

Generative AI's Role in Computer Science Classrooms: A Rapid Mapping Review

Michael Pin-Chuan Lin, Mount Saint Vincent University, Canada
Gaganpreet Jhaggi, Athabasca University, Canada
Fuhua Lin, Athabasca University, Canada
Eric Poitras, Dalhousie University, Canada
Daniel Chang, Simon Fraser University, Canada
Jeeho Ryoo, Fairleigh Dickinson University, Canada

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Abstract

The rapid adoption of generative artificial intelligence (GenAI) tools such as ChatGPT has outstripped empirical evidence regarding their instructional value, particularly in computer science education (CSE), where learning depends on debugging, problem-solving, and iterative reasoning. This study presents a rapid review of peer-reviewed empirical research published between 2022 and 2025, after the public release of ChatGPT, synthesizing evidence on how GenAI is used and perceived in CSE contexts. A systematic search of the EBSCO platform identified nine studies examining the active use of GenAI by learners or academics. Across the included studies, GenAI use clustered into five instructional roles: general learning support; programming and debugging assistance; code comprehension and self-explanation support; feedback and revision support; and assessment-oriented instructional support. Findings indicate that GenAI is typically positioned as on-demand support embedded within existing coursework, with learning benefits reflected primarily in process-level outcomes such as engagement, revision, and evaluative judgment. Student perceptions were generally positive but qualified by concerns about over-reliance, output reliability, and academic integrity, while academic perspectives reflected cautious and conditional adoption. The review highlights the need for principled integration approaches that emphasize instructional framing, assessment alignment, and self-regulated engagement, and identifies directions for future research on durable learning outcomes and responsible use in CSE.

Keywords: generative AI, ChatGPT, computer science education, programming education, educational technology

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Introduction

Common GenAI tools such as ChatGPT have entered educational practice at an unprecedented speed, particularly in CSE. Since late 2022, students have increasingly utilized these systems for academic tasks, such as explaining difficult concepts, debugging assistance, and seeking guidance for problem-solving (Chang et al., 2023). This rapid uptake raises important pedagogical questions, as learning in CSE requires learners to coordinate code production, error tracing, computational reasoning, and higher-order problem solving. These characteristics make CSE a productive context for examining whether GenAI supports disciplinary learning processes or risks displacing the cognitive work central to skill development.

Early empirical studies documented a range of GenAI applications across computing and related domains. In CSE, GenAI tools have been used to provide feedback on programming tasks, support debugging, and help learners interpret program behaviour (Laubscher, 2024; Poitras et al., 2024). Related evidence from foundational mathematics education, which shares structured problem-solving characteristics with introductory computing courses, suggests that AI-generated hints can yield learning gains comparable to human-authored support when accuracy safeguards are in place (Pardos & Bhandari, 2024). While these findings suggest potential instructional value, the evidence remains limited. Most studies focus on short-term outcomes or task-level performance, raising questions about how GenAI use shapes learning processes, engagement, and the development of lasting competence.

Perceptions of GenAI integration reflect pedagogical tensions regarding cognitive engagement and disciplinary practices in CSE. Students value the accessibility of AI assistance (Lin & Chang, 2024), but educators express concerns about diminished critical engagement, over-reliance, and academic integrity (Chang et al., 2023; Lin et al., 2024). These perspectives highlight the need to understand how GenAI is being integrated into CSE, how learners and educators experience it, and what challenges and future directions are emerging.

This review provides an early synthesis of empirical evidence on GenAI in CSE. It characterizes how GenAI tools such as ChatGPT are being used to support learning and how students and academics perceive their integration, while also identifying challenges and future directions discussed in the literature. Given the rapid pace of technological development and the emerging nature of empirical work in this area, a rapid review approach was adopted to capture early evidence and perspectives in a timely manner. With this purpose, the review addresses the following questions:

- A. How are GenAI tools being used in CSE to support student learning and skill development?
- B. How do students and academics perceive the integration of GenAI in CSE, and what challenges and future directions are identified?

Methods

This review employed a rapid review approach guided by PRISMA principles, an appropriate method given the pace of research on GenAI in education. Rapid reviews aim to provide timely syntheses while retaining transparent and systematic procedures for search, screening, and analysis (Dobbins, 2017; Tricco et al., 2015, 2017).

