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# Risk management strategy for generative AI in computing education: how to handle the strengths, weaknesses, opportunities, and threats?

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**Abstract**

The idea of Artificial intelligence (AI) has a long history in both research and fiction and has been applied in educational settings since the 1970s. However, the topic of AI underwent a huge increase of interest with the release of ChatGPT in late 2022, and more people were talking about generative AI (GenAI or GAI). According to some estimates, the number of publications on generative AI increased with 2269.49% between 2022 and 2023, and the increase was even higher when related to computing education. The aim of this study is to investigate the potential strengths, weaknesses, opportunities, and threats of generative AI in computing education, as highlighted by research published after the release of ChatGPT. The study applied a scoping literature review approach with a three-step process for identifying and including a total of 129 relevant research papers, published in 2023 and 2024, through the Web of Science and Scopus databases. Included papers were then analyzed with a theoretical thematic analysis, supported by the SWOT analysis framework, to identify themes of strengths, weaknesses, opportunities, and threats with generative AI for computing education. A total of 19 themes were identified through the analysis. Findings of the study have both theoretical and practical implications for computing education specifically, and higher education in general. Findings highlights several challenges posed by generative AI, such as potential biases, overreliance, and loss of skills; but also several possibilities, such as increasing motivation, educational transformation, and supporting teaching and learning. The study expands the traditional SWOT analysis, by providing a risk management strategy for handling the strengths, weaknesses, opportunities, and threats of generative AI.

**Keywords:** Generative AI, Computing education, Risk management strategy, Literature review, SWOT analysis

## Introduction

It can be difficult to pinpoint the exact roots of Artificial Intelligence (AI), but what can be considered an early example is that of Isaac Asimov's Science Fiction short story "Runaround" in the 1940s and the Three Laws of Robotics, which stipulates the rules an intelligent machine must follow (Haenlein & Kaplan, 2019). Some years later, Alan Turing published "Computing Machinery and Intelligence" in 1950, a seminal paper where it is discussed how to create and test the intelligence of machines, the famous Turing Test (Haenlein & Kaplan, 2019). The term Artificial Intelligence was then coined in 1955 when John McCarthy, by many considered the father of AI, together with Marvin Minsky, Nathaniel Rochester, and Claude Shannon wrote a proposal for a summer research project to the Rockefeller Foundation, with the title "Dartmouth Summer Research Project on Artificial Intelligence" (Haenlein & Kaplan, 2019; Rajaraman, 2014).

Applying AI in the field of education (AIEd) has been practiced and researched since the 1970s (Luckin et al., 2016; Robertson, 1976). Some notable examples are BUGGY, a system that teach subtraction and addition based on the user's potential misconceptions, and iTalk2Learn, a system that supports learners to understand fractions based on cognitive needs, mathematical knowledge, emotional state, and previous feedback (Luckin et al., 2016). Previous literature reviews in the field have noted that AIEd shows potential in supporting teachers and students through individualization of education, but that there are challenges related to, for example, biases, ethics, privacy, and limitations of the AIEd systems' capabilities (Chiu et al., 2023; Humble & Mozelius, 2022; Zhang & Aslan, 2021), AIEd systems, or Intelligent Tutoring Systems (ITS), with limited capabilities have by some been labelled as Stupid Tutoring Systems (Baker, 2016).

In November of 2022, OpenAI's ChatGPT was released to the public and researchers, educators and other stakeholders were both impressed and concerned by its capabilities (Humble et al., 2024). Articles discussed ChatGPT's potential effect on human interaction, art, writing, education, business, customer service, market research, programming and so on (Abdullah, Madain & Jararweh, 2022; Haleem et al., 2022). ChatGPT, and also Google Gemini and Microsoft Copilot, are examples of Generative Artificial Intelligence (GenAI or GAI) which leverages deep learning and generative modeling to generate synthetic artefacts based on training data such as graphics, text, video, and audio (Humphreys et al., 2024; Jovanović & Campbell, 2022). In the following year of 2023, more researchers started to take an interest in the concept of Artificial Intelligence and the keyword "Generative Artificial Intelligence" saw a huge increase of publications. Figure 1 shows the approximate number of publications between 2019 and 2023 when searching

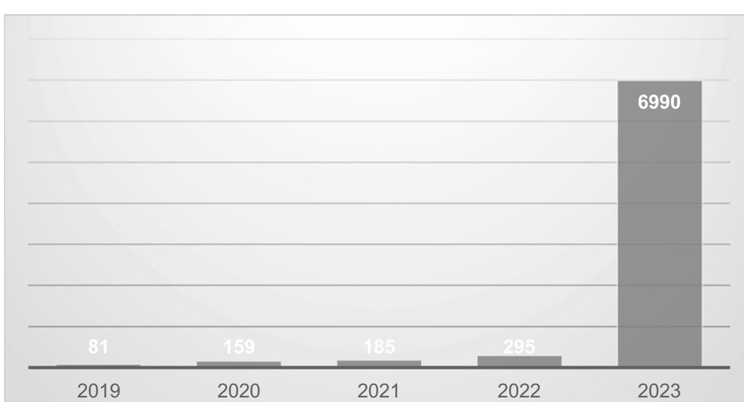


**Fig. 1** Search for "Generative Artificial Intelligence" in Google Scholar on the 18th of March 2024

for "Generative Artificial Intelligence" in Google Scholar. The increase from 2022 to 2023 was 2269.49%.

The big increase of publications has also been present in the field of computing education, where the increase was 4333.33% (from 3 to 133) between 2022 and 2023 when searching for "Generative Artificial Intelligence" AND "Computing Education" in Google Scholar (search conducted on the 19th of March 2024). With this enormous interest in the application of generative AI, together with its potential consequences for various fields, it is crucial for research to investigate potential strengths, weaknesses, opportunities and threats that have been highlighted in recent research.

The aim of this study has been to investigate the potential strengths, weaknesses, opportunities, and threats of Generative Artificial Intelligence in Computing Education, as highlighted by research published after the release of ChatGPT. The work has been guided by the following research questions:

*RQ1) What are the potential strengths of Generative Artificial Intelligence in Computing Education?*
*RQ2) What are the potential weaknesses of Generative Artificial Intelligence in Computing Education?*
*RQ3) What are the potential opportunities of Generative Artificial Intelligence in Computing Education?*
*RQ4) What are the potential threats of Generative Artificial Intelligence in Computing Education?*

## SWOT framework

Although the history and origin of the SWOT analysis is unclear, some trace it to the SOFT (safeguard the satisfactory, open the opportunities, fix the faults, and thwart the threats) approach (Puyt et al., 2023). It has been applied in academia since at least the 1960s to inform decision making in complex situations by reducing information quantity (Helms & Nixon, 2010). Although popular in use, SWOT analysis has been criticized for being a system of classification with little or no theoretical ground and naïve (Puyt et al., 2023). SWOT stands for strengths, weaknesses, opportunities, and threats and is often depicted as a two-by-two grid layout with internal strengths and weaknesses and external opportunities and threats (Helms & Nixon, 2010). Figure 2 shows an example of the grid layout for a SWOT analysis.

