Generative artificial intelligence in higher education: A systematic review of student use and learning outcomes

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Generative artificial intelligence (GenAI) is increasingly used in higher education, yet evidence remains fragmented on how students use it in learning tasks and how these uses relate to learning outcomes. This systematic literature review of 39 peer-reviewed empirical articles outlines seven ways higher education students use GenAI for learning and examines the resulting actual and perceived learning outcomes. Results indicate that students' actual learning outcomes were predominantly successful, while perceived outcomes vary. Specifically, using GenAI as a creator resulted in an approximately equal proportion of challenges and successes in learning effectiveness, learning efficiency, interactivity, self-regulation and personalised learning. In contrast, when students used GenAI as a translator, refiner, navigator, evaluator or dialoguer, they perceived higher challenge-to-success ratios. Notably, using GenAI as a self-regulatory supporter resulted in the lowest challenge-to-success ratio, with the few challenges attributed to insufficient integrated self-regulated learning skills and prompt strategy. Results suggest that students need to strengthen their integrated self-regulated learning skills to optimise GenAI for learning. Teachers and institutions must address these challenges by providing ready-to-use prompts or prompt training and bound the use of GenAI as a creator with the use of it as a self-regulatory supporter, academic-integrity guardrails and preservation of author voice.

Implications for practice or policy:

- Educators and instructional designers can improve student learning outcomes by designing curricula and pedagogical interventions that account for different ways of GenAI use and uneven learning outcomes.
- Institutions should develop policies and guidance to address the uneven learning outcomes associated with students' use of GenAI, as well as data protection for certain uses.
- Policymakers need to consider different ways of GenAI use when allocating funding, shaping regulations and strengthening ethical oversight mechanisms.

Keywords: generative artificial intelligence (GenAI), students' use, learning outcomes, self-regulated learning (SRL), higher education, systematic literature review

Introduction

Generative artificial intelligence (GenAI) systems produce text, images, videos or other data through generative models in response to prompts (Ardichvili et al., 2024). Their availability to the general public has challenged traditional educational paradigms (Park & Ahn, 2024), as students can now use them for content generation and error correction, tasks that were previously required to be mastered independently (Gimpel et al., 2023). Although a growing number of publications have highlighted GenAI's potential to enhance student learning (Dai et al., 2024), most of the literature has emphasised institutions' and educators' responsibility, relegating students to a secondary role, leaving their ways of use in learning tasks, as well as the actual and perceived learning outcomes from different uses, underexplored (Jensen et al., 2024; Tossell et al., 2024). Consequently, frameworks on GenAI use either outline student uses without addressing potential benefits or challenges (Ilieva et al., 2023) or guide GenAI integration without recognising how students may use GenAI in different ways (Gimpel et al., 2023; Su & Yang, 2023; Symeou et al., 2025). This limited understanding of how students use GenAI in their learning tasks and the learning outcomes associated with these different uses may explain why educators struggle to provide accurate guidance on GenAI use (McGuire et al., 2024; Van Horn, 2024), while students encounter challenges when using it (Lee, 2024; Symeou et al., 2025).

To date, some reviews have identified the general effects of GenAI use on students (Deng et al., 2025; Han et al., 2025; Ma & Zhong, 2025) and general GenAI roles like academic support or writing assistance (Ma et al., 2024). According to technology-mediated learning theory (Alavi & Leidner, 2001), students' interactions with GenAI influence learning outcomes. However, such general descriptions (e.g., Ma et al., 2024) do not clearly explain how students use GenAI in learning tasks and how different patterns of use influence their actual and perceived successful or challenged learning outcomes, which is crucial (Lee, 2024). This can provide teachers with a stronger foundation for guiding students to use GenAI in ways that achieve successful learning outcomes while minimising potential challenges (Park & Ahn, 2024). In this systematic review, we conducted a content and thematic analysis of 39 peer-reviewed articles published between January 2018 and June 2024, aiming to identify specific ways in which students use GenAI for learning, and their different influences on actual and perceived learning outcomes.

The following research questions (RQs) guided this review:

(1) How did the students use GenAI in their learning tasks?
(2) What were the actual and perceived outcomes of learning with GenAI arising from different uses from the students' perspective?

Methodology

Search process

This systematic review followed the PRISMA guidelines (Page et al., 2021) to guide the review process (see Figure 1). In collaborating with an experienced higher education research librarian to conduct several pilot searches, we finalised the following search strings to locate empirical studies on students' use of GenAI in learning tasks: ("higher education" OR HE OR tertiary OR university OR college) AND ("Generative artificial intelligence" OR "generative AI" OR GenAI OR chatbot OR ChatGPT) AND (use* OR using OR usage OR behavio* OR adoption) AND (student OR learn*). Given the multitude of GenAI, the term GenAI was replaced with specific GenAI tool names (e.g., Copilot, Gemini) during the manual searches.

In June 2024, a search of the articles was conducted from 10 databases indexing leading education journals: Academic Search Complete (via EBSCOhost), Education Research Complete (EBSCO), ERIC (ProQuest), ProQuest Education Journals, PsycInfo, Science Direct, Scopus, Web of Science Core Collection; and databases in fields of computer science and technology: IEEE Xplore, Association for Computing Machinery Digital Library.

The initial search identified 1,987 articles. After removing duplicates in Rayyan, 895 articles were screened for specific critical terms in the title, abstract or keywords. Using the inclusion and exclusion criteria, the articles were narrowed down to 187 and subjected to full-text review, complemented by backward searches to identify additional relevant studies. A total of 33 uncertain full-text cases were logged and then jointly reviewed by all of us in regular meetings. Ultimately, 39 studies met all criteria.

Inclusion criteria

- Publications from January 2018 to June 2024 were included, corresponding to the release of the first GenAI model, GPT-1 (Gimpel et al., 2023), with the literature search completed in June 2024.
- Only papers published in English were included.

- Only peer-reviewed empirical studies published as journal articles and conference papers were included to ensure the integrity and reliability of findings (e.g., preprints were excluded).
- Articles that reported empirical data on students' actual use of GenAI in learning tasks and contained findings that summarised or thematised qualitative evidence of students' use, successes and challenges were included.