The search was conducted on January 4, 2026, using the EBSCO platform, which aggregates ERIC, Education Source, PsycINFO, and Academic Search Complete. Search terms combined

GenAI and CSE concepts appearing in the title or abstract: “generative AI” OR “generative artificial intelligence” OR “ChatGPT” AND “comput* science education” OR “comput* science.” The search window was limited to studies published between 2022 and 2025, corresponding to the period following the public release of ChatGPT. Filters were applied to retain peer-reviewed articles published in English.

Studies were included if they reported original empirical research involving the active use of a GenAI tool in teaching or learning and were situated in CSE. CSE contexts were operationalized as involving learners or instructors engaged in computer science–related learning tasks, such as programming, code comprehension, or algorithmic reasoning. Review articles, conceptual papers, and studies not focused on CSE contexts were excluded.

The search yielded 55 records. After title and abstract screening, 45 records were excluded, and 10 articles underwent full-text review. One article was excluded at the full-text stage for not meeting the inclusion criterion of being situated in a CSE context. The remaining nine studies met all inclusion criteria and were included in the synthesis. Figure 1 presents the PRISMA flow diagram, and Table 1 summarizes key characteristics of the included studies.

Two independent coders sequentially reviewed each study, extracting data on instructional context, GenAI use, and learning/perception outcomes. Discrepancies were resolved through discussion, consulting senior scholars when needed. Analysis involved structured comparison to identify convergent patterns in instructional roles, stakeholder perceptions, and reported challenges, enabling synthesis across varied study designs.

Figure 1

PRISMA Flow Diagram of Article Selection

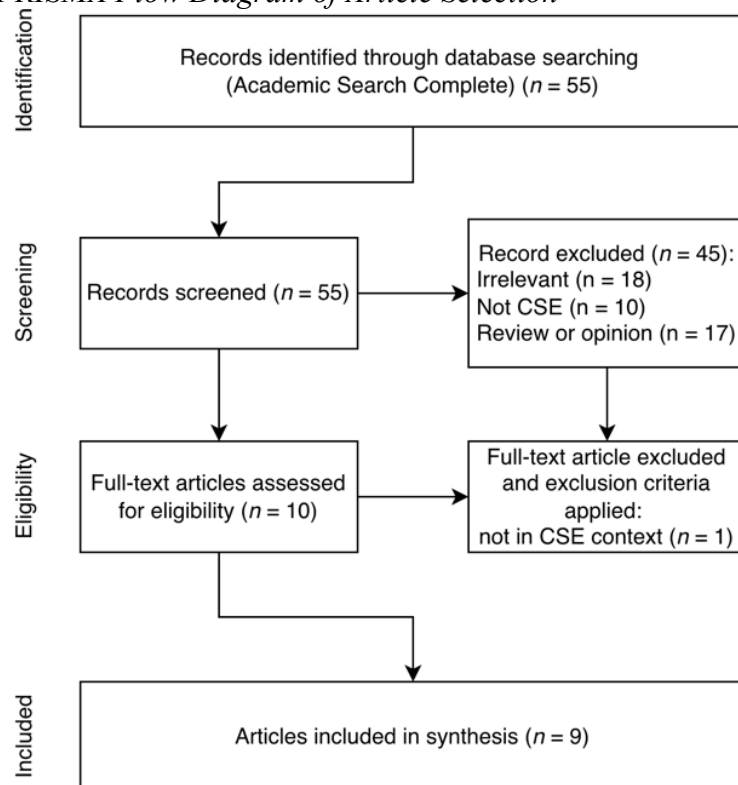


Table 1*Summary of Included Empirical Studies on the Use of GenAI Tools in CSE*

Author(s), Year	Context	Tool & Instructional Role	Primary Outcomes / Focus
Gandhi & Muldner, 2025	Undergraduate; Computer Science	ChatGPT; code comprehension and self-explanation (annotating code tracing solutions)	Learning processes and behaviours
Gimpel et al., 2025	Higher education; Information Systems	ChatGPT; assessment oriented instructional support	Perceptions and attitudes; academic evaluation
Kazanidis & Pellas, 2024	Undergraduate; Early Childhood Education & Computer Science	ChatGPT; general learning support	Course performance; perceptions and attitudes
Kosar et al., 2024	Undergraduate; Computer Science	ChatGPT; learning support plus programming and debugging assistance	Course performance; learning processes and behaviors; perceptions and attitudes
Kusper et al., 2025	Undergraduate; Informatics	ChatGPT, Copilot, Gemini; general learning support and code evaluation practices	Course performance; learning processes and behaviors; perceptions and attitudes
Lohr et al., 2025	Higher education; Computer Science	LLM pipeline; assessment-oriented instructional support (quiz item generation)	Feasibility and expert-rated quality of course-specific, semantically annotated, autogradable CS quiz questions and feedback
López-Fernández & Vergaz, 2024	Undergraduate; Computer Science	ChatGPT; learning support and programming assistance in course use	Course performance; learning processes and behaviors; student perceptions
Saúde et al., 2024	Undergraduate; Computer Science	ChatGPT; general learning support and course level adoption	Perceptions and attitudes
Ziqi et al., 2024	Undergraduate; Computer Science	ChatGPT; feedback and revision support	Learning processes and behaviors; perceptions and attitudes