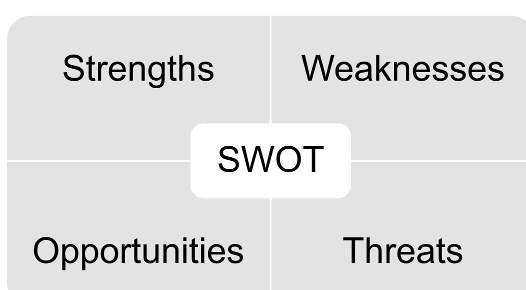


**Fig. 2** Grid layout for SWOT analysis

The SWOT analysis is often used as a starting point for strategic planning and can easily be applied for visualizing different viewpoint in, for example, a brainstorming session (Helms & Nixon, 2010). Potential risks should be identified before they can become problems (Dandage et al., 2019). A common next step of a SWOT analysis is to use it as a basis for a risk management (RM) strategy. Using the SWOT framework as a basis, it is possible to formulate four different strategies:

1) Strength-Opportunity (SO): strategies that use internal strengths to maximize the potential opportunities
2) Weakness-Opportunity (WO): strategies that use external opportunities to overcome or minimize weaknesses
3) Strength-Threat (ST): strategies that use internal strengths to overcome or minimize threats
4) Weakness-Threat (WT): strategies to overcome or minimize internal weaknesses and external threats (Dandage et al., 2019)

To support research, the SWOT framework has been applied in previous studies to identify, for example, strengths, weaknesses, opportunities, and threats with e-learning educational services in higher education (Cojocariu et al., 2014), effectiveness of e-learning applications in higher education (Safonov, Usov, & Arkhipov, 2021), and to evaluate online education during the covid-19 pandemic (Wang et al., 2022). The SWOT framework has also been applied in previous research on the implications of generative AI in education. For example, to investigate the strengths, weaknesses, opportunities, and threats of ChatGPT use to instructional design (Choi et al., 2024) and to education more generally (Farrokhnia et al., 2024). Although similar in scope, the studies by Choi et al. (2024) and Farrokhnia et al. (2024) have some differences from the one presented here. Both focuses on ChatGPT specifically, while this study encompasses a wider selection of generative AI tools. Both Choi et al. (2024) and Farrokhnia et al. (2024) apply a more general approach to education in their investigations and does not include as many papers, while this study focuses on generative AI in relation to computing education in higher education and has included and analyzed 129 included papers since the release of ChatGPT. Lastly, this study differentiates from the previous by presenting a risk management strategy, which is based on the conducted SWOT analysis of the topic.

## Material and methods

The study was conducted as a scoping literature review. A scoping review can be characterized as a literature review to identify available evidence in a field (Munn et al., 2018). They are commonly used in research to identify implications for practices and policies, and to inform agendas for research (Tricco et al., 2016). This scoping literature review was conducted to explore contemporary research and identify potential strengths, weaknesses, opportunities, and threats with generative AI in computing education, supported by the SWOT framework. Findings of this review could further be used to inform practice in computing education, by leveraging the identified strengths and opportunities and avoiding the weaknesses and threats, but also to inform future research, by highlighting topics of interests for further investigation. The processes for data collection and data analysis are described in subheadings below.

### Data collection

Data were collected in the early spring semester of 2024 and the early fall semester of 2024 with a three-step process for selecting relevant data. In the first step (early spring semester 2024), relevant keywords for the query string were decided through an initial search in databases Web of Science and Scopus by combining keywords "generative", "artificial intelligence", and "computer science" with the Boolean operator AND. The searches were filtered for publication year 2023, open access, and proceeding/conference papers and journal articles. After removing duplicates, 41 papers remained which were screened for relevance of the study. This resulted in the following exclusions: 1 not being published in 2023, 2 not being in English, and 31 not relating to computer science (CS)/computing education. This left 7 potentially relevant papers which were used to identify additionally relevant keywords, based on the keywords used in these papers, that could be used in the second step query string (see all keywords in Table 1).

In the second step (early spring semester 2024), all identified keywords were combined with Boolean operators AND and OR to form the following query string:

> *("generative artificial intelligence" OR "generative AI" OR "ChatGPT" OR "conversational agent" OR "large language models" OR "chatbots" OR "code generation" OR "copilot" OR "openai" OR "ai-assisted" OR "ai assisted") AND ("computer science" OR "computing" OR "code writing" OR "programming" OR "cs1") AND ("education")*

This query string was then applied to a title, abstract and keywords search in Web of Science and Scopus with the inclusion and exclusion criteria depicted in Table 2.

A total of 886 papers were identified through this search (134 in Web of Science and 752 in Scopus). After applying the inclusion/exclusion criteria and removing duplicates, 77 potentially relevant papers remained. These 77 papers underwent a full text screening

**Table 1** Keywords for query string

| Identified/used in step 1: | Identified in step 2: |
|---|---|
| Generative | ChatGPT |
| Artificial Intelligence | Computing |
| Computer Science | Computing Education |
| | Conversational Agent |
| | Large Language Models |
| | Chatbots |
| | Code Generation |
| | Code Writing |
| | Computer Programming |
| | Copilot |
| | CS1 |
| | OpenAI |
| | AI-assisted Programming |

**Table 2** Second step inclusion and exclusion criteria

| Inclusion: | Exclusion: |
|---|---|
| Published in 2023 | Published before or after 2023 |
| Conference or journal paper | Not conference or journal paper |
| English | Not English |
| Open Access | Not Open Access |
| Subject/Research area of Computer Science | Not Subject/Research area of Computer Science |
| On CS/Computing Education in higher education | Not on CS/Computing Education in higher education |
| On Artificial Intelligence | Not on Artificial Intelligence |

**Table 3** Third step inclusion and exclusion criteria

| Inclusion: | Exclusion: |
|---|---|
| Published in 2024 | Not published in 2024 |
| Conference or journal paper | Not conference or journal paper |
| English | Not English |
| Open Access | Not Open Access |
| Subject/Research area of Computer Science | Not Subject/Research area of Computer Science |
| On CS/Computing Education in higher education | Not on CS/Computing Education in higher education |
| On Artificial Intelligence | Not on Artificial Intelligence |

where additionally 37 papers were excluded based on not clearly relating to or addressing computer science/computing in higher education or the topic of Artificial Intelligence, which left 40 papers published in 2023 that were included for analysis in the study.

The third step (early fall semester 2024) consisted of repeating the search conducted in the second step but with the year filter set to 2024 (see Table 3). This was conducted to capture more recent research on the topic, published in the first half of 2024. With inclusion/exclusion criteria applied, and removing 35 duplicates, 166 potentially relevant papers remained. These under underwent full text screening where additionally 77 papers were excluded for not clearly relating to or addressing computer science/computing in higher education or the topic of Artificial Intelligence. 89 papers published in 2024 were then left which were included in the study. This brings the total of included papers for analysis, from 2023 and 2024, to 129 papers (see Appendix 1).

### Data analysis

Data were analyzed through a theoretical thematic analysis. Thematic analysis as a method is used for identifying themes or patterns in collected data and can be conducted both inductively (without pre-decided coding frame) and theoretically (with pre-decided coding frame) (Braun & Clarke, 2006). In this study, the SWOT analysis framework with the four categories of strengths, weaknesses, opportunities, and threats were used as the pre-decided coding frame for the analysis. As outlined in previous literature on thematic analysis, this study applied a six-phase approach to the analysis consisting of: (1) data familiarization, (2) initial code generation, (3) theme searching, (4) theme reviewing, (5) theme naming and defining, and (6) report production (Braun & Clarke, 2006). The analysis was conducted in two cycles. First cycle encompassed all included papers published in 2023 and the second cycle encompassed all included papers published in 2024, adding codes to the initial analysis and forming new themes. A detailed description of analysis is provided below.

In the first phase, data familiarization with paper published in 2023 was achieved through reading and re-reading the collected data, and multiple screenings of potentially relevant papers for inclusion. In the second phase, initial codes were generated through highlighting and extracting paragraphs in the collected data that were of interest for answering the aim and research questions of the study. These were collected in a separate spreadsheet document sorted under the categories of strengths, weaknesses, opportunities, and threats. In the third phase, themes were sought for by rearranging and grouping collected codes, within the categories, based on similarities and differences. This produced a total of 22 potential themes. In the fourth phase, themes were reviewed and re-considered with the goal of creating fewer and more coherent themes. After re-grouping, combining, and splitting up previous codes and themes, the new set of themes consisted of 17 themes spanning over the four categories.

At this stage, phase one to four was repeated for included papers published in 2024. Data familiarization was achieved through the screening process, codes were added to existing themes or forming new themes. Old themes were reconsidered and, in some instances, divided into new themes. The repetition of phase one to four produced an extended list of themes, consisting of 19 themes spanning over the four categories in the SWOT framework. In the fifth phase, the themes were named and defined based on their common denominators. In the sixth phase, the report was produced, and themes presented in the results section according to the categories of strengths, weaknesses, opportunities, and threats.

## Results

In this section, the results from the study are presented. Results from the literature review consists of 19 themes, highlighting strengths, weaknesses, opportunities, and threats of generative AI in computing education (Fig. 3). These are presented in subheadings below, according to the categories outlined by the SWOT framework.