Exclusion criteria

Studies were excluded if they (a) described or assessed GenAI functionalities without participant involvement; (b) involved participants but did not involve students' use to perform actual learning tasks; (c) involved students' self-initiated use of GenAI rather than directed or required by researchers or educators; (d) involved students' actually using GenAI but did not capture their insights about use experience; or (e) examined GenAI use by teachers or K–12 students. These exclusions ensured a focus on higher education students' insights into their use of GenAI for learning.

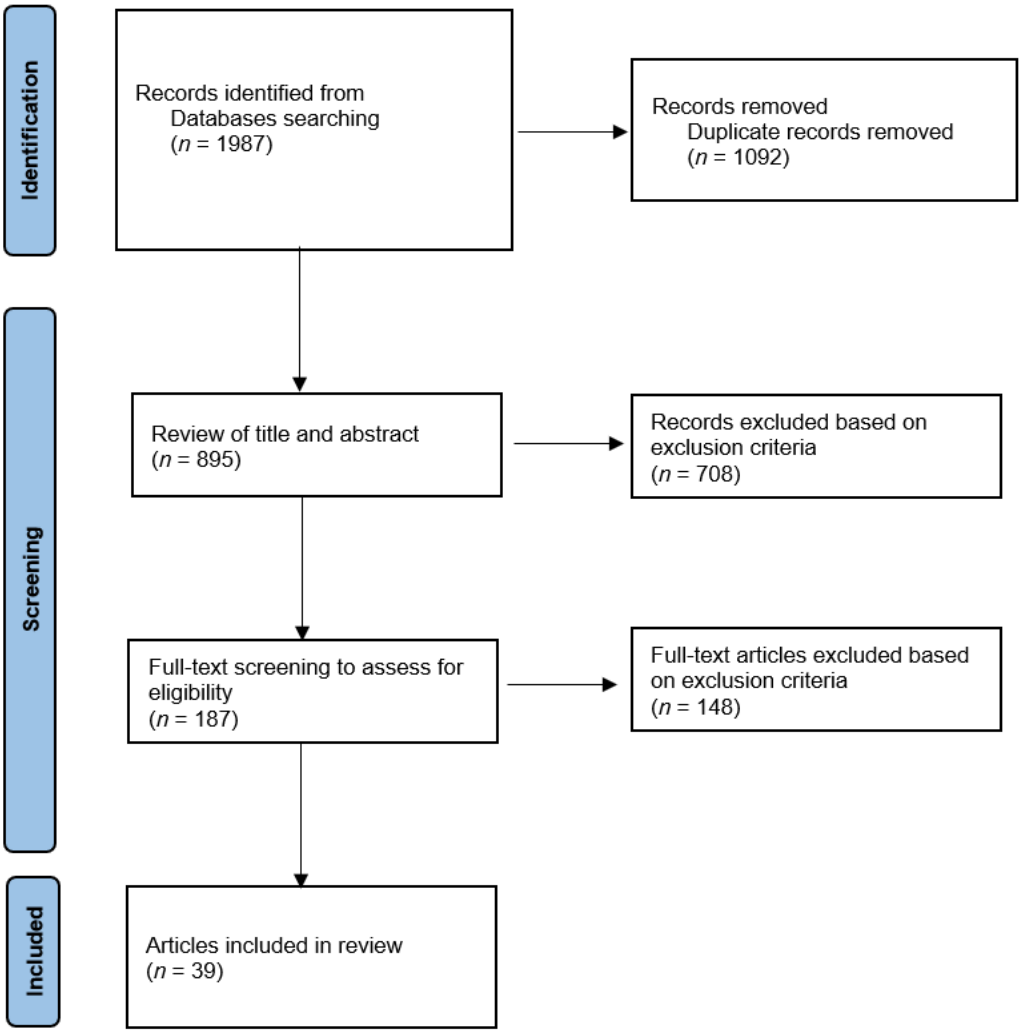

Figure 1. Database search and results depicted as a PRISMA flow diagram

The mixed methods appraisal tool, developed by Hong et al. (2018) was used to assess the quality of included studies (see supplementary material online: Quality assessment score of selected articles at https://github.com/qinan5661/supp-material-QA-score-selected-articles/blob/main/Supp-material-QA-score-selected-articles.pdf). Although some studies were rated as medium quality because of limited methodological reporting (e.g., analytic detail or sample size clarity), their data were sufficiently robust and directly relevant to inform our analysis. After quality appraisal, we extracted data from the included articles based on the RQs.

Data analysis process

Descriptive statistics were used to summarise the characteristics of the reviewed literature and identify overall research trends, such as publication year.

Content analysis and thematic analysis were used to answer the RQs. First, we used content analysis to identify types of use. Following Hsieh and Shannon’s (2005) approach, we repeatedly read the extracted text (Results or Findings sections) to be immersed in the data, generated codes inductively and iteratively compared and refined codes. We used this method to identify all reported types of GenAI use in the included articles. If an article reported multiple use types, each instance of the use type was recorded once. These codes were then categorised into seven use types based on the nature of how students used GenAI. Throughout the process, we conducted peer debriefing among us to refine category boundaries and resolve ambiguities. We then formalised category definitions in a codebook to support consistent coding, maintaining an audit trail and analysing frequency counts. An inter-rater analysis was conducted, with a second rater recoding a random selection of nine articles (23.07% of the total); before this, the second rater received brief codebook training and double-coded one article for calibration, and any disagreements were resolved through discussion to reach consensus. Cohen’s kappa values (see Table 2 in the Results section) indicated strong agreement at the category level.

The second part of the analysis involved coding the outcomes of students’ GenAI use for learning tasks reported in each article. If an article reported multiple learning outcomes, each instance of learning outcomes was coded once for each GenAI use type. This approach allowed us to capture the full diversity of reported outcomes. Each outcome was coded as “success”, “challenge” or “mixed”. “Success” outcomes were indicated by positive descriptions of learning experiences or improved performance (e.g., higher quiz scores), whereas “challenge” outcomes suggest otherwise. “Mixed” outcomes included both positive and negative aspects (e.g., positive and negative descriptions of learning experiences). Frequency distributions were then used to compare the successes and challenges of GenAI use by use type (Tables 3 and Figure 4 in the Results section). Following this, Braun and Clarke’s (2006) six phases of thematic analysis were used. Various GenAI use outcomes were repeatedly reviewed, collated into potential themes and iteratively reviewed for internal coherence and external distinctiveness, with refinements made through peer debriefings among us. Throughout this process, a detailed audit trail was kept to track the development of the themes. Each theme was defined and named before being integrated into the result report. An inter-rater analysis was also conducted (23.07%), and adequate Cohen's kappa values were confirmed (learning outcome: 0.826).

