is the possibility of **lower quality learning**, particularly where learners become over-reliant on AI. Mitigations will vary with the learners' age groups, educational contexts, subject or disciplinary domains, intended learning outcomes and other factors. Here are a few important illustrative mitigations:

- include **learning activities without AI**, sometimes referred to as “unplugged” activities. There is emerging evidence that students are deliberately taught core skills, such as writing and information management, without AI (Peterson, 2025). The intention is to remove the need for misuses of GenAI. In addition, some assignments are or maybe designed so that they cannot be completed using GenAI, for example reflective journals, case study analysis, or personal projects. This approach supports the development of independent skills. The intention is to have assignments which

GenAI cannot do, so that students are motivated to work without it and not become dependent on it. To be clear this mitigation relates to removing AI from some specific tasks in certain contexts, but not all tasks.

- use **GenAI when there is evidence of its effectiveness in supporting learners to achieve the desired learning outcomes.** Thirteen categories of such learning outcomes are explained in detail in sections 4.4 and 5.4. One example is the development of computational thinking skills. For instance, in GenAI-based lessons, South Korean primary school pupils identify problems and use GenAI tools to support solutions, recognise a problem and used GenAI to solve it (Aravantinos et al., 2024; Joo & Park, 2022). These are key elements of computational thinking and can support effective learning across a range of subjects.

An important issue is the environmental impact of GenAI. Surprisingly this remains unaddressed in the systematic reviews. GenAI systems require energy and water for operation. A GenAI query typically emits 4.3 grams of Carbon emissions, which is much higher than sending an email but much lower than boiling a litre of water in a kettle (Sidorkin, 2025). The same query uses about 10 millilitres of water. This is much higher than sending an email, but the same or higher than video conferencing per minute. While the impact of individual uses appears small, large-scale use has significant environmental consequences due to the supporting infrastructure. Water consumption, largely attributable to AI, stands at approximately 1 and 0.4 billion gallons for Google and Microsoft respectively in 2022 (Sidorkin, 2025). This represents a substantial negative environmental impact. At the same time, as AI systems become more efficient, they use less energy and water, and produce fewer emissions. Despite these improvements, there remains a clear environmental cost associated with the use of GenAI. This suggests that, if educators and learners wish to act in an environmentally responsible manner, the judicious use of GenAI is essential.

5.6. Conclusions

Overall, we considered how GenAI is used and integrated pedagogically in education. We also examined associated patterns, learning outcomes, challenges, and gaps in the evidence.

Learners make pedagogical use of GenAI. Teachers use GenAI in both instructional and administrative contexts. GenAI is applied across a wide range of instructional approaches. These approaches often involve providing information, supporting task completion, enabling interaction, and facilitating student-centred one-to-one learning.

Although a variety of instructional approaches are evident, they represent only a small proportion of those used more generally in primary and secondary education. In addition, GenAI may have given rise to new instructional approaches or adaptations of existing ones.

The GenAI tools used are diverse. This is unsurprising, given that beyond education, 4,800 new GenAI tools were launched globally in 2025 (Thakur, 2025). These tools are mainly focused on content generation, code assistance, and customer service (Thakur, 2025).

When used effectively, GenAI can support a range of cognitive, socio-emotional, and behavioural learning outcomes. However, several challenges remain. These include teacher readiness, technical and practical issues, ethical and data concerns, and lower-quality

learning and negative socio-emotional impacts. Nevertheless it is important to teach students to use GenAI in a positive way, as well as to function without it.

In relation to the implications of AI for the future of assessment, particularly high-stakes examinations, several considerations may become increasingly important.

First, assessment may need to place greater emphasis on knowledge, skills and capabilities that remain uniquely human and cannot currently be replicated effectively by AI. Second, it may be necessary to determine which knowledge, skills and understanding should be assessed through unaided performance, and which should be assessed through AI-supported performance. Assessments would therefore need to be designed to function effectively in each relevant scenario. Third, assessments may need to evaluate whether learners can use AI effectively, responsibly and efficiently to achieve specific outcomes. This would involve assessing learners' capacity to harness AI as a tool while ensuring that appropriate assessment controls are in place to preserve the integrity of the assessment process. Fourth, AI may provide opportunities to create sophisticated simulations in which learners can demonstrate their knowledge, skills and understanding within realistic environments without the risks involved in the real experiences in the physical world. For example, learners could engage with simulations of climate change, propose and develop potential interventions, test these within the simulated environment, and evaluate their effectiveness. Such approaches could assess knowledge, skills and understanding without requiring learners to experience the real-world consequences of climate change directly. Assessment may also need to determine whether learners understand the limitations, risks and ethical challenges associated with AI. This includes evaluating their awareness of issues such as bias, misinformation, hallucinations, privacy concerns and inappropriate reliance on AI-generated outputs. In addition, assessments may need to examine learners' ability to identify misinformation, scams, manipulative content, inaccurate claims and low-quality AI-generated material. A further priority is ensuring that assessments measure actual learning rather than learners' perceptions of learning. These do not always align (Kreijkes et al., 2026) learners may feel that they have learned effectively even when they have not. Across all of these approaches, it remains imperative to uphold the fundamental principles of high-stakes assessment: validity, reliability and fairness.