### Strengths

Themes related to the category of strengths are depicted in Table 4, together with examples from the included papers.

Regarding the theme of solving CS assignments, included papers highlight that recent GAI technologies have the capabilities to handle many assignments in computing education (Denny, Kumar & Giacaman 2023; Dobslaw & Bergh, 2023; Dwivedi et al., 2023; Finnie-Ansley et al., 2023; Jalil et al., 2023; Li et al., 2023; Piccolo et al., 2023; Santos et al., 2023; Savelka et al., 2023a, 2023b; Cipriano & Alves, 2024; Hou et al., 2024b; Kizilcec et al., 2024; MacNeil et al., 2024; Poulsen et al., 2024; Quille et al., 2024; Richards et al., 2024; Shen et al., 2024; Tang et al., 2024; Xu et al., 2024). It is noted that ChatGPT has taken a leap in capabilities between the GPT-3 model and GPT-4 model (Cipriano & Alves, 2024; Savelka et al., 2023a), where the later could pass higher education programming courses without human intervention (Savelka et al., 2023a) and in some cases

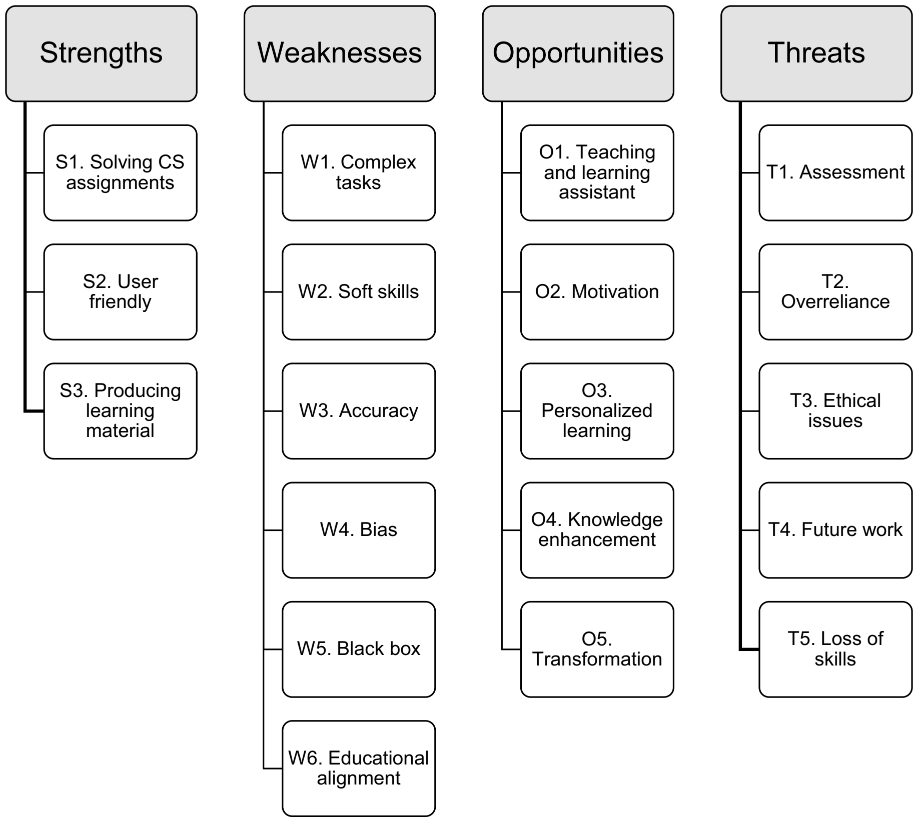


**Fig. 3** Identified themes

**Table 4** Strengths: themes and connections to included papers

| S1. Solving CS assignments | S2. User friendly | S3. Producing learning material |
|---|---|---|
| Denny et al., 2023 | Chen et al., 2023 | MacNeil et al., 2023 |
| Dobslaw & Bergh, 2023 | Shoufan, 2023 | Becker et al., 2023 |
| Dwivedi et al., 2023 | Alshammari & Alshammari, 2024 | Aboalela 2024 |
| Finnie-Ansley et al., 2023 | Kimmel et al., 2024 | Agrawal et al., 2024 |
| Jalil et al., 2023 | | Azaiz, Kiesler & Strickroth 2024 |
| Li et al., 2023 | | Barambones et al., 2024 |
| Piccolo et al., 2023 | | Cambaz & Zhang, 2024 |
| Santos et al., 2023 | | Canedo et al., 2024 |
| Savelka et al., 2023a | | Doughty et al., 2024 |
| Savelka et al., 2023b | | Du et al., 2024 |
| Cipriano & Alves, 2024 | | Grévisse et al., 2024 |
| Hou et al., 2024b | | Hang et al., 2024 |
| Kizilcec et al., 2024 | | Hou et al., 2024a |
| MacNeil et al., 2024 | | Husain, 2024 |
| Poulsen et al., 2024 | | Jordan, Ly & Soosai Raj 2024 |
| Quille et al., 2024 | | Joshi et al., 2024 |
| Richards et al., 2024 | | Kuramitsu et al., 2024 |
| Shen et al., 2024 | | Ling & Afzaal, 2024 |
| Tang et al., 2024 | | Nguyen & Allan, 2024 |
| Xu & Sheng 2024 | | |

pass with a top grade (Dobslaw & Bergh, 2023). Findings even indicate that that some Large Language Models (LLM) can match or surpass student abilities (MacNeil et al., 2024; Poulsen et al., 2024; Quille et al., 2024). Studies have noted that ChatGPT can provide correct, or partly correct, explanations and solutions in software testing education and programming education (Cipriano & Alves, 2024; Hou et al., 2024b; Jalil et al., 2023; Kizilcec et al., 2024; Shen et al., 2024), which could be increased further by applying strategies for prompt engineering (Jalil et al., 2023; Shen et al., 2024). Similar results have been noted about Copilot, where a study found that about half of the programming assignments could be solved with the original programming description, and more than half of the remaining assignments by adding prompt engineering (Denny et al., 2023).

Included papers have further highlighted that users find some GAI tools easy to use or user friendly (Alshammari & Alshammari, 2024; Chen et al., 2023; Kimmel et al., 2024; Shoufan, 2023). One study noted that students in a computer engineering program appreciated ChatGPT's human-like interface and found it easy to use with good descriptions and replies that were well-structured (Shoufan, 2023). The chat-type interfaces of many GAI tools have quickly become the gold standard for interactions with generative AI, which affects students' expectations when using GAI tools (Kimmel et al., 2024). Further, the perceived usefulness of GAI tools has been noted as an important step for building students' positive use intentions with GAI tools (Alshammari & Alshammari, 2024). Similar results have been highlighted in a study where teachers and students were provided ChatGPT powered feedback on programming, which indicated that they perceived the feedback as user friendly and code explanations satisfactory (Chen et al., 2023).

Included papers further note that GAI tools can be used for producing learning material (Aboalela, 2024; Agrawal et al., 2024; Azaiz et al., 2024; Barambones et al., 2024; Becker et al., 2023; Cambaz & Zhang, 2024; Canedo et al., 2024; Doughty et al., 2024; Du et al., 2024; Grévisse et al., 2024; Hang et al., 2024; Hou et al., 2024a; Husain, 2024; Jordan et al., 2024; Joshi et al., 2024; Kuramitsu et al., 2024; Ling & Afzaal, 2024; MacNeil et al., 2023; Nguyen & Allan, 2024). Papers report that GAI can be used to save time for teachers by producing novel learning resources such as programming exercises, assignment questions, tests, and presentation slides (Aboalela 2024; Agrawal et al., 2024; Cambaz & Zhang, 2024; Canedo et al., 2024; Husain, 2024; Joshi et al., 2024; Becker et al., 2023). One study report on the use of LLMs to create an interactive e-learning book on software development (MacNeil et al., 2023). Other highlighted use cases of GAI in the papers include translation programming assignments to students' native languages (Jordan et al., 2024) and providing timely student feedback (Azaiz et al., 2024; Du et al., 2024; Nguyen & Allan, 2024).