Findings

RQ1: How are GenAI tools being used in CSE to support student learning and skill development?

Across the nine included studies, all research was situated in higher education, with the majority conducted in undergraduate contexts (7 of 9 studies). ChatGPT was the most examined tool, although several studies investigated alternative or complementary systems,

including GitHub Copilot, Gemini, and customized large language model pipelines. We then clustered GenAI use into five instructional roles: (1) general learning support, (2) programming and debugging assistance, (3) code comprehension and self-explanation support, (4) feedback and revision support, and (5) assessment-oriented instructional support. Individual studies often instantiated multiple roles, reflecting the flexible and overlapping ways GenAI was integrated into computer science education contexts.

The most prevalent role was general learning support and course-level adoption, reported in five studies (Kazanidis & Pellas, 2024; Kosar et al., 2024; Kusper et al., 2025; López-Fernández & Vergaz, 2024; Saúde et al., 2024). In these studies, students used GenAI tools alongside coursework to assist with studying, problem-solving, or task completion. GenAI functioned primarily as an on-demand support resource rather than a tightly scripted instructional intervention, and learning support was inferred from indicators such as engagement patterns, self-reported use, or course-related performance measures. Two studies also positioned GenAI as programming and debugging assistance (Kosar et al., 2024; López-Fernández & Vergaz, 2024), emphasizing learners' interactions with AI-generated code and their evaluative and corrective actions when reviewing model outputs. Here, learning support was framed in terms of strategic engagement with programming processes, including troubleshooting, interpretation, and refinement, rather than immediate performance gains.

More targeted instructional roles were less frequently examined. One study focused on code comprehension and self-explanation support (Gandhi & Muldner, 2025), in which ChatGPT-generated code-tracing solutions served as artifacts for student annotation and interpretation. Feedback and revision support was examined in two studies (Kosar et al., 2024; Ziqi et al., 2024), where learners engaged with AI-generated feedback to guide revision activity, making learning contingent on evaluative judgment and self-regulation. Finally, two studies examined assessment-oriented instructional support (Gimpel et al., 2025; Lohr et al., 2025), in which GenAI was used to support assessment design, generate course-aligned learning materials, or inform instructional planning.

Assessment practices across studies were heterogeneous and emphasized short-horizon indicators. Measures included course grades or assignment scores, rubric-based evaluations, surveys and questionnaires, qualitative analyses of learner artifacts or behaviors (e.g., annotations, revisions), and expert ratings of AI-generated materials. Taken together, the evidence base operationalized “learning support” primarily through performance proxies, behavioral indicators of engagement, and evaluations of output quality, with limited attention to longitudinal development or transfer beyond the immediate learning context.

RQ2: How do students and academics perceive the integration of GenAI in CSE, and what challenges and future directions are identified?

Across the nine included studies, perceptions of GenAI integration in CSE were examined predominantly through student-facing measures, with only one study explicitly capturing academic perceptions (Gimpel et al., 2025). Student perceptions were measured using instruments such as surveys, questionnaires, interviews, or reflective prompts, while academic perspectives were elicited through an instructor-facing evaluation approach in the assessment-focused study.

Student perceptions were examined in six studies (Kazanidis & Pellas, 2024; Kosar et al., 2024; Kusper et al., 2025; López-Fernández & Vergaz, 2024; Saúde et al., 2024; Ziqi et al., 2024).

Across these studies, students generally perceived GenAI tools as useful and supportive for learning activities such as clarifying concepts, assisting with programming tasks, and supporting revision or task completion. These positive evaluations were consistently accompanied by student-expressed reservations, including concerns about overreliance on AI tools, uncertainty regarding the accuracy of AI-generated outputs, and ambiguity around appropriate boundaries of use. Taken together, student perceptions reflected conditional endorsement rather than unqualified acceptance of GenAI in CSE contexts.