Results

Descriptive characteristics

The review identified 39 studies published between January 2018 and June 2024, with over 79% published between 2023 and 2024 (see Table 1). More than one third of the studies were conducted in the United States of America. Nearly 90% focused on undergraduate programmes. About 30% of the studies were in computer science, while 20% covered multiple disciplines. Most studies used mixed methods approaches. All interventions, varying in duration (45% lasting over 4 weeks), were aimed at improving writing (30%), speaking, or programming skills (skill-based learning tasks) or focusing on the acquisition of domain-specific knowledge (theoretical conceptual learning tasks). Nearly two thirds of the studies offered no teacher support, while about 10% included both prompt training and pre-activity practice. Approximately 75% of the studies utilised commercial GenAI, and text-to-text interactions comprised nearly 90% of the GenAI functions.

Table 1
Descriptive characteristics

Characteristic	Number (*N*)	% of total articles (*N* = 39)
Publication year		
2018–2021	3	7.69%
2022	5	12.82%
2023	7	17.95%
2024	24	61.54%
Total	39	100%
Site of study		
United States of America	13	33.33%
Asia	11	28.21%
Europe	6	15.38%
Middle East	4	10.26%
Africa	3	7.69%
Latin America	1	2.56%
Australia	1	2.56%
Total	39	100%
Level		
Undergraduates	34	87.18%
Postgraduates	3	7.69%
Multiple programme levels	2	5.13%
Total	39	100%
Discipline		
Business and Law	7	17.50%
Computer Science	6	15.38%
Health Sciences	4	10.26%
Linguistics and Education	2	5.12%
Chemistry and Engineering	2	5.56%
Multiple disciplines	8	20.51%
Not mentioned	10	25.64%
Total	39	100%
Sample number		
Below 50	24	58.54%
51–149	12	29.27%
150 or more	3	7.32%
Total	39	100%
Research method		
Qualitative	12	30.77%
Mixed methods	27	69.23%
Total	39	100%
Learning task		
Skill-based learning task (e.g., writing, speaking or programming skills)	26	66.67%
Theoretical conceptual learning task (e.g., domain-specific knowledge)	13	33.33%
Total	39	100%
Length of intervention		
Less than 1 week	10	25.64%
2–4 weeks	11	28.21%
More than 4 weeks	18	46.15%
Total	39	100%
Type of GenAI		
Commercial GenAI (e.g., ChatGPT, Elicit, DALL·E2)	29	74.36%

Characteristic	Number (*N*)	% of total articles (*N* = 39)
In-house GenAI (e.g., Duck-CS50.ai, Alex.ai)	10	25.64%
Total	39	100%
Function of GenAI		
Text-text	35	89.74%
Text-audio	1	2.56%
Audio-audio	2	5.13%
Text-picture	1	2.56%
Total	39	100%
Teacher support		
Prompt training and pre-activity practice	4	10.26%
Prompt training only	13	33.33%
No support	22	56.41%
Total	39	100%

GenAI use types (RQ1)

Students used GenAI in learning in seven ways (see Table 2). Most of these patterns were supported primarily by higher quality studies, as assessed by Hong et al.'s (2018) mixed methods appraisal tool, with the exception of the translator pattern. More than half of the articles indicated students using it as a navigator, evaluator, creator, dialoguer or self-regulatory supporter. Notably, studies published after 2022 reported more diverse use types (including more frequent navigator, self-regulatory supporter, creator use and the emergence of refiner).

Table 2
Use of GenAI in learning tasks

Use of GenAI in learning	Definition	Number (*N*)	% of total articles (*N* = 39)	Category-level reliability
Translator	Translate between target and native languages; transcribe or convert one representation, like text, speech, chart, graphical or geometric into another representation or vice versa.	6	15%	0.9852
Refiner	Refine the students' work by synthesising, combining, and summarising; condensing, simplifying, and shortening; elaborating and expanding; editing, rewriting, polishing, paraphrasing, rephrasing and modifying.	10	26%	0.9852
Navigator	Access academic and non-academic sources that exist in the databases, just like a search engine.	27	69%	0.9606
Evaluator	Grade or assess the correctness or incorrectness of the answers in students' tests or quizzes; correct, fix, rectify and proofread students' mistakes or misconceptions; evaluate and review the strengths and weaknesses of inputted work.	19	49%	0.9754
Creator	Generate well-thought-out, original content in coherent formatting, unavailable in existing databases.	20	51%	0.9557
Dialoguer	Interact or converse with students to practice students' skills, to solve their learning problems or to satisfy their emotional needs.	25	64%	0.9458

Use of GenAI in learning	Definition	Number (*N*)	% of total articles (*N* = 39)	Category-level reliability
Self-regulatory supporter	Support students to set specific proximal goals and plans and to improve their confidence and motivation; for self-instructional learning, task strategies development; for self-evaluation, adaptive or defensive self-reactions, self-satisfaction.	33	85%	0.9712

Students' learning outcomes (RQ2)

Six learning outcomes were identified (see Table 3), and these were predominantly supported by higher quality articles, as assessed by Hong et al.'s (2018) mixed methods appraisal tool. Most of the articles reported outcomes such as perceived learning effectiveness, learning efficiency and self-regulation.

Table 3
Outcomes of the use of GenAI in learning tasks

Outcomes of the use of GenAI in learning	Definition	Number (*N*)	% of total articles (*N* = 39)
Actual learning effectiveness	Actual improvement of students' knowledge or skill, identified through the reported results of tests, quizzes or evaluation of their assignments.	16	41%
Perceived learning effectiveness	Students' opinion of the degree to which something meets their expectations in delivering the desired results, as evidenced by verbatim quotations of students or third-person paraphrases provided by teachers.	38	97%
Perceived learning efficiency	Students' views on the speed and ease with which tasks can be completed, as evidenced by verbatim quotations of students or third-person paraphrases provided by teachers.	35	90%
Perceived self-regulation	Students' perception of their ability to actively regulate their learning process through (for example) goal setting, self-monitoring of progress, self-evaluation, and self-motivation, as evidenced by verbatim quotations of students or third-person paraphrases provided by teachers.	31	79%
Perceived interactivity	Students' feelings of interaction or engagement with peers, teachers or GenAI, as evidenced by verbatim quotations of students or third-person paraphrases provided by teachers.	19	49%
Perceived personalized learning	Students' viewpoint of how well the learning experience is tailored to their individual needs and preferences, as evidenced by verbatim quotations of students or third-person paraphrases provided by teachers.	15	38%

Improved actual learning effectiveness associated with GenAI use was reported in 15 studies, with only one study (Mennella & Quadros-Mennella, 2024) reporting no significant difference. However, perceived learning outcomes varied based on how students used GenAI. The following sections discuss these outcomes by use types (see Figure 2). Notably, studies published after 2022 reported more challenging or mixed outcomes. For details on the articles referenced, see the Appendix.