### Weaknesses

Themes related to the category of weaknesses are depicted in Table 5, together with examples from the included papers.

Included papers highlight that GAI often show weaknesses when it comes to handling more complex task in computing education (Cipriano & Alves, 2024; Dunder et al., 2024; Finnie-Ansley et al., 2023; Jalil et al., 2023; Koutcheme et al., 2024; Li et al., 2023; Poulsen et al., 2024; Richards et al., 2024; Savelka et al., 2023b; Yilmaz & Yilmaz, 2023), such as

**Table 5** Weaknesses: themes and connections to included papers

| W1. Complex tasks | W2. Soft skills | W3. Accuracy | W4. Bias | W5. Black box | W6. Educational alignment |
|---|---|---|---|---|---|
| Finnie-Ansley et al., 2023 | Gumina et al., 2023 | Albdrani & Al-Shargabi, 2023 | Albdrani & Al-Shargabi, 2023 | Albdrani & Al-Shargabi, 2023 | Finnie-Ansley et al., 2023 |
| Jalil et al., 2023 | Wermelinger, 2023 | Dobslaw & Bergh, 2023 | Becker et al., 2023 | Sakib et al., 2023 | Gumina et al., 2023 |
| Li et al., 2023 | | Hellas et al., 2023 | Sakib et al., 2023 | Wang et al., 2023 | Prather et al., 2023 |
| Savelka et al., 2023b | | Jalil et al., 2023 | Sánchez-Gordón et al., 2023 | Zastudil et al., 2023 | Grévisse et al., 2024 |
| Yilmaz & Yilmaz, 2023 | | Paschoal et al., 2023 | Denny et al., 2024c | Amoozadeh et al., 2024 | Nguyen et al., 2024a |
| Cipriano & Alves, 2024 | | Rajala et al., 2023 | Joshi et al., 2024 | Husain, 2024 | Shibani et al., 2024 |
| Dunder et al., 2024 | | Shue et al., 2023 | | | |
| Koutcheme et al., 2024 | | Shoufan, 2023 | | | |
| Poulsen et al., 2024 | | Wermelinger, 2023 | | | |
| Richards et al., 2024 | | Azaiz et al., 2024 | | | |
| | | Azaria et al., 2024 | | | |
| | | Budhiraja et al., 2024 | | | |
| | | Cambaz & Zhang, 2024 | | | |
| | | Cipriano & Alves, 2024 | | | |
| | | Estévez-Ayres et al., 2024 | | | |
| | | Frankford et al., 2024 | | | |
| | | Grande et al., 2024 | | | |
| | | Grévisse et al., 2024 | | | |
| | | Haindl & Weinberger, 2024 | | | |
| | | Hou et al., 2024c | | | |
| | | Humble et al., 2024 | | | |
| | | Husain, 2024 | | | |
| | | Jordan et al., 2024 | | | |
| | | Joshi et al., 2024 | | | |
| | | Kimmel et al., 2024 | | | |
| | | Kozov et al., 2024 | | | |
| | | Lehtinen et al., 2024 | | | |
| | | Ouhbi, 2024 | | | |
| | | Pirzado et al., 2024 | | | |
| | | Roest et al., 2024 | | | |

**Table 5** (continued)

| W1. Complex tasks | W2. Soft skills | W3. Accuracy | W4. Bias | W5. Black box | W6. Educational alignment |
|---|---|---|---|---|---|
| | | Shibani et al., 2024 | | | |
| | | Xue et al., 2024 | | | |

detecting complex vulnerabilities in software (Li et al., 2023), handling object oriented practices in programming (Cipriano & Alves, 2024), and tasks including both concepts and programming code (Jalil et al., 2023). Research further notes that tasks that are challenging for GAI may be the same that are challenging for students (Finnie-Ansley et al., 2023). This relates to another theme, weaknesses regarding soft skills (Gumina et al., 2023; Wermelinger, 2023). Research points out that modern software development, especially on a larger scale, requires more of future developers than writing programming code, which GAI tools can do. It also requires teamwork, communication skills, and ongoing human interactions with co-workers and users, which GAI so far cannot perform at a human level (Gumina et al., 2023; Wermelinger, 2023).

Several included papers further highlight the weaknesses of GAI when it comes to accuracy (Albdrani & Al-Shargabi, 2023; Dobslaw & Bergh, 2023; Hellas et al., 2023; Jalil et al., 2023; Paschoal et al., 2023; Rajala et al. 2023; Shue et al., 2023; Shoufan, 2023; Wermelinger, 2023; Azaiz, Kiesler & Strickroth 2024; Azaria et al., 2024; Budhiraja et al., 2024; Cambaz & Zhang, 2024; Cipriano & Alves, 2024; Estévez-Ayres et al., 2024; Frankford et al., 2024; Grande et al., 2024; Grévisse et al., 2024; Haindl & Weinberger, 2024; Hou et al., 2024c; Humble et al., 2024; Husain, 2024; Jordan et al., 2024; Joshi et al., 2024; Kimmel et al., 2024; Kozov et al., 2024; Lehtinen et al., 2024; Ouhbi, 2024; Pirzado et al., 2024; Roest et al., 2024; Shibani et al., 2024; Xue et al., 2024). For example, papers report reliability issues with outputs from GAI (Azaiz et al., 2024; Budhiraja et al., 2024; Cambaz & Zhang, 2024; Rajala, 2023) and that using GAI requires strong foundational knowledge, iterative use or supervision because of this (Azaria et al., 2024; Cipriano & Alves, 2024; Joshi et al., 2024; Kozov et al., 2024; Pirzado et al., 2024; Shoufan, 2023). Research further report that the accuracy issues of GAI become even more problematic because of its own cluelessness about these inaccuracies which could mislead students (Humble et al., 2024; Jalil et al., 2023; Shibani et al., 2024). It is therefore crucial that students learn about these weaknesses (Ouhbi, 2024; Shue et al., 2023).

Included papers further raise the potential issue of biases in GAI tools (Albdrani & Al-Shargabi, 2023; Becker et al., 2023; Denny et al., 2024c; Joshi et al., 2024; Sakib et al., 2023; Sánchez-Gordón et al., 2023). It is highlighted that GAI biases could reinforcing stereotypes and discrimination through the representation of specific demographics and genders (Albdrani & Al-Shargabi, 2023; Denny et al., 2024c). It is suggested to incorporate a critical understanding of GAI technologies when implementing them in education, so that students are aware of the limitations and potential biases (Sakib et al., 2023). Related to the weakness of potential biases, is the weakness of transparency or black box nature of many AI models. Included papers points out this weakness with GAI (Albdrani & Al-Shargabi, 2023; Amoozadeh et al., 2024; Husain, 2024; Sakib et al., 2023; Wang et al., 2023; Zastudil et al., 2023), and highlight the importance of transparency when it comes to assessing accountability of GAI as assistance in education (Albdrani & Al-Shargabi, 2023; Sakib et al., 2023). Further, lack of transparency can have ethical and legal consequences, such as privacy and social impact issues (Husain, 2024).

Included papers have further highlighted concerns about the applicability of GAI in education when it comes to its educational alignment (Finnie-Ansley et al., 2023; Grévisse et al., 2024; Gumina et al., 2023; Nguyen et al., 2024a; Prather et al., 2023; Shibani et al., 2024). It should be noted that the AI models are often not trained on repositories intended for educational context (Gumina et al., 2023) and sometimes the interactions with GAI are not suited for learning (Prather et al., 2023). Students can, for example, have challenges understanding or using the generated content that GAI tools provide (Nguyen et al., 2024a). Therefore, oversight by, for example, a teacher is recommended when using GAI in educational context to ensure that student use and system output is in educational alignment with course content (Grévisse et al., 2024). Effective use of, and partnership with, AI in education should also incorporate thoughtful curriculum and assessment design with learners' skill development in mind (Shibani et al., 2024).

### Opportunities

Themes related to the category of opportunities are depicted in Table 6, together with examples from the included papers.