With regard to education more broadly, rather than solely high-stakes assessment, whilst, this research provides a valuable high-level overview of several key elements of education, designing high-quality learning experiences requires more than an understanding of the individual elements involved. It necessitates understanding how these elements interact and can be combined to create coherent, evidence-informed pedagogical designs. This is beyond the scope of the current project. This will require identifying and synthesising existing research where available, or conducting further research to determine which combinations of factors are most suitable for achieving the desired learning outcomes. The factors include learner uses of generative AI, teachers' pedagogical applications of AI, instructional approaches, AI tools, learners' age groups (and other characteristics), educational contexts, subject or disciplinary domains, and whether the objective is to teach about AI or to use generative AI to support learning, together with appropriate strategies for addressing the associated challenges and risks. This information is inherently complex and context dependent. It is, nevertheless, essential for educators and curriculum developers seeking to design effective provision. At the same time, the rapid pace of development in AI means that

such evidence may remain incomplete, and decisions will necessarily need to be informed by a combination of available evidence and professional judgement.

The next step may be to consider how AI can be used in ways that enhance learning and promote equity. Some frameworks already exist in this area. Although evaluating these frameworks is beyond the scope of this review, a logical next step would be to assess their content. This would support decisions about whether existing frameworks can be adopted or whether a new framework should be developed.

6. AI Disclosure statement

AI (Co-pilot) was used to assist with the editing and proofreading of the text of the report and to write the code for searching databases and creating Figure 8.

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8. Appendices

Appendix 1 Example search string used in bibliographic databases

This appendix gives details about searching the literature. The search spanned three major databases: Scopus, Web of Science (WoS), and Google Scholar. Search strings combined terms related to generative AI technologies (e.g., *“generative AI”, “ChatGPT”, “large language models”*), cognitive constructs (e.g., *“cognitive offloading”, “critical thinking”, “memory”, “learning outcomes”*), educational contexts (e.g., *“student”, “school”, “K-12”*) and methodological terms (e.g., “experiment”, “survey”, “case study”). Searches were limited to English-language publications within education, psychology and related social science disciplines, and publications between 2022 and 2025. Comparable Boolean logic was applied across databases, for example the search string used for Scopus is below (Figure 8).

Figure 8 search string for Scopus

(TITLE-ABS-KEY("generative AI" OR "large language model*" OR "AI assistance" OR "AI tools" OR "ChatGPT" OR "Human-AI interaction" OR "Human-computer interaction") AND TITLE-ABS-KEY("cognitive offloading" OR "cognitive externalization" OR "memory offloading" OR "task offloading" OR "cognitive miser" OR "human cognition" OR "memory" OR "learning outcomes") AND TITLE-ABS-KEY("education" OR "higher education" OR "school" OR "classroom" OR "student" OR "learner" OR "teacher" OR "child" OR "children" OR "adolescent" OR "teenager" OR "pupil" OR "primary school" OR "elementary school" OR "middle school" OR "secondary school" OR "high school" OR "K-12" OR "undergraduate" OR "bachelor student") AND TITLE-ABS-KEY(method* OR survey OR interview* OR experiment* OR "data collection" OR "case study" OR "mixed methods" OR "quantitative" OR "qualitative") AND NOT TITLE-ABS-KEY(editorial OR commentary OR "opinion" OR "conceptual")) AND PUBYEAR > 2021 AND PUBYEAR > 2021 AND PUBYEAR < 2027 AND (LIMIT-TO (SUBJAREA,"EDUC") OR LIMIT-TO (SUBJAREA,"PSYC") OR LIMIT-TO (SUBJAREA,"SOCI")) AND (LIMIT-TO (LANGUAGE,"English")).