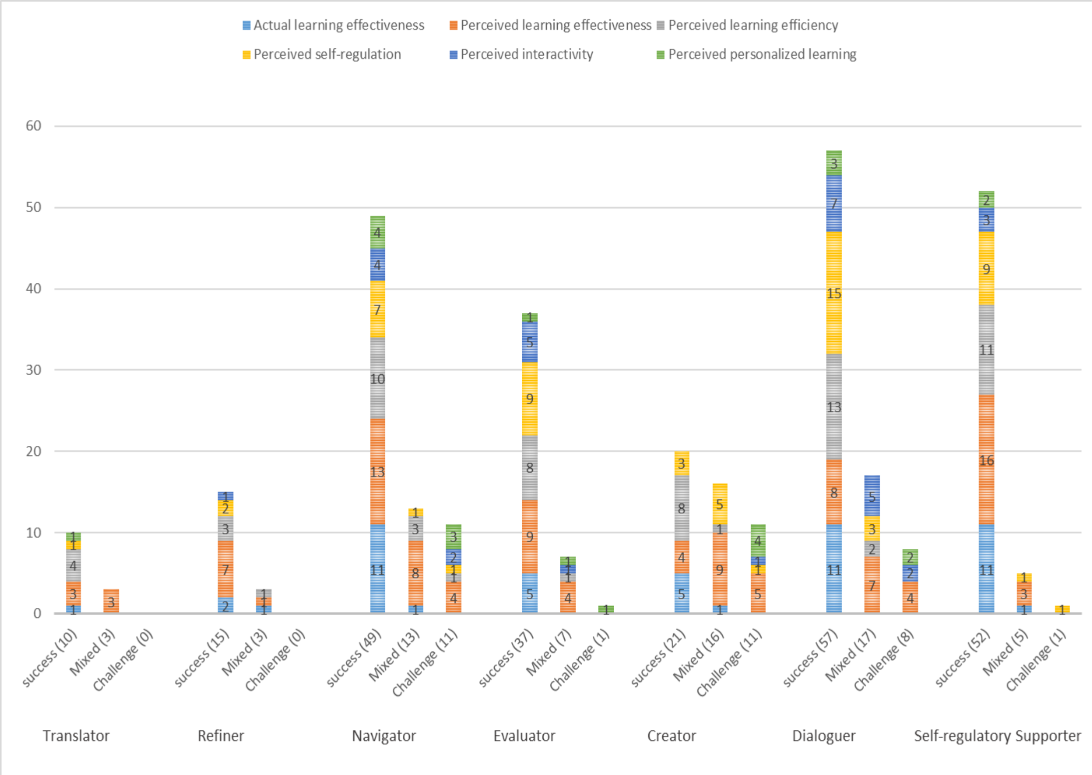

Figure 2. Frequency of reported learning outcomes by GenAI use type

Translator

When GenAI was used as a translator, its impacts on students' perceived learning effectiveness were mixed. In six articles, students reported better comprehension, stronger information understanding and categorisation, improved task completion and even support for publishing academic work (e.g., Hu et al., 2024). However, students in three articles found it less effective because of mechanical translations, poor handling of non-native pronunciation in speech-to-text and students' challenges in prompting (e.g., Wang & Feng, 2023).

Using GenAI as a translator positively influenced students' perceived self-regulation, learning efficiency and personalised learning. In terms of perceived self-regulation, students were motivated by the interesting speech-to-text practices (Gallacher et al., 2018). In terms of perceived learning efficiency, students in four articles could quickly and easily read, comprehend, categorise knowledge, compare pronunciation nuances and take notes with GenAI (e.g., Hu et al., 2024). In terms of personalised learning, GenAI supported students with hearing or vision impairments through its text-to-speech and speech-to-text functions (Park & Ahn, 2024).

Refiner

When students used GenAI as a refiner, its impacts on students' perceived learning efficiency and effectiveness were mixed, but it positively influenced students' perceived self-regulation and interactivity. In terms of perceived learning efficiency, students in four articles found GenAI fast, time-saving and handy (e.g., Yang et al., 2024), though some felt frustrated when it returned repetitive responses despite prompt modifications (Ardichvili et al., 2024). In terms of learning effectiveness, students in eight articles perceived that GenAI supported expression and content comprehension across online, in-person or out-of-class contexts by making information more eloquent, specific and coherent (e.g., Habib et al., 2024). However, others found it ineffective for lengthy or multiple tasks and limited input ranges (Park & Ahn, 2024). In terms of perceived self-regulation, GenAI motivated students to learn, encouraged self-reflection and provided a sense of satisfaction (Park & Ahn, 2024; Mennella & Quadros-Mennella, 2024). In terms of perceived interactivity, students felt more engaged when using GenAI to combine information (Ardichvili et al., 2024).

Navigator

When students used GenAI as a navigator, its impacts on students' perceived learning effectiveness, efficiency, personalised learning, self-regulation and interactivity were mixed. In terms of perceived learning effectiveness, students in 21 articles enhanced skills through credible, diverse and well-organised sources (e.g., Liu et al., 2024), while those in 12 articles cited GenAI failed to help them better understand the content because of GenAI's outdated, incomplete or biased information and insufficient guidance for students to prompt GenAI (e.g., Park & Ahn, 2024). In terms of perceived learning efficiency, students in 13 articles could quickly and easily retrieve information and complete tasks (e.g., Rojas, 2024), though students in four articles faced usability issues, Internet dependency and prompt-crafting difficulties (e.g., Cummings et al., 2024). In terms of perceived personalised learning, students in four articles received targeted support (e.g., Alhammad, 2024), but students in three articles criticised overly general or insufficiently scientific content (e.g., Essel et al., 2022). In terms of perceived self-regulation, students in eight articles improved information verification, confidence and learning focus (e.g., Chang et al., 2022), but students in two articles reported that broken links and incorrect and limited reference visibility led to frustration (Essel et al., 2022; Park & Ahn, 2024). In terms of perceived interactivity, students in four articles felt more interactive and improved relationships with teachers and peers (e.g., Elkhodr et al., 2023), though incorrect responses reduced trust of GenAI (Jiang et al., 2024; Yang et al., 2024).