Several of the included papers points to the opportunity of using GAI as teaching and learning assistants (Aggrawal & Magana, 2024; Ahmad et al., 2024; Bassner et al., 2024; Budhiraja et al., 2024; Cambaz & Zhang, 2024; Canedo et al., 2024; Denny et al., 2024c; Frankford et al., 2024; Gumina et al., 2023; Haindl & Weinberger, 2024; Hang et al., 2024; Hellas et al., 2023; Husain, 2024; Ishizue et al., 2024; Jacques, 2023; Jamieson et al., 2023; Joshi et al., 2024; Karnalim et al., 2023; Koutcheme et al., 2024; Kuramitsu et al., 2024; Liao et al., 2024; Liffiton et al., 2023; Lin et al., 2024; López-Pernas et al., 2023; Lyu et al., 2024; MacNeil et al., 2024; Nikolic et al., 2024; Nizamudeen et al., 2024; Ouhbi, 2024; Pankiewicz & Baker, 2024; Phung et al., 2024; Prather et al., 2023; Sheese et al., 2024; Silva et al., 2024; Wang et al., 2023; Wermelinger, 2023; Wieser et al., 2023; Woodrow et al., 2024; Xiao et al., 2024; Zastudil et al., 2023; Zhang et al., 2024; Zheng, 2023). Research highlight students' use and perceptions of GAI as helpful for learning (Ahmad et al., 2024; Bassner et al., 2024; Budhiraja et al., 2024; Cambaz & Zhang, 2024; Haindl & Weinberger, 2024; Karnalim et al., 2023; Kuramitsu et al., 2024; Liffiton et al., 2023; López-Pernas et al., 2023; Nizamudeen et al., 2024), and that it could be seen as democratizing tutoring due to the low cost compared to human tutoring (Zastudil et al., 2023). Research further highlights the possibility of using GAI to assist the teacher role, for example, by facilitating learning (Canedo et al., 2024), predict student learning behavior (Lin et al., 2024), and support assessments (Denny et al., 2024c; Wieser et al., 2023).

Included papers further notes that GAI can be an opportunity for enhancing students' motivation for learning (Alshammari & Alshammari, 2024; Amoozadeh et al., 2024; Denny et al., 2024a, 2024b; Hou et al., 2024a; Kosar et al., 2024; Liao et al., 2024; Sakib et al., 2023; Shoufan, 2023; Stampfl, 2024; Wang et al., 2023; Yilmaz & Yilmaz, 2023). Papers highlight several positive aspects of GAI related to motiving students, such as fostering creativity, collaboration (Sakib et al., 2023), communication, critical thinking

**Table 6** Opportunities: themes and connections to included papers

| O1. Teaching and learning assistant | O2. Motivation | O3. Personalized learning | O4. Knowledge enhancement | O5. Transformation |
|---|---|---|---|---|
| Gumina et al., 2023 | Sakib et al., 2023 | Albdrani & Al-Shargabi, 2023 | Ahmed & Hasnine, 2023 | Denny et al., 2023 |
| Hellas et al., 2023 | Shoufan, 2023 | Hobert, 2023 | Becker et al., 2023 | Dwivedi et al., 2023 |
| Jacques, 2023 | Wang et al., 2023 | Chen et al., 2023 | Chen et al., 2023 | Gumina et al., 2023 |
| Jamieson et al., 2023 | Yilmaz & Yilmaz, 2023 | Jalil et al., 2023 | Denny et al., 2023 | Hellas et al., 2023 |
| Karnalim et al., 2023 | Alshammari & Alshammari, 2024 | Liffiton et al., 2023 | Li et al., 2023 | Jacques, 2023 |
| Liffiton et al., 2023 | Amoozadeh et al., 2024 | Pérez-Mercado et al., 2023 | Rajala, 2023 | Sakib et al., 2023 |
| López-Pernas et al., 2023 | Denny et al., 2024a | Piccolo et al., 2023 | Shue et al., 2023 | Sánchez-Gordón et al., 2023 |
| Prather et al., 2023 | | Wang et al., 2023 | Singh et al., 2023 | Yilmaz & Yilmaz, 2023 |
| Wang et al., 2023 | Denny et al., 2024b | Xie et al., 2023 | Azaria et al., 2024 | Abrahamsson et al., 2024 |
| Wermelinger, 2023 | Hou et al., 2024a | Al-Hossami et al., 2024 | Canedo et al., 2024 | Baalsrud Hauge & Jeong, 2024 |
| Wieser et al., 2023 | Kosar et al., 2024 | Bassner et al., 2024 | Garg & Rajendran, 2024 | Garg & Rajendran, 2024 |
| Zastudil et al., 2023 | Liao et al., 2024 | Bernstein et al., 2024 | Grande et al., 2024 | Humble et al., 2024 |
| Zheng, 2023 | Stampfl, 2024 | Bobadilla et al., 2024 | Groothuijsen et al., 2024 | Kizilcec et al., 2024 |
| Aggrawal & Magana, 2024 | | Carpio Gutierrez et al., 2024 | Huesca et al., 2024 | Kozov et al., 2024 |
| Ahmad et al., 2024 | | Denny et al., 2024b | Husain, 2024 | Ouhbi, 2024 |
| Bassner et al., 2024 | | Glynn et al., 2024 | Jin et al., 2024 | Stampfl, 2024 |
| Budhiraja et al., 2024 | | Huesca et al., 2024 | Lehtinen et al., 2024 | Tang et al., 2024 |
| Cambaz & Zhang, 2024 | | Husain, 2024 | Liao et al., 2024 | |
| Canedo et al., 2024 | | Jordan et al., 2024 | Stampfl, 2024 | |
| Denny et al., 2024c | | Joshi et al., 2024 | | |
| Frankford et al., 2024 | | Roest et al., 2024 | | |
| Hang et al., 2024 | | Xiao et al., 2024 | | |
| Haindl & Weinberger, 2024 | | | | |
| Husain, 2024 | | | | |
| Ishizue et al., 2024 | | | | |
| Joshi et al., 2024 | | | | |
| Koutcheme et al., 2024 | | | | |
| Kuramitsu et al., 2024 | | | | |
| Liao et al., 2024 | | | | |
| Lin et al., 2024 | | | | |
| Lyu et al., 2024 | | | | |
| MacNeil et al., 2024 | | | | |
| Nikolic et al., 2024 | | | | |
| Nizamudeen et al., 2024 | | | | |
| Ouhbi, 2024 | | | | |
| Pankiewicz & Baker, 2024 | | | | |
| Phung et al., 2024 | | | | |

**Table 6** (continued)

| O1. Teaching and learning assistant | O2. Motivation | O3. Personalized learning | O4. Knowledge enhancement | O5. Transformation |
|---|---|---|---|---|
| Sheese et al., 2024 | | | | |
| Silva et al., 2024 | | | | |
| Woodrow et al., 2024 | | | | |
| Xiao et al., 2024 | | | | |
| Zhang et al., 2024 | | | | |

(Stampfl, 2024), and computational thinking (Denny et al., 2024a). It is further noted that GAI can provide engaging support (Denny et al., 2024b; Hou et al., 2024a) and create learning experiences that are engaging (Wang et al., 2023). Research also suggests that students' trust is an important factor to consider when integrating GAI in education (Amoozadeh et al., 2024).

The theme of personalized learning is noted as an opportunity in several of the included papers (Albdrani & Al-Shargabi, 2023; Al-Hossami et al., 2024; Bassner et al., 2024; Bernstein et al., 2024; Bobadilla et al., 2024; Chen et al., 2023; del Carpio et al., 2024; Denny et al., 2024b; Glynn et al., 2024; Hobert, 2023; Huesca et al., 2024; Husain, 2024; Jalil et al., 2023; Jordan et al., 2024; Joshi et al., 2024; Liffiton et al., 2023; Pérez-Mercado et al., 2023; Piccolo et al., 2023; Roest et al., 2024; Wang et al., 2023; Xiao et al., 2024; Xie et al., 2023). Research highlight, for example, the opportunity of individualized and automated feedback and support immediate when students need it (Albdrani & Al-Shargabi, 2023; Bassner et al., 2024; Bobadilla et al., 2024; Hobert, 2023; Liffiton et al., 2023; Piccolo et al., 2023; Roest et al., 2024), but also of tailoring education to each student's skill level, needs, culture, individual capabilities, and course goals (Carpio Gutierrez et al., 2024; Glynn et al., 2024; Huesca et al., 2024; Jordan et al., 2024; Joshi et al., 2024; Xiao et al., 2024; Xie et al., 2023).