In contrast, the academic-facing perspective reported by Gimpel et al. (2025) treated GenAI primarily as a tool for assessment-oriented instructional support, emphasizing potential efficiency and utility for assessment design and instructional planning. At the same time, this perspective foregrounded pedagogical constraints, including the need to align AI-generated materials with learning objectives and to preserve assessment validity and fairness. Academic perceptions in the dataset are therefore best characterized as pragmatic and cautious, oriented toward conditional adoption under clear design and governance conditions.

Beyond perceptions, the reviewed literature consistently identified challenges associated with GenAI integration in CSE. These challenges clustered around four recurring themes: risks of overreliance and weakened independent problem solving; concerns about the accuracy and trustworthiness of AI-generated outputs; issues related to academic integrity and boundary-setting for appropriate use; and insufficient instructional and institutional guidance to support coherent integration. These concerns underscore persistent tensions between the perceived utility of GenAI and its implications for disciplinary learning and assessment practices.

Correspondingly, future directions emphasized the need for more rigorous empirical research designs that move beyond self-report measures to examine learning processes and outcomes over time. The literature also highlighted the importance of developing clearer pedagogical frameworks and course-level guidance to support critical evaluation, self-regulation, and responsible use of GenAI in CSE contexts, alongside institutional policies that clarify expectations for both students and instructors.

Discussion

The Role of GenAI in Supporting Learning and Skill Development

This review suggests GenAI serves primarily as a learning resource in CSE, not a replacement for instruction. Studies show GenAI integrated into five instructional roles, mainly for general learning support and programming/debugging assistance. Learners use AI tools alongside coursework for clarification, exploration, or feedback, consistent with prior work on iterative and feedback-driven learning processes (Barak & Shachar, 2008; McCormick, 2004; Williams, 2000). Evidence indicates changes in learning processes and engagement, especially in student interaction with problems, feedback, and revisions, rather than broad learning gains.

In studies examining programming and debugging assistance (Kosar et al., 2024; López-Fernández & Vergaz, 2024), GenAI appeared to support iterative engagement with programming tasks, including cycles of code generation, evaluation, debugging, and refinement. Although performance advantages over comparison conditions were not consistently observed, learners' interactions with AI-generated code frequently emphasized explanation-seeking, troubleshooting, and corrective action. From a learning sciences perspective, such behaviors align with productive engagement in structured problem spaces,

where feedback is immediate and solution paths can be articulated stepwise. In programming education, these conditions are especially salient, as novices benefit from rapid feedback that supports planning, monitoring, and adjustment of strategies during task execution. Consistent with prior work, the instructional value of GenAI in these contexts appears to lie in supporting metacognitive processes such as self-monitoring and reflection, particularly when AI outputs are treated as prompts for evaluation rather than as final solutions (Park et al., 2025).

GenAI was also frequently used as a general learning support tool, particularly in course-level adoption scenarios where students consulted AI systems to assist with studying, concept clarification, or task completion. This form of use emphasizes accessibility and immediacy, allowing learners to test ideas and receive responses without waiting for instructor intervention. Prior work similarly shows that students use AI to calibrate comprehension and regulate their learning (Poitras et al., 2024, 2026). However, the instructional value of such support appears contingent on how learners interact with AI outputs. When students engage critically by comparing alternatives, requesting explanations, or justifying revisions, GenAI can function as a resource that supports self-regulated learning processes. Conversely, when outputs are accepted uncritically, the tool becomes a shortcut that may weaken understanding (Park et al., 2025). These findings underscore the importance of instructional framing that positions GenAI as a complement to cognitive work, not a shortcut that bypasses it (Seo et al., 2021).

More targeted instructional roles, including code comprehension and self-explanation support and feedback and revision support, were less frequently examined in CSE but point to additional pathways through which GenAI may contribute to learning. In these configurations, AI-generated artifacts such as code-tracing solutions or feedback served as prompts for interpretation, annotation, and revision, foregrounding learners' evaluative judgment. Such uses align with instructional approaches that emphasize explanation, reflection, and revision as mechanisms for durable skill development (Arega & Hunde, 2025). Nevertheless, across these roles, assessment practices remained largely short-term and task-bound, limiting conclusions about longer-term learning trajectories or transfer.