Evaluator

GenAI helped students realise positive outcomes in terms of perceived self-regulation. In nine articles, students perceived enhanced self-evaluation, learning focus, motivation, satisfaction and stress reduction (e.g., Rojas, 2024).

When students used GenAI as an evaluator, its impacts on their perceived learning effectiveness, learning efficiency, interactivity, and personalised learning were mixed. In terms of perceived learning effectiveness, students in 13 articles mentioned GenAI enhanced their skills, productivity and quality of work through its error identification, quizzes and concise feedback (e.g., Karataş et al., 2024), though in four articles, students cited GenAI's inadequate identification of strengths and weaknesses, incorrect feedback and lack of transparency (e.g., Tossell et al., 2024). In terms of perceived learning efficiency, students in nine articles saved time and thus accelerated their learning by receiving immediate GenAI feedback (e.g., Diachenko et al., 2019), though GenAI's occasionally repetitive questions reduced efficiency (Terblanche et al., 2022). In terms of perceived interactivity, students in six articles valued GenAI's neutral, supportive feedback (e.g., Hew et al., 2023) but noted its lack of diversity compared to teachers (Park & Ahn, 2024). In terms of perceived personalised learning, students received topic-specific and level-based feedback (McGuire et al., 2024; Park & Ahn, 2024), yet some felt human instructors better addressed individual needs (Hew et al., 2023; Park & Ahn, 2024).

Creator

When students used GenAI as a creator, it negatively influenced their perceived personalised learning and interactivity. In terms of personalised learning, students in four articles felt GenAI-created content was too generic or too professional or failed to support hands-on tasks (e.g., McGuire et al., 2024). In terms of perceived interactivity, biased responses and online dependency made students feel disengaged (Park & Ahn, 2024).

Additionally, using GenAI as a creator had mixed impacts on students' perceived learning effectiveness, learning efficiency and self-regulation. In terms of perceived learning effectiveness, students in 13 articles noted that GenAI created well-structured content, enabling them to inspire ideas and complete tasks, (e.g., Manley et al., 2024). However, students in 14 articles mentioned GenAI's ineffectiveness in improving skills, knowledge retention and task completion due to inaccuracies, bias, poor contextualisation and limited databases, and students' difficulty in use or misuse of GenAI (e.g., Šedlbauer et al., 2024). In terms of perceived learning efficiency, students in nine articles quickly and easily brainstormed or used ready-to-use content, reducing effort and helping meet deadlines (e.g., Yang et al., 2024), though incorrect content required relearning, offsetting efficiency gains (Park & Ahn, 2024). In terms of perceived self-regulation, students in eight articles mentioned that GenAI enhanced focus, selfassessment and motivation (e.g., Šedlbauer et al., 2024), while students in six articles highlighted that it narrowed learning focus and increased emotional stress (e.g., Tossell et al., 2024).

Dialoguer

When students used GenAI as a dialoguer, its impacts on students' perceived learning effectiveness, self-regulation, interactivity, efficiency and personalised learning were mixed. In terms of perceived learning effectiveness, GenAI enhanced students' skills and enriched their knowledge in 15 articles (e.g., Sun et al., 2024). However, in 11 articles, GenAI was perceived as ineffective because of misunderstandings, repetitive and irrelevant replies, and technical issues (e.g., Karataş et al., 2024). In terms of perceived self-regulation, in 18 articles, students felt boosted confidence and satisfaction, and support for goal-setting and strategic planning (e.g., Yang et al., 2024), though in three articles, students felt frustrated or stressed (e.g., Van Horn, 2024). In terms of perceived interactivity, in 12 articles, GenAI's confidential, responsive and non-judgemental nature encouraged students' comfort, openness and peer communication (e.g., Hu, 2024). However, in seven articles, students found their interaction with GenAI robotic because of missing facial, verbal and emotional cues and unsatisfying answers (e.g., Jiang et al., 2024). In terms of perceived learning efficiency, in 15 articles, students praised GenAI's accessibility, speed and ease of interaction (e.g., Vázquez-Cano et al., 2021), though technical limitations and character restrictions failed to make dialogue or language learning easier (e.g., Polakova & Klimova, 2024). In terms of perceived personalised learning, in three articles, students noted tailored responses (e.g., Lee et al., 2022), but students in two articles found GenAI's personalisation insufficient (Chen et al., 2022; Karataş et al., 2024).

Self-regulatory supporter

Using GenAI as a self-regulatory supporter positively influenced students' perceived learning efficiency, interactivity and personalised learning. In terms of perceived learning efficiency, in 11 articles, with GenAI's instant support and free accessibility, students performed tasks, crafted better prompts and verified responses more easily and efficiently (e.g., Manley et al., 2024). In three articles, GenAI enhanced perceived interactivity by enabling students to freely ask for clarifications without interrupting lectures (e.g., Alhammad, 2024). In terms of perceived personalised learning, students engaged in individually instructed learning, tailored learning methods and selected areas of interest (Hu et al., 2024; Park & Ahn, 2024).

Additionally, using GenAI as a self-regulatory supporter had mixed impacts on students' perceived learning effectiveness and self-regulation. In terms of learning effectiveness, GenAI supported students in enhancing information utilisation and understanding, critical thinking, language organisation and the completion of learning tasks at a higher quality compared with students' prior task performance in 19 articles (e.g., Alhammad, 2024). However, overly overreliance on GenAI-generated content or identification of its limitations through self-assessments led to reduced effectiveness in four studies (e.g., Yang et al., 2024). In terms of perceived self-regulation, in 10 articles, students experienced improved self-evaluation and self-satisfaction (e.g., Šedlbauer et al., 2024). However, students felt disappointed when comparing results from different GenAIs or overwhelmed by constant prompt revisions (Jiang et al., 2024; Yang et al., 2024).

Discussion and implications

This review identified seven distinct ways students use GenAI for learning and showed that these use types are differentially associated with learning successes and challenges (Figure 3).