Another theme noted in the included papers is that of knowledge enhancement (Ahmed & Hasnine, 2023; Azaria et al., 2024; Becker et al., 2023; Canedo et al., 2024; Chen et al., 2023; Denny et al., 2023; Garg & Rajendran, 2024; Grande et al., 2024; Groothuijsen et al., 2024; Huesca et al., 2024; Husain, 2024; Jin et al., 2024; Lehtinen et al., 2024; Li et al., 2023; Liao et al., 2024; Rajala, 2023; Shue et al., 2023; Singh et al., 2023; Stampfl, 2024). Research show that students can, or perceive that they can, use GAI to enhance their learning, knowledge, skills, self-efficacy, comprehension, and writing (Ahmed & Hasnine, 2023; Azaria et al., 2024; Denny et al., 2023; Garg & Rajendran, 2024; Grande et al., 2024; Huesca et al., 2024; Husain, 2024; Li et al., 2023; Liao et al., 2024; Rajala, 2023; Shue et al., 2023; Singh et al., 2023). Papers also notes that GAI can be used to lower the threshold of interacting with high level algorithms, optimizing programming solutions, and support in solving more challenging problems (Becker et al., 2023; Groothuijsen et al., 2024).

Included papers highlight the transformation of computing education with the introduction of GAI (Abrahamsson et al., 2024; Baalsrud Hauge & Jeong, 2024; Denny et al., 2023; Dwivedi et al., 2023; Garg & Rajendran, 2024; Gumina et al., 2023; Hellas et al., 2023; Humble et al., 2024; Jacques, 2023; Kizilcec et al., 2024; Kozov et al., 2024; Ouhbi, 2024; Sakib et al., 2023; Sánchez-Gordón et al., 2023; Stampfl, 2024; Tang et al., 2024;

Yilmaz & Yilmaz, 2023). The transformation of computing education with GAI could provide opportunities for students, such as preparing them for future work (Baalsrud Hauge & Jeong, 2024; Denny et al., 2023; Gumina et al., 2023; Jacques, 2023; Sánchez-Gordón et al., 2023; Stampfl, 2024), introducing them to new educational methodologies and technologies (Garg & Rajendran, 2024; Kozov et al., 2024; Ouhbi, 2024), and making them more competitive on the job market (Sakib et al., 2023). It is further noted that GAI can transform, rather than replace, what it means to be a teacher with increasing numbers of students (Hellas et al., 2023).

### Threats

Themes related to the category of threats are depicted in Table 7, together with examples from the included papers.

Included papers points out the threat to assessment in computing education with the introduction of GAI (Azoulay et al., 2024; Budhiraja et al., 2024; Cambaz & Zhang, 2024; Dwivedi et al., 2023; Finnie-Ansley et al., 2023; French et al., 2023; Gumina et al., 2023; Humble et al., 2024; Jalil et al., 2023; Karnalim et al., 2023; Li et al., 2023; Nguyen et al., 2024b; Nikolic et al., 2024; Pan et al., 2024; Quille et al., 2024; Rajala, 2023; Richards et al., 2024; Sağlam et al., 2024; Savelka et al., 2023a, 2023b; Singh et al., 2023; Tang et al., 2024; Wang et al., 2023; Wermelinger, 2023; Xie et al., 2023; Xu et al., 2024; Zastudil et al., 2023; Zeng et al., 2024). Research highlights that GAI can be used by students to pass exams with little to no effort or knowledge in the topic at hand (Karnalim et al., 2023; Li et al., 2023; Savelka et al., 2023a; Xie et al., 2023; Zeng et al., 2024) or seek unauthorized assistance during examinations (Budhiraja et al., 2024; Cambaz & Zhang, 2024; Humble et al., 2024; Richards et al., 2024; Xu et al., 2024). It is further suggested that teachers should re-evaluate their methods for teaching and reliable assessment due to the access of GAI technologies (French et al., 2023; Rajala et al. 2023; Savelka et al., 2023b; Zastudil et al., 2023). Included papers highlighted that misconduct with GAI can be very difficult to detect (Jalil et al., 2023; Pan et al., 2024; Quille et al., 2024; Sağlam et al., 2024; Singh et al., 2023; Xu et al., 2024; Zeng et al., 2024) and that educators therefore should avoid reusing old problems as assignment and instead opt for more complex problems with nuanced paths to solutions (Wermelinger, 2023).

Related to the threat towards assessment is that towards students' learning, by overreliance on GAI technologies (Albdrani & Al-Shargabi, 2023; Amoozadeh et al., 2024; Becker et al., 2023; Budhiraja et al., 2024; Cambaz & Zhang, 2024; Denny et al., 2024c; Fernandez et al., 2024; Finnie-Ansley et al., 2023; Groothuijsen et al., 2024; Gumina et al., 2023; Hellas et al., 2023; Husain, 2024; Jošt et al., 2024; Kuramitsu et al., 2024; Liao et al., 2024; Liffiton et al., 2023; Prasad & Sane, 2024; Prather et al., 2023; Rajala, 2023; Savelka et al., 2023a; Shibani et al., 2024; Shoufan, 2023; Xue et al., 2024; Zastudil et al., 2023). Research highlight that the seemingly good responses from GAI may cause students to be less critical and get a sense of precision that is false (Hellas et al., 2023; Liao et al., 2024; Prather et al., 2023; Shoufan, 2023; Xue et al., 2024). Similarly, research notes potentially conflicting views where student think that AI models are more transparent than they actually are and therefore trust and rely on them (Amoozadeh et al., 2024). This can be especially problematic with GAI technologies that are embedded in environments that students use, for example for programming, where students can quickly

**Table 7** Threats: themes and connections to included papers

| T1. Assessment | T2. Overreliance | T3. Ethical issues | T4. Future work | T5. Loss of skills |
|---|---|---|---|---|
| Dwivedi et al., 2023 | Albdrani & Al-Shargabi, 2023 | Albdrani & Al-Shargabi, 2023 | French et al., 2023 | French et al., 2023 |
| Finnie-Ansley et al., 2023 | Becker et al., 2023 | Becker et al., 2023 | Jacques, 2023 | Shue et al., 2023 |
| French et al., 2023 | Finnie-Ansley et al., 2023 | French et al., 2023 | Jamieson et al. (2023) | Singh et al., 2023 |
| Gumina et al., 2023 | Gumina et al., 2023 | Gumina et al., 2023 | Sakib et al., 2023 | Frankford et al., 2024 |
| Jalil et al., 2023 | Hellas et al., 2023 | Prather et al., 2023 | Sánchez-Gordón et al., 2023 | Groothuijsen et al., 2024 |
| Karnalim et al., 2023 | Liffiton et al., 2023 | Rajala, 2023 | | Haindl & Weinberger, 2024 |
| Li et al., 2023 | Prather et al., 2023 | Sánchez-Gordón et al., 2023 | | Husain, 2024 |
| Rajala, 2023 | Rajala et al. 2023 | Azaria et al., 2024 | | Kizilcec et al., 2024 |
| Savelka et al., 2023a | Savelka et al., 2023a | Glynn et al., 2024 | | Lyu et al., 2024 |
| Savelka et al., 2023b | Shoufan, 2023 | Husain, 2024 | | Sheard et al., 2024 |
| Singh et al., 2023 | Zastudil et al., 2023 | Xue et al., 2024 | | |
| Wang et al., 2023 | Amoozadeh et al., 2024 | | | |
| Wermelinger, 2023 | Budhiraja et al., 2024 | | | |
| Xie et al., 2023 | Cambaz & Zhang, 2024 | | | |
| Zastudil et al., 2023 | Denny et al., 2024c | | | |
| Azoulay et al., 2024 | Fernandez et al., 2024 | | | |
| Budhiraja et al., 2024 | Groothuijsen et al., 2024 | | | |
| Cambaz & Zhang, 2024 | Husain, 2024 | | | |
| Humble et al., 2024 | Jošt et al., 2024 | | | |
| Nguyen et al., 2024b | Kuramitsu et al., 2024 | | | |
| Nikolic et al., 2024 | Liao et al., 2024 | | | |
| Pan et al., 2024 | Prasad & Sane, 2024 | | | |
| Quille et al., 2024 | Shibani et al., 2024 | | | |
| Richards et al., 2024 | Xue et al., 2024 | | | |
| Sağlam et al., 2024 | | | | |
| Tang et al., 2024 | | | | |
| Xu et al., 2024 | | | | |
| Zeng et al., 2024 | | | | |

become accustomed to simply accepting the suggested solutions (Becker et al., 2023; Denny et al., 2024c; Fernandez et al., 2024; Liao et al., 2024).