Finally, assessment-oriented instructional support emerged as an instructor-facing role in which GenAI was used to generate learning materials or support assessment design. While these uses do not directly target student learning processes, they shape the instructional conditions under which learning occurs. The inclusion of this role highlights that GenAI integration in CSE is unfolding simultaneously at the levels of learner activity and instructional infrastructure. Taken together, the early evidence suggests that GenAI's educational value in CSE lies less in automated solution provision and more in how it is embedded within learning activities that preserve planning, evaluation, and revision as central learner responsibilities.

Challenges Related to Critical Thinking, Over-Reliance, and Output Reliability

Across the reviewed literature, the integration of GenAI in CSE was accompanied by recurring concerns about its potential impact on learners' cognitive engagement and disciplinary practices. While students valued GenAI's accessibility and responsiveness, they also expressed unease about over-reliance and the risk that uncritical use could weaken independent problem solving, reasoning, or creativity (Kim et al., 2025; Malik et al., 2023; Smolansky et al., 2023). These concerns highlighted tensions between GenAI's perceived utility and the need to preserve learner responsibility for sense-making and verification (Rusandi et al., 2023; Spector & Ma, 2019).

Concerns related to the reliability and trustworthiness of AI-generated outputs further shaped these perceptions. Students expressed uncertainty about the correctness and completeness of GenAI responses, especially in technical contexts where plausible but flawed outputs can be difficult for novices to detect. As a result, learning support was often framed as contingent on learners' capacity to evaluate, question, and verify AI-generated information. This emphasis on verification aligns with disciplinary expectations in CSE, where errors may propagate if left unchecked (Kohen-Vacs et al., 2025).

Academic integrity is another prominent concern, particularly given the fluency of GenAI outputs and the risk of students inappropriately substituting AI-generated work for their own. Prior work emphasizes explicit disclosure expectations and assessment designs that prioritize learning processes over polished products (Chan, 2023; Chang et al., 2023). Clearer instructional and policy guidance is needed to support transparency and fairness in CSE contexts, where the line between learning support and task completion can blur (Laubscher, 2024). Together, these concerns highlight the challenge of aligning GenAI use with assessment practices that prioritize process, justification, and method over output alone.

Finally, several studies pointed to instructional and institutional uncertainty as a barrier to coherent integration. Students reported ambiguity regarding when and how GenAI use was appropriate, while instructors faced challenges associated with rapidly evolving tools and limited guidance (Chan, 2023; Laubscher, 2024). These findings suggest that many challenges associated with GenAI integration stem not from the technology itself, but from gaps in instructional framing, assessment alignment, and shared understanding of educational purpose.

Implications for Instructional Design and Research

Embedding GenAI use within structured learning sequences can help preserve learners' responsibility for planning, monitoring, and evaluation. This aligns with self-regulated learning principles, in which learners articulate goals, engage strategically with resources, and reflect on outcomes (Chang et al., 2023; Zimmerman, 2000). In programming and problem-solving contexts, GenAI interactions can be organized around routines—for example, prompting learners to plan, request explanations, evaluate outputs, and reflect on revisions. Such designs shift GenAI from answer-generation to a scaffold for inquiry and iterative improvement.

Teaching prompting as a learning strategy rather than a technical skill further supports this orientation. Prompts that emphasize explanation, justification, or self-critique help maintain a focus on reasoning and mitigate the risk of uncritically relying on AI outputs. Prior work therefore emphasizes designing AI-supported activities that foreground reflection, comparison, and evaluative judgment as explicit learning practices (Lin & Chang, 2023; Yusuf et al., 2024). Conceptually, frameworks such as CHAT-ACTS emphasize the learner's role as an active planner and evaluator of AI interactions within self-regulated activity (Ballantyne et al., 2025; Lin & Chang, 2023).

These implications extend to assessment and institutional practice. Method-focused assessment designs that value intermediate artifacts—such as prompt logs, annotations, or revision histories—can help align GenAI use with disciplinary expectations while supporting transparency and integrity. Future research should build on these design principles by examining how instructional framing, assessment alignment, and institutional guidance shape learners' engagement with GenAI over time, moving beyond short-term or self-reported

outcomes to investigate learning processes, transfer, and durability of skill development (Kong & Yang, 2024; Lin et al., 2025; Ruiz-Rojas et al., 2023).

Conclusion and Limitations

This rapid review provides a structured snapshot of how GenAI is currently being integrated into CSE and how such use is understood by learners and educators. The reviewed studies collectively indicate that GenAI is being adopted primarily as a supportive component within existing instructional arrangements, with its educational relevance shaped by how it is framed, constrained, and evaluated. These findings point toward the value of principled integration, in which the use of AI is coupled with requirements for process evidence and reflection so that students remain active agents who plan, monitor, and evaluate their work (Chang et al., 2023; Lin & Chang, 2023). The contribution of this review lies in clarifying emerging patterns of use and concern, and in distinguishing between exploratory adoption and evidence-informed integration in a rapidly evolving research landscape.