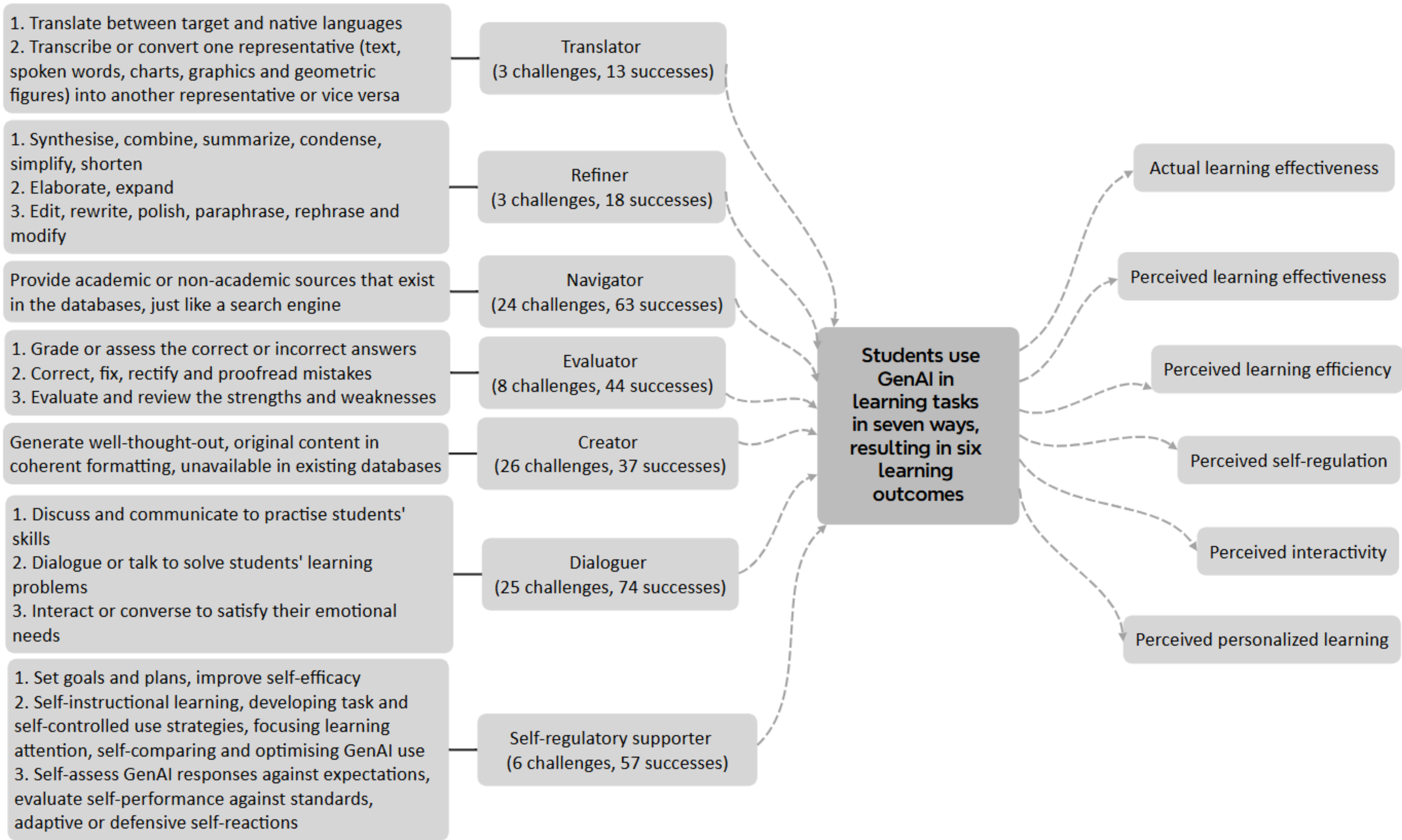

Figure 3. Seven distinct ways and six resulting learning outcomes of students' GenAI use in learning

Our classification identified a set of distinct GenAI functions that capture what students are doing with GenAI, with most of the studies supported primarily by higher quality studies, as assessed by Hong et al.'s (2018) mixed methods appraisal tool. Research has reported that students use GenAI for tasks such as academic support or writing assistance (Ma et al., 2024) whereas our results indicate that students often combine multiple GenAI uses within a single task (Jiang et al., 2024; Park & Ahn, 2024), which complicates instructional support and may reduce instructions effectiveness, resulting in mixed learning outcomes even when teachers provide guidance, hands-on activities or iterative instructional adjustments (Hu et al., 2024; Naamati-Schneider & Alt, 2024). Research has also reported use types such as rephrasing, summarising, proofreading, writing and brainstorming (Gasaymeh et al., 2025; Ravšelj et al., 2025); these labels are rarely synthesised. For instance, rephrasing and summarising are different forms of text refinement, whereas writing and brainstorming are creating; without such synthesis, it becomes difficult to attribute learning outcomes and challenges to the use types, which in turn risks leaving teachers without actionable guidance for different uses, particularly for creating (e.g., brainstorming and drafting), where stronger scaffolding and monitoring are often essential. This synthesised seven GenAI use types with each linked to different learning outcomes, providing a more actionable basis for teachers to provide targeted guidance and instructional support in higher education.

Overall, the results suggest that the successes of using GenAI in learning outweigh the challenges, aligning with research highlighting GenAI's potential to enhance students' learning (Chang et al., 2023). However, the actual and perceived outcomes are mixed, particularly regarding perceived outcomes, which vary by use type (see Figure 4). Using GenAI as a creator yields a relatively balanced challenge-to-success ratio (0.729) based on coded instances, suggesting only a slightly more perceived success. Because this use does not require students to input content into prompts, GenAI may generate generic, irrelevant, inaccurate or biased responses, thereby limiting personalised support and eroding trust (Kodish et al., 2025), raising cognitive load and potentially challenging epistemic agency and academic integrity as students rely on the tool to determine what constitutes appropriate content (An et al., 2024; Yan et al., 2025). However, using GenAI as a navigator (0.387), dialoguer (0.337), translator (0.230), evaluator (0.182), refiner (0.166) or self-regulatory supporter (0.105) yields substantially more perceived success, according to the ratios derived from the coded instances. Using GenAI as a navigator appears to result in greater perceived success even without user input, because it provides sources that can be quickly verified. Compared to general search engines, GenAI synthesises diverse sources into well-organised explanations, enabling students to receive more personalised sources (Tibau et al., 2024). Interestingly, as a dialoguer, GenAI offers accessible, responsive and non-judgemental interaction that supports communication and confidence, but replies can be repetitive and emotionally poor, diminishing social presence and interaction naturalness (Ortega-Ochoa et al., 2024). Notably, using GenAI as a translator, evaluator or refiner requires students to input content into their prompts have a low ratio (approximately 0.200), indicating significantly more perceived success, possibly because GenAI respond based on their input by improving readability, enhancing comprehension and offering instant feedback (Jiang et al., 2024).