The theme of ethical issues concerning GAI in computing education is also present in the included papers (Albdrani & Al-Shargabi, 2023; Azaria et al., 2024; Becker et al., 2023; French et al., 2023; Glynn et al., 2024; Gumina et al., 2023; Husain, 2024; Prather et al., 2023; Rajala, 2023; Sánchez-Gordón et al., 2023; Xue et al., 2024). Papers highlight the risk of students' personal data not being safeguarded when interacting with GAI tools (Albdrani & Al-Shargabi, 2023; Gumina et al., 2023; Husain, 2024; Prather et al., 2023; Rajala, 2023; Sánchez-Gordón et al., 2023). The practice of reusing code and using training data that may have licenses could also have ethical implications when it comes to GAI (Becker et al., 2023; Prather et al., 2023). Further, the consumption of energy can be significant when training AI models, which have implications for sustainability (Becker et al., 2023; French et al., 2023). Included papers also highlight the threat of GAI for future work (French et al., 2023; Jacques, 2023; Jamieson et al. (2023); Sakib et al., 2023; Sánchez-Gordón et al., 2023). Research notes that certain work that involve, for example, processing of information or being repetitive, could be reduced in the future due to automation with GAI (Sakib et al., 2023), which could also include some academic fields (Jamieson et al. (2023)). It is also suggested that GAI could have a negative impact on students' well-being, making them feel uncertain and anxious about future job prospects (French et al., 2023).

Lastly, included papers highlight concerns about potential loss of skills due to increased use of GAI technology (Frankford et al., 2024; French et al., 2023; Groothuijsen et al., 2024; Haindl & Weinberger, 2024; Husain, 2024; Kizilcec et al., 2024; Lyu et al., 2024; Sheard et al., 2024; Shue et al., 2023; Singh et al., 2023). Research points out concerns about erosion of students' cognitive skills, creativity, critical thinking, communication, and collaboration due to increased use of GAI technology (French et al., 2023; Groothuijsen et al., 2024; Husain, 2024; Kizilcec et al., 2024; Lyu et al., 2024; Shue et al., 2023). Students have also voiced their concern about GAI use having a negative impact on their learning, skill development, and work proficiency (Frankford et al., 2024; Haindl & Weinberger, 2024; Singh et al., 2023).

## Discussion

In this study, a total of 19 strengths, weaknesses, opportunities, and threats with generative AI for computing education have been presented. The identified themes that GAI can solve many CS assignments in higher education (S1) and support producing learning material (S3), but often struggles with more complex tasks (W1) and have issues with accuracy (W3), are important to note. However, these themes should not be considered surprising due to the many reports of similar findings in recent years. The same could be said about potential biases (W4) and lack of transparency, or the black box nature (W5), of GAI. These are important topics for continuing ethical discussions and have been raised as concerns since before the release of ChatGPT in late 2022 (Chiu et al., 2023; Humble & Mozelius, 2022; Zhang & Aslan, 2021). The many identified opportunities with GAI can serve as inspiration for educators in computing education, such as that GAI can be used as a teaching and learning assistant (O1), induce students' motivation (O2), provide personalized learning (O3), and enhance students' knowledge (O4).

Some interesting findings of the study are the user-friendly and perceived human-like interaction design (S2) with many GAI systems and its relation to soft skills (W2) in computing professions. A human-like and user-friendly interface could potentially explain the popularity of GAI among students, even though many are aware of the associated weaknesses and threats such as accuracy problems (W3), ethical issues (T3), becoming over-reliant (T2), and potential loss of skills due to excessive use of the technology (T5). Related to this, educators should consider the educational alignment, or lack thereof (W6), in many GAI systems. Many of these systems have not been developed with education in mind and may not be trained on data that are suitable for learning. Highlighting the need for fostering soft skills (W3), such as communication and teamwork, in computing education is also important, since development of these skills could ensure students a place in future job market with GAI. The author suggests that further research should be conducted on topics investigating GAI in relation user-friendly design and development of soft skills in computing education. These are important factors for educating future professionals in computing and were not addressed in included papers to the same extent as, for example, the opportunity of GAI as a teaching and learning assistant (O1) and its potential threat to assessment (T1). This suggest that there is more work to be done, investigating GAI in relation to user-friendly design and development of soft skills in computing education.

### Developing a risk management strategy

Following the outline presented by Dandage et al. (2019), it is possible to elevate the SWOT analysis by formulating a risk management strategy based on identified strengths, weaknesses, opportunities, and threats. Based on the findings presented in this paper and the different types of strategies that can be formulated from the SWOT framework, the author suggests the following strategies for GAI in computing education:

1) utilize the strengths of GAI at solving CS assignments (S1) and producing learning material (S3) to optimize GAI as a teaching and learning assistant (O1)
2) utilize user friendly GAI tools (S2) to maximize student motivation for learning (O2)
3) utilize the opportunity of GAI to lower the threshold of interacting with high level algorithms and challenging problems (O4) to minimize the effects of GAI's limited ability to handle complex tasks on its own (W1)
4) utilize the opportunity of GAI to introduce new educational methodologies and technologies (O5) where students and AI complement each other to minimizes the GAI weakness of soft skills (W2)
5) utilize the opportunity of GAI to develop skills (O4), such as critical thinking skills, to minimize the effects of GAI's limited accuracy in generated content (W3)
6) utilize the strength of GAI to support development of innovative teaching and learning materials (S3) that reduces the risk for cheating (T1) or make cheating less likely
7) utilize the strengths of GAI, such as solving CS assignments (S1) and producing learning material (S3), to teach effective use of GAI, which hopefully can mitigate the threat for future work prospects (T4)
8) highlight the GAI weakness of accuracy in generated content (W3) to minimize the threat of overreliance (T2)
9) highlight biases (W4) and lack of transparency (W5) in GAI to foster critical use and potentially minimize the effects of ethical issues (T3)
10) highlight the GAI weaknesses of handling complex tasks (W1) and soft skills (W2) to minimize the threat of humans losing important skills (T5)

The risk management (RM) strategy, which is summarized in Fig. 4, should not be viewed as a complete strategy plan for GAI in computing education. New risks and possibilities of GAI are bound to be discovered as technology develops and they can also vary depending on context. The RM strategy presented here should instead be viewed as

| | SO strategy | WO Strategy | ST strategy | WT strategy |
|---|---|---|---|---|
| #1 | *Use S1 and S3 to maximize O1* | | | |
| #2 | *Use S2 to maximize O2* | | | |
| #3 | | *Use O4 to minimize W1* | | |
| #4 | | *Use O5 to minimize W2* | | |
| #5 | | *Use O4 to minimize W3* | | |
| #6 | | | *Use S3 to minimize T1* | |
| #7 | | | *Use S1 and S3 to minimize T4* | |
| #8 | | | | *Address W3 to minimize T2* |
| #9 | | | | *Address W4 and W5 to minimize T3* |
| #10 | | | | *Address W1 and W2 to minimize T5* |

**Fig. 4** Risk management strategy for GAI in Computing Education

a set of recommendations based on the specific research included and analyzed in this study. The RM strategy could also serve as a steppingstone for discussions on the risks and possibilities of GAI in computing education.

