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Beyond Programming Assistance towards the Integration of Generative AI into Computer Science Education: A Scoping Review

Sonia Proust-Androwkha¹, Valéry Psyché², Revekka Kyriakoglou³, Anis Boubaker⁴, Sébastien Lallé⁵, Lamprini Chartofylaka⁶, Guilherme M. Machado⁷, and Nour El Mawas⁸

¹Université de Sherbrooke, Sherbrooke, Canada
sonia.proust-androwkha@usherbrooke.ca (affiliated researcher)

²Université TÉLUQ, Québec, Canada

³Université Paris 8 Vincennes - Saint-Denis, Saint-Denis, France

⁴École de Technologie Supérieure, Montréal, Canada

⁵Sorbonne Université, CNRS, LIP6, F-75005 Paris, France

⁶Université des Antilles, Guadeloupe, France

⁷LyRIDS, École centrale d'électronique, Paris, France

⁸CREM, Université de Lorraine, Metz, France

Abstract. This paper presents a scoping review of literature on using generative artificial intelligence (GenAI) in computer science (CS) education at the higher education (HE) level. This review's primary research question is: "How is GenAI utilized in the teaching and learning of CS in HE?" A total of 890 articles were initially identified following a protocol based on PRISMA guidelines. After the selection screening, 38 articles were included for quantitative and qualitative analysis. Students mainly use GenAI to assist with programming tasks. However, there is a lack of research for developing effective pedagogical strategies to fully integrate GenAI into CS education. While opinions on its effectiveness in HE are mixed, students' growing enthusiasm for GenAI stresses the critical need for research on pedagogical approaches to effectively handle its integration and facilitate the current educational paradigm shift. This shift calls for proactive pedagogical strategies and research to adapt teaching methods to an AI-driven context. Strategic GenAI use and regulation will equip new CS learners to thrive in the evolving tech landscape.

Keywords: Scoping Review · Computer Science in Higher Education (HE) · Generative Artificial Intelligence (GenAI) in Education (AIED)

1 Introduction

Every introduction of technology that affects learning comes with its share of fears and excitement, and the democratization of generative AI tools is no exception. Free access to tools like ChatGPT, Gemini, and Mistral that reach the general public led to a significant increase in GenAI use by students to complete

their computer programming tasks. Such use raises questions on the impact of these models in learning and teaching coding in HE. Innovative approaches for GenAI are beginning to emerge in CS pedagogy. They could positively impact students' skill acquisition [40] and the pedagogical strategies to be implemented. However, using GenAI could lead students to focus more on mastering the formulation of effective prompts to obtain correct responses instead of mastering programming skills. One concern from the teaching perspective is how academic institutions and professors respond to these new practices. Milano et al. [21] described how universities generally adopt three responses: (i) banning the use of GenAI, (ii) using exclusively paper-based assessments, and (iii) proactively integrating GenAI into the learning experience. Each approach has its pros and cons, and may not be directly applicable in the field of CS. Kendon et al. [17] suggest that educators should reconsider the design of learning activities and assessment methods in light of recent developments, focusing on how students construct knowledge, apply skills, and develop processes. In this context, this paper's main research question is: ***"How is GenAI utilized in the teaching and learning of CS in HE?"*** To answer this question, we propose a scoping review of literature on the integration of GenAI in higher CS education.

2 Review Methodology

The literature review presented in this article is based on a scoping review, a method aimed at identifying and synthesizing the state of knowledge on a broad, underexplored, or complex question [41]. The protocol followed the PRISMA guidelines, a recognized method for structuring the stages of a review and minimizing bias or errors [22]. An advanced research was conducted within Web of Science, arXiv, and Érudit, using a search string combining three main components, each using keywords linked by the boolean operator "AND": GenAI: "generative artificial intelligence" OR "genAI" OR "generative AI" OR "large language model" OR "chatbot" OR "conversational agent" OR "chatGPT" OR "copilot" OR "gemini" OR "Bing" OR "Bard". Education: "computer science education" OR "computer education" OR "CS". Degree: "higher education" OR "college" OR "university" OR "undergrad" OR "graduate" OR "postgraduate" OR "adult education". After removal of duplicates, the references were imported in Covidence, a platform designed for conducting PRISMA-based systematic reviews. The inclusion criteria were as follows: (a) peer-reviewed scientific publications, (b) written in English, (c) from the past three years, and (d) a context specific to HE. The identification stage, completed on October 17, 2024, yielded 227 references. Each document was independently reviewed by two team members via Covidence. In case of disagreement, one or two additional members intervened. At the end of the selection process, 66 articles were retained (see Fig. 1). A thematic analysis was conducted to identify the main emerging categories and to structure the results according to the dominant orientations in the selected papers. This analysis revealed several research avenues. However, due to

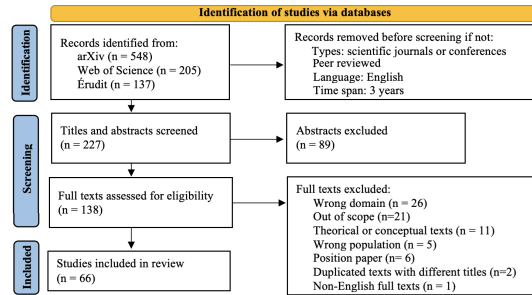


Fig. 1. PRISMA Flow Diagram

editorial constraints, we chose to focus the presentation on the main axis in the corpus: *uses of GenAI and their impact on learning* (38 out of the 66 articles).