Notably, when GenAI functions as a self-regulatory supporter, it achieves the lowest ratio, indicating that students generally perceived success. This suggests that using GenAI as a self-regulatory supporter is more likely to achieve optimal perceived learning outcomes. When GenAI acts as a self-regulatory supporter, it directly scaffolds self-regulated learning (SRL) processes (Zimmerman, 2002): helping students set goals, plan strategies, monitor progress and regulate learning, leading to more effective task completion and personalised, interactive support (Sardi et al., 2025). Consistent with empirical evidence, teacher-guided use of GenAI to support SRL has been shown to enhance autonomy, adaptability, metacognition, SRL and interpersonal communication (Hu, 2024; Hu et al., 2024; Lodge et al., 2023; Yan et al., 2024). Moreover, students with SRL awareness can sustain successful use despite challenges: when responses are non-academic or erroneous, students self-verify with reliable sources or professional knowledge (Elkhodr et al., 2023); when responses are excessive or generic, they adaptively refine prompts to obtain satisfactory results (Ardichvili et al., 2024); and those preferring teacher-peer interaction may avoid GenAI in class but use it for homework (Van Horn, 2024). However, some students may feel overwhelmed by iterative interactions with GenAI.

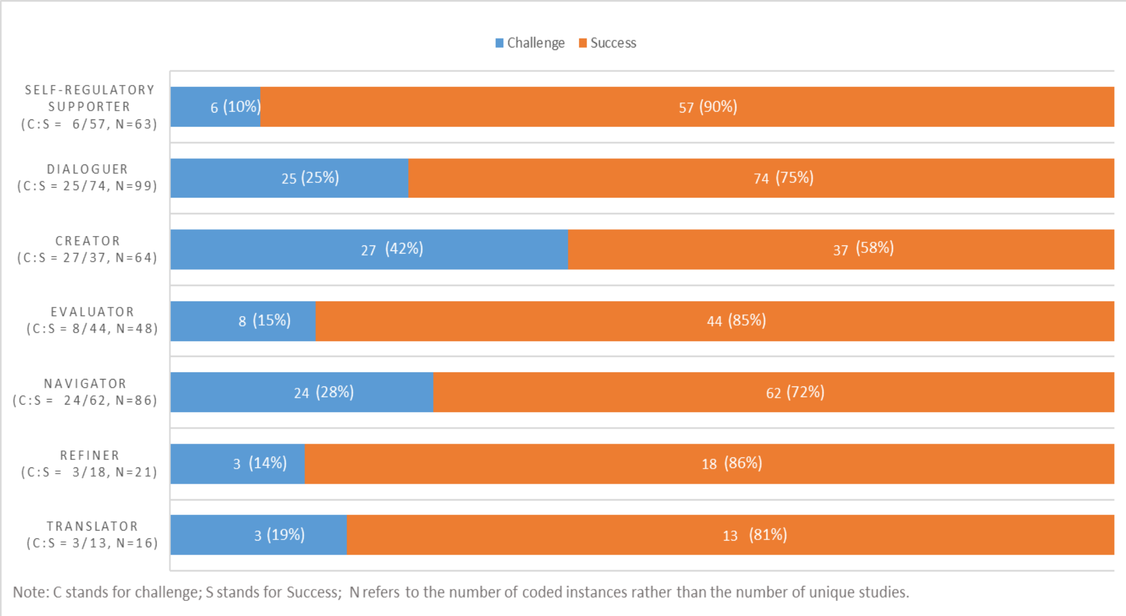

Figure 4. Challenge-to-success ratios for GenAI use types

These seven GenAI use types offer actionable guidance for teaching and learning, particularly in enhancing students' learning and reducing uneven learning performance. Key implications include the following:

- Different uses of GenAI lead to different levels of success; educators' GenAI integration should pair with a self-regulatory supporter, embedding SRL processes (Zimmerman, 2002) such as goal setting, outcome expectation, strategy adoption, self-monitoring and self-evaluation for most learning activities. This use can also be combined with dialoguer, navigator, evaluator, translator, refiner or creator to maximise their effectiveness.
- To prevent overload from repeated interactions used as a self-regulatory supporter, instructors should provide ready-to-use prompts or prompt training to make sure responses from GenAI can meet students' needs, to make interactions manageable (Juhaňák et al., 2025). For example, prompts should clarify task context, audience, rubric criteria and constraints to obtain personalised and pedagogically aligned responses.
- When using GenAI as a creator, additional challenges arise. This use should be bound with self-regulatory supporter, and academic integrity guardrails and preservation of author voice are important (Singh et al., 2025).
- Educators should expose students to diverse use types, creating opportunities to either expand to multiple uses or critically reflect on each use (Nedungadi et al., 2024).
- Certain uses require students to upload drafts, notes, or voice data, which raises privacy and data protection concerns when such data are submitted to GenAI tools (An et al., 2024).
- Institutional policy should keep in mind that GenAI use is heterogeneous and avoid treating it as one construct, either embraced or banned; instead, they should be aware of differences in student use and its potential advantages and disadvantages for students, while ensuring access and supporting the development of students' skills in using GenAI.

Limitations and future directions

With the rapid advancements in GenAI technology, research in this field is highly dynamic; our review mainly captures the field's early evidence before 2024. Our review already showed that more recent studies report uses differently from studies before 2022, suggesting that as technology matures, use evolves. Future studies should use our findings as a starting point for investigation, rather than treating the findings as static ways to use GenAI. The included studies also show a clear imbalance: nearly 90%

focused on text-to-text tools, around one third examined writing tasks and one third were based in the United States of America, which limits transferability to other GenAI functionalities (e.g., text-to-video), to non-text learning activities and to underrepresented countries. Additionally, conclusions regarding learning outcomes are constrained by small and predominantly non-randomised samples; heterogeneity in outcome measurements across studies further limits cross-study comparability. To test generalisability, future research should validate the seven methods of GenAI use beyond writing-dominant tasks, outside the United States of America, with multimodal GenAI functionalities and larger samples across a wider range of learning activities.