The findings must be interpreted in light of several limitations. As a rapid review, the search scope was necessarily limited, and the included studies varied substantially in design, context, and outcome measures (Dobbins, 2017; Tricco et al., 2017). Most evidence relied on short-term or perception-based indicators, with limited attention to longer-term learning, transfer, or instructional decision-making at scale. These constraints underscore the need for future research that examines GenAI-supported learning across extended timescales, considers instructional framing and assessment alignment, and systematically investigates how learners regulate and evaluate AI use. Thus, the present review does not offer prescriptive solutions, but instead delineates a research agenda for future work. Within this space, frameworks grounded in self-regulated learning—such as CHAT-ACTS—can be productively explored and empirically tested.

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Declaration of Generative AI and AI-Assisted Technologies in the Writing Process

The authors declare that Grammarly was used to support proofreading and language refinement, including correction of grammatical and spelling errors and minor rephrasing to improve clarity. In addition, ChatGPT was used as an AI-assisted tool to support language editing, structural organization, and clarity of expression during manuscript preparation. The use of these tools was limited to assisting with writing quality and organization and did not involve generating original scholarly content. All ideas, research design, data extraction, analysis, interpretation, and conclusions presented in this manuscript are the authors' own and are based on the systematic conduct of the review.

References

- Arega, N. T., & Hunde, T. S. (2025). Constructivist instructional approaches: A systematic review of evaluation-based evidence for effectiveness. *Review of Education*, 13(1), e70040. <https://doi.org/10.1002/rev3.70040>
- Ballantyne, E., Lin, M. P.-C., Chang, D. H., & Poitras, E. (2025). Bridging educational equity gaps: Expanding the CHAT-ACTS framework for personalized GenAI chatbots in higher education. *Journal of Computing in Higher Education*. <https://doi.org/10.1007/s12528-025-09475-z>
- Barak, M., & Shachar, A. (2008). Projects in Technology Education and Fostering Learning: The Potential and Its Realization. *Journal of Science Education and Technology*, 17(3), 285–296. <https://doi.org/10.1007/s10956-008-9098-2>
- Chan, C. K. Y. (2023). A comprehensive AI policy education framework for university teaching and learning. *International Journal of Educational Technology in Higher Education*, 20(1), 38. <https://doi.org/10.1186/s41239-023-00408-3>
- Chang, D. H., Lin, M. P.-C., Hajian, S., & Wang, Q. Q. (2023). Educational Design Principles of Using AI Chatbot That Supports Self-Regulated Learning in Education: Goal Setting, Feedback, and Personalization. *Sustainability*, 15(17), 12921. <https://doi.org/10.3390/su151712921>
- Dobbins, M. (2017). Rapid review guidebook. *Natl Collab Cent Method Tools*, 13, 25.
- Gandhi, A., & Muldner, K. (2025). Beyond verbal self-explanations: Student annotations of a code-tracing solution produced by ChatGPT. *British Journal of Educational Technology*, 1–26. <https://doi.org/10.1111/bjet.13600>
- Gimpel, H., Hall, K., Decker, S., Eymann, T., Gutheil, N., Lämmermann, L., Braig, N., Maedche, A., Ruiner, C., Schoch, M., Schoop, M., Urbach, & Vandirk, S. (2025). Using Generative AI in Higher Education: A Guide for Instructors. *Journal of information systems education*, 36(3), 237–256. <https://doi.org/10.62273/QLLG7172>
- Kazanidis, I., & Pellas, N. (2024). Harnessing Generative Artificial Intelligence for Digital Literacy Innovation: A Comparative Study between Early Childhood Education and Computer Science Undergraduates. *AI*, 5(3), 1427–1445. <https://doi.org/10.3390/ai5030068>
- Kim, J., Yu, S., Detrick, R., & Li, N. (2025). Exploring students' perspectives on Generative AI-assisted academic writing. *Education and Information Technologies*, 30(1), 1265–1300. <https://doi.org/10.1007/s10639-024-12878-7>
- Kohen-Vacs, D., Usher, M., & Jansen, M. (2025). Integrating Generative AI into Programming Education: Student Perceptions and the Challenge of Correcting AI Errors. *International Journal of Artificial Intelligence in Education*, 35(5), 3166–3184. <https://doi.org/10.1007/s40593-025-00496-4>