3 Results

3.1 Corpus characteristics

Among the 38 papers of the corpus, 61% are from conferences, and 39% from journals. The number of publications remains low until the end of 2023, then steadily increases from January 2024. No articles precede March 2023. The types of research identified include experimental studies (21 articles) and case studies (20), 3 studies combining both. The most frequent data collection method is surveys, used in 30 studies. Digital trace analysis are also widespread (12 papers), and may include the collection of logs, student submissions, and eye-tracking data. Other methods, such as interviews (8 papers), analysis of academic records (5 papers) and observations (4 papers), are used to a lesser extent. 53% of the studies combine multiple methods. 68% of the studies focus on programming courses, 8% on software engineering, and 5% on algorithms/AI/data science (the rest being unreported). 92% of the courses are undergraduate. For students, the sample sizes range from 8 to 983 (mean of 181, median of 88, st. dev. of 246). Gender distribution is provided in 13 studies. On average, 72% of participants are men, 27% are women, and 1% have other gender identities. For the 7 studies that involve teachers, the sample sizes range from 1 to 57 (mean of 16, median of 8, std. dev. of 19). 95% of the studies involve participants from Western countries (50% North America, 29% Europe, 16% Australasia). Next, 16% focus on East Asia, 8% on the Middle East, one on South America, and none on Africa. 5 studies involve multiple countries.

3.2 Thematic analysis on uses of GenAI and its impact on learning

In the corpus, 38 studies focus on students' perceptions of GenAI or its impact on their learning [1–16,18–20,23–30,32–40,42], while seven studies examine teachers'

perceptions [1, 5, 26, 27, 29, 31, 39]. They highlight several advantages and issues related to using GenAI in teaching and learning CS in HE.

•**Positive perceptions of GenAI use:** GenAI applications are mainly categorized into code generation and debugging, searching for theoretical explanations or reformulations, and rapid solution validation. LLMs are used to create code skeletons, generate solution fragments, identify and correct errors, provide debugging suggestions, or speed up coding tasks. For example, in [14], students primarily use AI to verify or compare their own code, while in [30], some leverage AI to generate alternative solutions, broadening their perspectives and enhancing their problem-solving skills. One of the main appeals of AI for students is time efficiency. They appreciate how quickly AI provides answers, often more effectively than traditional search engines [2]. AI also serves as a virtual tutor, helping to clarify theoretical concepts, providing code examples, and generating ideas [2, 6, 14, 25, 30, 37]. In [40], students note that AI simplifies repetitive technical aspects, freeing time for complex and creative tasks. The sometimes unexpected suggestions of AI [25] also provide new coding perspectives, enhancing the enjoyment of learning. Finally, AI usage appears to play a significant role in reducing student stress and increasing engagement [37, 40]. AI supports self-paced learning beyond instructors' availability and offers a judgment-free space for questions [5, 14, 40]. This autonomy enhances their sense of control over their progress and helps alleviate academic pressure.

•**Barriers, challenges, and ambivalence in trusting AI use:** Students exhibit ambivalence regarding their trust in AIED: On one hand, they find it useful, but on the other, they worry about inaccurate or incomplete responses. They note that AI can generate inconsistent, hard-to-validate, or even contradictory results depending on the context, reinforcing their skepticism. At times, they feel the need to consult a human expert to verify the information [30]. In another study [12], six out of 22 students feared that using ChatGPT might hinder the development of essential skills and jeopardize their success in the final exam. Similarly, the study [35] highlights that students' intention to use AI depends largely on their overall attitude: They weigh both the perceived usefulness of the tool and the risk of being penalized for unauthorized use by their institution. A study with nearly 150 students [24] indicates that while most students believed that ChatGPT improved productivity, more than half felt that it negatively affected intelligence and creativity.

Formulating adequate queries for AI remains a challenge. Students express dissatisfaction when their queries are too long or complex. Writing well-structured prompts to obtain accurate responses is challenging for many. The study [14] reveals that students unfamiliar with AI or with negative experiences of it, are much more reluctant to adopt it. Their apprehension stems mainly from the fear of receiving incorrect responses and being unable to distinguish facts from misinformation. In the same study, more experienced students appear more tolerant of AI, knowing that they must apply their knowledge to filter out inaccurate or irrelevant responses. Furthermore, some studies emphasize that while AI is considered useful for quickly generating ideas [6], it is also perceived as potentially

detrimental to deep learning. Some students even describe its use in academia as unethical, seeing it as a shortcut that induces guilt and stifles creativity. In study [1], where five instructors evaluated ChatGPT’s performance, they confirmed the necessity of human intervention, especially for novice students.