Further qualitative studies are needed to examine these seven GenAI use types across diverse learning tasks and to better define the competencies underlying GenAI use in learning (Chun et al., 2019). When using GenAI as a self-regulatory supporter, students perceived fewer challenging outcomes (Urban et al., 2024). Future research should define GenAI as a self-regulatory supporter and explore how SRL skills optimise GenAI use.

Conclusion

GenAI's rapid advancements have disrupted traditional education. This review identified seven GenAI use types based on students' actual use of it in learning tasks, which generally improved students' actual and perceived learning outcomes and were predominantly supported by higher-quality articles. However, a mixed picture of successes and challenges has also emerged across five perceived learning outcomes, whereas creator use showed a roughly balanced challenge-to-success ratio and self-regulatory support yielded the most favourable success, with remaining issues mainly stemming from prompt strategy and insufficient self-regulated learning skills. These findings suggested that students are encouraged to improve their SRL skills to optimise the use of GenAI as a self-regulatory supporter. Teachers and institutions must address these challenges by providing ready-to-use prompts or prompt training and bound using as creators with the self-regulatory supporter, academic-integrity guardrails, and preservation of author voice.

Author contributions

Qin An: Conceptualisation, Data curation and analysis, Investigation, Writing – original draft, Writing - review and editing; **Joyce Hwee Ling Koh:** Conceptualisation, Data analysis, Writing – review and editing; **Qian Liu**: Conceptualisation, Data analysis, Writing – review and editing.

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Appendix: Selected articles and coding

No.	Author, year	How students learn with GenAI (E: evaluator; R: refiner; T: translator; N: navigator; C: creator; D: dialoguer; S: self-regulatory support)			Outcomes arising from students' learning with GenAI (S: success; C: challenge; M: mixed outcome)		
		Actual knowledge & skill	Perceived learning effectiveness	Perceived learning efficiency	Perceived self-regulation	Perceived interactivity	Perceived personalised learning
1	(Alhammad, 2024)	S	NS, CM, DS, SS		ES	NS, SS	NS
2	(Ardichvili et al., 2024)		RS, CC	RM		RS	CC
3	(Chang et al., 2022)	S	NS, ES, SS	NS, DS	NS, DS	NS	
4	(Chen et al., 2022)		NS, ES, CS, DM	ES, DS, SS	ES, DS	NS, ES, DM	DC
5	(Cummings et al., 2024)		RS, NC, CC	NC,	CM		CC
6	(Diachenko et al., 2019)	S		ES,			
7	(Elkhodr et al., 2023)	S	NS, CC	NS,	CC, DS	NS	
8	(Essel et al., 2024)		NS, ES, DS, SS	DS,	DS, SS		
9	(Essel et al., 2022)	S	NC, DM	NS, DS	NM	DS	NC
10	(Gallacher et al., 2018)		TM, DM	DS	TS, DS	DC	
11	(Glenda et al., 2024)		NC, CM	CS			
12	(Habib et al., 2024)	S	RS, NS, CM, SS	RS	CM,		
13	(Hew et al., 2023)		DC	ES	NS, DM, SS	ES, DS	EC
14	(Hu, 2024)		DS, SS	DS	DS	DS, SS	
15	(Hu et al., 2024)		TS, NS, SS	TS, NS, DS, SS	NS, DS	DS	NS, DS, SS
16	(Jiang et al., 2024)		RS, NM, ES, CM, DC, SM	RS, CS	CM, DS, SM	NC, DC	
17	(Karataş et al., 2024)		NS, ES, CM, DC, SM	NM, ES, CS, DM	CS, DS, SS	DM	DC
18	(Kucuk, 2024)	S	NM, DS	NS	NS		NS
19	(Lee et al., 2022)	S	NM, DM	NS, DS	DS		DS
20	(Li, 2023)	S	SS	DS, SS			
21	(Liu et al., 2024)		NS, SS	DS, SS	DS	DS	
22	(Manley et al., 2024)		EM, CS, SS	CS, SS	ES		
23	(McGuire et al., 2024)		EM, CS, SS	ES	CS	ES	ES, CC
24	(McInnis-Domínguez, 2023)		CC, SS				

No.	Author, year	How students learn with GenAI (E: evaluator; R: refiner; T: translator; N: navigator; C: creator; D: dialoguer; S: self-regulatory support)			Outcomes arising from students' learning with GenAI (S: success; C: challenge; M: mixed outcome)		
		Actual knowledge & skill	Perceived learning effectiveness	Perceived learning efficiency	Perceived self-regulation	Perceived interactivity	Perceived personalised learning
25	(Mennella & Quadros-Mennella, 2024)	M	NM, CS NS, CS	RS	NS		
26	(Naamati-Schneider & Alt, 2024)		NM, SS	NS	NS, SS		
27	(Park & Ahn, 2024)		TS, RM, NM, EM, CM, DM, SM	TS, ES, CM, DS, SS	RS, NC, DS, SS	EM, CC, DS, SS	TS, EM, CC, DS, SS
28	(Polakova & Klimova, 2024)	S	EM, DM	DM,	ES, DM, SS	DM	
29	(Qasem et al., 2023)	S	NS	NM,			
30	(Rojas, 2024)		RS, NS, CM	NS, CS, SS	ES		
31	(Santiago-Ruiz, 2023)		TM, NS				
32	(Šedlbauer et al., 2024)	S	NM, CM, SS	CS, SS	NS, CS, SS		NC,
33	(Sun et al., 2024)	S	NS, ES, CC, DS	ES	ES, SS		
34	(Terblanche et al., 2022)		ES, DC	EM, SS	ES, DS	ES, DM	
35	(Tossell et al., 2024)		ES,		CM,		
36	(Van Horn, 2024)		TS, RS, NM, DS, SS	TS, NM, ES, DS, SS	NS, ES, DM, SS	ES, DM	NC
37	(Vázquez-Cano et al., 2021)	S	DS	DS	DS,		
38	(Wang & Feng, 2023)	S	TM, DM, SS	TS, SS			
39	(Yang et al., 2024)		RS, NC, ES, CM, DS, SM	RS, NS, CS	ES, CM, DS, SC	NC, DS	