Appendix 2 Tools used in GenAI education

This appendix contains a list of GenAI tools used in education, based on how they are framed in the literature. These tools are presented in Table 3, where column 1 lists the tools and column 2 records the number of reviews in which each is mentioned. 152 tools are noted in only one review. Fourteen tools, including Micro:bit and social robots, are each cited in two reviews. Chatbots, Midjourney and NAO humanoid robots are each referred to in three reviews. e DALL·E and Scratch are each mentioned in two. Large language models are referenced in five reviews, and both ChatGPT and Teachable Machine are mentioned in seven.

Table 3 Tools used in GenAI education

Tool	**Frequency of review**
A.I. Duet, Adaptive AI systems, AI Algorithms, AI Coach , AI feedback systems, AI for Kids, AI for oceans, AI modeling games, AI Voice Agent (Ddongddong), AI-based chatbots, AIGC (AI-generated content), AI-integrated platforms, AI-powered writing assistants, AIThaiGen, AI-Writer, ALEKS, AMBY (AI Made By You), Anaconda python, AR based drawings, Artificial Neural Networks (ANNs), Augmented Reality , Automated feedback tools, Autonomous toy cars, AWS, Bard, Bert, Bing Chat, Blockly, Botsify, Camp Dialogs, Canva, Canvas platform (GenAI integration), Capsule Networks (CapsNet), Character.AI, Chat PDF, ChatGPT- based intelligent learning aid, ChatGPT-3, ChatGPT-4, CILA tool, Claude, Code.org, Coding Steps platform, Cognimates, Computer Vision , Computer-Assisted Instruction (CAI) Program, Consensus, Contextualised dilemma discussion, Convolutional Neural Networks (CNNs), Copilot, Copy.ai, Cornrow Curves, Cozmo Robots, Custom bots, Customised AI tools , Deepfake detection , Dialog-based AI systems, D-ID website (avatar tool), Doodle bach (AI music program), Dream studio, Dtable Diffusion, Ebbot, Edmodo, Educational Robot Kiddo (shared whiteboard system), Educational robotics, Elicit, Ernie, Essay Writer, ExpliClas, Fischer Technik kits, GANs, Genie, GitHub Copilot, Google CoLab, GPT-3, GPT-3.5, GPT-based writing assistants, Humanoid robots, Huskylen, IBM Watson engine, iLife, Intelligent Tutoring Systems (ITS), Jasper AI, Jenni AI, Jibo, Jupiter notebook, Kahoot, Khan Academy, Knowledge tracing systems (AI systems), Kodu Game Lab, Laser AI, Lateral AI, Leap Motion Controller, Leonardo.AI, LilyPad Arduino, Ludwig, Machine Learning model-building tools integrated into block coding platforms, Magenta, MagicSchool, Media analysis activities, Melody Mixer, Microsoft Copilot, Mitsuku website, Mobile app, Natasha, Natural Language Processing, NCERT, Nemobot, Neural networks, Nvidia's GauGan, OpenAI Codex, OpenCV, Ospaces Edu, PaperPal, Personalised Learning Platform, Plaito, Pop Bots, Pounce Chatbot, Quantum computing, Querium , Quickdraw, Quillbot, Reinforcement learning simulation environments, Research Rabbit, Rhythm Wheels, Robot kiddo, Robot-based learning environments, Robotics platforms, RopBots Platform, Scholarcy, School-Book, Scikit Learn, SciSpace, SimsTM, Single-Neuron toolkit, Snickas, Speech Recognition, Sphero Bolt, SRLbot, STEM-based AI programs, Storyjumper, StoryQ, Symmi, Taiwanese Adaptive learning platform (TALP), Teachable Machine 2, Teen Second Life, Tensor flow, Variational Autoencoder, VotestratesML, Wisio, Wordtune, Writely AI, Zenbo Robot,	1
AIY Voice Kit, Alexa, Conversational agent, Deep learning, Drone, Duolingo, GPT-4 Machine learning, Machine learning for Kids, Micro:bit, MIT App Inventor, Python, Robots, Social Robots	2
Chatbots, Midjourney, Nao humanoid robots	3
DALL-E, Scratch	4
Large Language Models	5
ChatGPT, Teachable machine	7

These frequencies should be interpreted with caution, as the number of articles that mention a tool does not necessarily reflect the prevalence of tools in practice. Terminology is also inconsistent: some reviews refer to broad categories (e.g. “robots”), others to specific tools (e.g. “BERT”), versions (e.g. “ChatGPT-3”), or underlying concepts (e.g. “artificial neural networks”). In addition, tools are often cited illustratively rather than as part of a comprehensive inventory within each review.