- Kong, S., & Yang, Y. (2024). A Human-Centered Learning and Teaching Framework Using Generative Artificial Intelligence for Self-Regulated Learning Development Through Domain Knowledge Learning in K–12 Settings. *IEEE Transactions on Learning Technologies*, 17, 1588–1599. <https://doi.org/10.1109/TLT.2024.3392830>
- Kosar, T., Ostojić, D., Liu, Y. D., & Mernik, M. (2024). Computer Science Education in ChatGPT Era: Experiences from an Experiment in a Programming Course for Novice Programmers. *Mathematics*, 12(5), 629. <https://doi.org/10.3390/math12050629>
- Kusper, G., Mátyás, G. I., & Balla, T. (2025). We are not afraid of the wolf!—AI usage attitudes among Hungarian informatics students. In *Annales Mathematicae et Informaticae* (Vol. 61, pp. 186–201). <https://doi.org/10.33039/ami.2025.10.004>
- Laubscher, M. C. (2024). AI and Computer Science Education: The Need for Improved Regulation for the Use of AI in Computer Science Education. In C. Bosch, L. Goosen, & J. Chetty (Eds.), *Navigating Computer Science Education in the 21st Century* (pp. 282–298). IGI Global Scientific Publishing. <https://doi.org/10.4018/979-8-3693-1066-3.ch014>
- Lin, M. P.-C., & Chang, D. (2023). CHAT-ACTS: A pedagogical framework for personalized chatbot to enhance active learning and self-regulated learning. *Computers and Education: Artificial Intelligence*, 5, 100167. <https://doi.org/10.1016/j.caeai.2023.100167>
- Lin, M. P.-C., & Chang, D. (2024). Exploring Inclusivity in AI Education: Perceptions and Pathways for Diverse Learners. In A. Sifaleras & F. Lin (Eds.), *Generative Intelligence and Intelligent Tutoring Systems* (pp. 237–249). Springer Nature Switzerland.
- Lin, M. P.-C., Chang, D. H., & Winne, P. H. (2025). A proposed methodology for investigating student-chatbot interaction patterns in giving peer feedback. *Educational Technology Research and Development*, 73(1), 353–386. <https://doi.org/10.1007/s11423-024-10408-3>
- Lin, M. P.-C., Liu, A. L., Poitras, E., Chang, M., & Chang, D. H. (2024). An Exploratory Study on the Efficacy and Inclusivity of AI Technologies in Diverse Learning Environments. *Sustainability*, 16(20), 8992. <https://doi.org/10.3390/su16208992>
- Lohr, D., Berges, M., Chugh, A., Kohlhase, M., & Müller, D. (2025). Leveraging Large Language Models to Generate Course-Specific Semantically Annotated Learning Objects. *Journal of Computer Assisted Learning*, 41(1), e13101. <https://doi.org/10.1111/jcal.13101>
- López-Fernández, D., & Vergaz, R. (2024). Adoption and Impact of ChatGPT in Computer Science Education: A Case Study on a Database Administration Course. *AI*, 5(4), 2321–2337. <https://doi.org/10.3390/ai5040114>