•***Self-efficacy and the effects of GenAI use on learning:*** Several studies explore GenAI’s impact on learning, self-efficacy and skill development. For instance, study [40] shows that ChatGPT enhances computational thinking skills and self-efficacy by reducing purely syntactical writing blocks, enabling more creative and critical thinking. Likewise, [11] reports reduced cognitive load on repetitive tasks, helping students focus on complex skills. However, these benefits are not systematic. Study [20] finds that students with higher self-efficacy or better prior grades tend to use AI less, perceiving less need for it. In contrast, those who feel less competent rely more heavily on AI. Study [29] highlights a phenomenon of illusion of competence, particularly among novice programmers: Some students overestimate their abilities due to AI assistance. This phenomenon, also noted in [7], suggests a non-reflective use of AI that may lead to plagiarism.

Furthermore, other studies [16, 29] observe lower performance in students during coding exams requiring deep understanding and application, compared to exercises focused on code reading and debugging. These findings suggest that AI reliance may hinder deep learning. On the other hand, study [18] finds that ChatGPT use had no statistically significant impact on student performance in both practical tasks and midterm exams. Conversely, research study [9] indicates that students using ChatGPT to create UML diagrams perform better than those who do not. By actively leveraging their skills to produce meaningful results, these students avoid total dependence on AI, which fosters learning.

4 Discussion and Conclusion

This scoping review outlines research on GenAI in teaching and learning CS in HE. We discuss here four key findings, perspectives and limitations of this work.

Finding 1 – The evolution of learners’ and teachers’ perceptions is poorly documented. Most research focuses on students’ perceptions and self-reported uses of GenAI, highlighting their motivations and concerns regarding its use. These studies often rely on one-time data collection, conducted after a short exposure period to GenAI or without real pedagogical integration. Furthermore, no research investigates how these perceptions evolve as students integrate these tools more permanently. Teachers’ perceptions in these processes are also under-explored, despite their key role in guiding and regulating these uses.

Finding 2 – Contrasting, even contradictory, views on the impact of GenAI on learning. Twelve studies examine the impact of GenAI on learning based on empirical data. The conclusions are mixed: some studies suggest that GenAI facilitates knowledge acquisition and improves understanding of complex concepts, while others highlight risks of over-reliance, superficial thinking, and a weakening of fundamental skills.

Finding 3 – Lack of theoretical frameworks. A striking observation across the reviewed studies is the near-total absence of theoretical frameworks, particularly in research focused on perceptions of GenAI use. This gap limits the scope of findings and complicates the development of well-founded recommendations on how to integrate GenAI effectively in education.

Finding 4 – Need of pedagogical approaches to structure learning with GenAI. In programming courses, where the ability to apply knowledge is more crucial than mere theoretical acquisition, this duality raises a question: How can GenAI be leveraged to promote active learning and problem-solving rather than providing merely automated answers? This issue underscores the need to develop specific pedagogical approaches that frame the use of these tools to maximize their benefits without undermining students’ skill development.

Perspectives. These findings raise several key issues that warrant further research. A first research avenue could explore how to prevent GenAI from replacing the cognitive effort necessary for developing programming skills. This would involve designing pedagogical strategies that enable students to use GenAI as a tool for reflection and problem-solving, which calls for the need to rethink learning and assessment. Another critical issue is analyzing how students’ perceptions and practices evolve after prolonged exposure to GenAI to better understand the long-term effects of these tools on students’ autonomy, engagement, and ability to develop critical and analytical CS skills. Additionally, it would be relevant to examine the impact of integrating GenAI on students’ academic and professional trajectories. Research could explore whether early exposure to GenAI influences their adaptability to technological advancements, their relationship with knowledge, and their integration into a job market where AI is playing an increasingly significant role. Finally, teacher training appears to be a crucial lever to ensure an effective and ethical integration of GenAI. To guide students in using these tools, educators must be trained both in technical aspects and in pedagogical strategies that optimize benefits while mitigating potential drawbacks.

Limitations. This work has some limitations. First, we focused only on conference and journal articles, possibly omitting other promising initiatives. Second, thematic analyses inherently involve a degree of subjectivity. Although we sought to improve the reliability of our analysis through reflection and discussions, the identified themes reflect our interpretation of the available literature.

Conclusion. This paper presents a current panorama of the use of GenAI in CS education in HE. For this purpose, a systematic review was conducted, and we focused on 38 papers reporting on uses of GenAI and their impact on learning. This review highlights both the potential and challenges associated with integrating GenAI into the teaching and learning of CS in HE. It calls for in-depth reflection on pedagogical strategies, assessment methods, and usage frameworks in this context. More broadly, it raises the following question: Does the future of GenAI integration in CS education rely on a balanced approach that combines instructional support with critical reflection on its implications? This emerging paradigm invites a rethinking of learning practices and the role of students in an environment where AI is becoming ubiquitous.

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