- Malik, A. R., Pratiwi, Y., Andajani, K., Numertayasa, I. W., Suharti, S., Darwis, A., & Marzuki. (2023). Exploring Artificial Intelligence in Academic Essay: Higher Education Student's Perspective. *International Journal of Educational Research Open*, 5, 100296. <https://doi.org/10.1016/j.ijedro.2023.100296>
- McCormick, R. (2004). Issues of Learning and Knowledge in Technology Education. *International Journal of Technology and Design Education*, 14(1), 21–44. <https://doi.org/10.1023/B:ITDE.0000007359.81781.7c>
- Pardos, Z. A., & Bhandari, S. (2024). ChatGPT-generated help produces learning gains equivalent to human tutor-authored help on mathematics skills. *PLOS ONE*, 19(5), e0304013. <https://doi.org/10.1371/journal.pone.0304013>
- Park, S. M., Ho, M., Lin, M. P.-C., & Ryoo, J. (2025). Evaluating the Impact of Assistive AI Tools on Learning Outcomes and Ethical Considerations in Programming Education. *2025 IEEE Global Engineering Education Conference (EDUCON)*, 1–10. <https://doi.org/10.1109/EDUCON62633.2025.11016517>
- Poitras, E., Crane, B. G., Dempsey, D., Bragg, T. A., Siegel, A. A., & Lin, M. P. (2024). Cognitive Apprenticeship and Artificial Intelligence Coding Assistants. In C. Bosch, L. Goosen, & J. Chetty (Eds.), *Navigating Computer Science Education in the 21st Century* (pp. 261–281). IGI Global Scientific Publishing. <https://doi.org/10.4018/979-8-3693-1066-3.ch013>
- Poitras, E., Durai, J. P., Yunus Raida, N. Z., Sachdeva, J., Doucette, K., & Lin, M. P. (2026). Data-Informed Decision Making in Introductory Programming Instruction. In R. Dhakal, W. Davis, & K. Heske (Eds.), *Fostering Educational Culture for Student Success* (pp. 305–336). IGI Global Scientific Publishing. <https://doi.org/10.4018/979-8-3373-6960-0.ch009>
- Ruiz-Rojas, L. I., Acosta-Vargas, P., De-Moreta-Llovet, J., & Gonzalez-Rodriguez, M. (2023). Empowering Education with Generative Artificial Intelligence Tools: Approach with an Instructional Design Matrix. *Sustainability*, 15(15), 11524. <https://doi.org/10.3390/su151511524>
- Rusandi, M. A., Ahman, Saripah, I., Khairun, D. Y., & Mutmainnah. (2023). No worries with ChatGPT: building bridges between artificial intelligence and education with critical thinking soft skills. *Journal of Public Health*, 45(3), e602–e603. <https://doi.org/10.1093/pubmed/fdad049>
- Saúde, S., Barros, J. P., & Almeida, I. (2024). Impacts of Generative Artificial Intelligence in Higher Education: Research Trends and Students' Perceptions. *Social Sciences*, 13(8), 410. <https://doi.org/10.3390/socsci13080410>
- Seo, K., Tang, J., Roll, I., Fels, S., & Yoon, D. (2021). The impact of artificial intelligence on learner–instructor interaction in online learning. *International Journal of Educational Technology in Higher Education*, 18(1), 54. <https://doi.org/10.1186/s41239-021-00292-9>

- Smolansky, A., Cram, A., Radulescu, C., Zeivots, S., Huber, E., & Kizilcec, R. F. (2023). Educator and Student Perspectives on the Impact of Generative AI on Assessments in Higher Education. *Proceedings of the Tenth ACM Conference on Learning @ Scale*, 378–382. <https://doi.org/10.1145/3573051.3596191>
- Spector, J. M., & Ma, S. (2019). Inquiry and critical thinking skills for the next generation: From artificial intelligence back to human intelligence. *Smart Learning Environments*, 6(1), 8. <https://doi.org/10.1186/s40561-019-0088-z>
- Tricco, A. C., Antony, J., Zarin, W., Striffler, L., Ghassemi, M., Ivory, J., Perrier, L., Hutton, B., Moher, D., & Straus, S. E. (2015). A scoping review of rapid review methods. *BMC Medicine*, 13(1), 224. <https://doi.org/10.1186/s12916-015-0465-6>
- Tricco, A. C., Langlois, E. V., & Straus, S. E. (2017). *Rapid reviews to strengthen health policy and systems: a practical guide*. World Health Organization Geneva.
- Williams, P. J. (2000). Design: The Only Methodology of Technology. *Journal of Technology Education*, 11(2). <https://doi.org/10.21061/jte.v11i2.a.4>
- Yusuf, A., Bello, S., Pervin, N., & Tukur, A. K. (2024). Implementing a proposed framework for enhancing critical thinking skills in synthesizing AI-generated texts. *Thinking Skills and Creativity*, 53, 101619. <https://doi.org/10.1016/j.tsc.2024.101619>
- Zimmerman, B. J. (2000). Chapter 2—Attaining Self-Regulation: A Social Cognitive Perspective. In M. Boekaerts, P. R. Pintrich, & M. Zeidner (Eds.), *Handbook of Self-Regulation* (pp. 13–39). Academic Press. <https://doi.org/10.1016/B978-012109890-2/50031-7>
- Ziqi, C., Xinhua, Z., Qi, L., & Wei, W. (2024). L2 students' barriers in engaging with form and content-focused AI-generated feedback in revising their compositions. *Computer Assisted Language Learning*, 1–21. <https://doi.org/10.1080/09588221.2024.2422478>

Contact email: Michael.lin@msvu.ca