### Limitations and future research

There are limitations with this study that should be noted when interpreting the results. This study only encompasses research published after the release of ChatGPT in late 2022, that is 2023 and the first half of 2024. There were of course research published on generative AI before the release of ChatGPT and more important research will likely be published in the years to come. Future research could therefore increase the included years and present a more comprehensive analysis of conducted research in the field. Another alternative could be to conduct a comparative analysis on AI in education, investigate potential similarities and differences in research before and after the release of ChatGPT. Further, this study was conducted as a scoping literature review, which could be considered limited compared to, for example, a systematic literature review. However, since this study explored an emerging topic in recent research, the scoping review was deemed an appropriate approach. Future research could expand on the findings presented in this study and conduct a systematic literature review. Such a study should incorporate a wider span for data collection, including several databases and follow the PRISMA guidelines (http://www.prisma-statement.org/).

The SWOT framework was applied to guide the (theoretical) thematic analysis conducted in this study, but the framework has previously been criticized for being naïve and lacking theoretical ground (Puyt, Lie & Wilderom 2023). However, because of its long history of being applied in academia to analyze complex situations and identifying both the internal and external (Helms & Nixon, 2010), it was deemed an appropriate framework for supporting analysis in this study. However, there are also other limitations with the SWOT framework that should be mentioned, such as:

1) that SWOT analyses can present an overly simplified picture that lacks important details
2) that SWOT analyses can be contextual and miss important stakeholders
3) that SWOT analyses only present the current state and can miss the evolving nature of technology and education
4) that SWOT analyses does not prioritize between the different strengths, weaknesses, opportunities, and threats or offer guidance

To address the potential issue of presenting a too simplistic picture of generative AI in computing education or missing important stakeholders, this study has strived for presenting a comprehensive analysis of research in the field, including 129 published papers. However, the study is still limited by its timeframe, databases, and potential investigator subjectivity. Future research should address this by conducting a systematic literature review with a wider timeframe and include more databases in the search. The systematic literature review should further apply investigator triangulation in effort to mitigate potential subjectivity in the analysis. Future research should also investigate generative AI in computing education with a more rigorous theory for analysis. Studies could for example investigate teachers' technological, pedagogical, and content knowledge concerning GAI by applying the TPACK model or investigate potential teaching and learning activities with GAI in computing education by applying the idea of constructive alignment. This could to some extent address the potential issue of missing the new trends and evolution in the field. However, the risk of findings becoming outdated is always present.

To address the issue of SWOT analyses not prioritizing between different strengths, weaknesses, opportunities, and threats and not offering guidance on how to handle these; this study presents a risk management strategy for GAI in computing education (Fig. 4). This risk management strategy relates the different strengths, weaknesses, opportunities, and threats identified in this study to each other and recommends strategies for utilizing strengths and opportunities and minimizing weaknesses and threats of GAI in computing education. The RM strategy provides guidance for institutions and stakeholders affected by the introduction of GAI in education and could, as highlighted above, serve as a steppingstone for further discussions on the risks and possibilities of generative AI.

## Concluding remarks

This study was conducted as a scoping literature review, supported by the SWOT framework, to investigate the potential strengths, weaknesses, opportunities, and threats of generative AI in computing education, as these have been highlighted in research published after the release of ChatGPT. Findings from the analysis are summarized in Fig. 3 and encompasses the following:

*Strengths with GAI in computing education: S1) Solving CS assignments, S2) User friendly, and S3) Producing learning material.*
*Weaknesses with GAI in computing education: W1) Complex tasks, W2) Soft skills, W3) Accuracy, W4) Bias, W5) Black box, and W6) Educational alignment.*
*Opportunities of GAI for computing education: O1) Teaching and learning assis-*

*tant, O2) Motivation, O3) Personalized learning, O4) Knowledge enhancement, and O5) Transformation.*
*Threats of GAI for computing education: T1) Assessment, T2) Overreliance, T3) Ethical issues, T4) Future work, and T5) Loss of skills.*

Findings from the SWOT analysis have been discussed and compared to each other and a risk management (RM) strategy for GAI in computing education has been suggested (Fig. 4). The RM strategy provides 10 strategies or recommendations, based on the conducted SWOT analysis, for how to utilize the strengths and opportunities of GAI while minimizing the weaknesses and threats. The RM strategy provides guidance for institutions and stakeholders on educational use of generative AI and could serve as a basis for further discussions on the future role of GAI in higher education.

## Appendix 1

### Included papers

| No | Author(s) | Year | Title | Published in |
|---|---|---|---|---|
| 1 | Ahmed & Hasnine | 2023 | Improving essential knowledge and self-efficacy in computers network course: The potential of chatbots | *Procedia Computer Science* |
| 2 | Albdrani & Al-Shargabi | 2023 | Investigating the Effectiveness of ChatGPT for Providing Personalized Learning Experience: A Case Study | *International Journal of Advanced Computer Science and Applications (IJACSA)* |
| 3 | Becker et al | 2023 | Programming is hard-or at least it used to be: Educational opportunities and challenges of ai code generation | *Proceedings of the 54th ACM Technical Symposium on Computer Science Education* |
| 4 | Chen et al | 2023 | GPTutor: a ChatGPT-powered programming tool for code explanation | *International Conference on Artificial Intelligence in Education* |
| 5 | Denny et al | 2023 | Conversing with copilot: Exploring prompt engineering for solving cs1 problems using natural language | *Proceedings of the 54th ACM Technical Symposium on Computer Science Education* |
| 6 | Dobslaw & Bergh | 2023 | Experiences with Remote Examination Formats in Light of GPT-4 | *Proceedings of the 5th European Conference on Software Engineering Education* |
| 7 | Dwivedi et al | 2023 | "So what if ChatGPT wrote it?" Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy | *International Journal of Information Management* |
| 8 | Finnie-Ansley et al | 2023 | My ai wants to know if this will be on the exam: Testing openai's codex on cs2 programming exercises | *Proceedings of the 25th Australasian Computing Education Conference* |
| 9 | French et al | 2023 | Creative use of OpenAI in education: case studies from game development | *Multimodal Technologies and Interaction* |

| No | Author(s) | Year | Title | Published in |
|---|---|---|---|---|
| 10 | Gumina, Dalton & Gerdes | 2023 | Teaching IT Software Fundamentals: Strategies and Techniques for Inclusion of Large Language Models: Strategies and Techniques for Inclusion of Large Language Models | *Proceedings of the 24th Annual Conference on Information Technology Education* |
| 11 | Hellas et al | 2023 | Exploring the responses of large language models to beginner programmers' help requests | *Proceedings of the 2023 ACM Conference on International Computing Education Research* |
| 12 | Hobert | 2023 | Fostering skills with chatbot-based digital tutors – training programming skills in a field study | *i-com* |
| 13 | Jacques | 2023 | Teaching CS-101 at the Dawn of ChatGPT | *ACM Inroads* |
| 14 | Jalil et al | 2023 | Chatgpt and software testing education: Promises & perils | *2023 IEEE international conference on software testing, verification and validation workshops (ICSTW)* |
| 15 | Jamieson, Bhunia & Rao | 2023 | With ChatGPT, do we have to rewrite our learning objectives-CASE study in Cybersecurity | *2023 IEEE Frontiers in Education Conference (FIE)* |
| 16 | Karnalim et al | 2023 | Plagiarism and AI Assistance Misuse in Web Programming: Unfair Benefits and Characteristics | *2023 IEEE International Conference on Teaching, Assessment and Learning for Engineering (TALE)* |
| 17 | Li et al | 2023 | Evaluating the impact of chatgpt on exercises of a software security course | *2023 ACM/IEEE International Symposium on Empirical Software Engineering and Measurement (ESEM)* |
| 18 | Liffiton et al | 2023 | Codehelp: Using large language models with guardrails for scalable support in programming classes | *Proceedings of the 23rd Koli Calling International Conference on Computing Education Research* |
| 19 | López-Pernas et al | 2023 | Scaling student feedback in software engineering MOOCs | *IEEE Software* |
| 20 | MacNeil et al | 2023 | Experiences from using code explanations generated by large language models in a web software development e-book | *Proceedings of the 54th ACM Technical Symposium on Computer Science Education* |
| 21 | Paschoal et al | 2023 | An experimental study on a conversational agent in software testing lessons | *Informatics in Education* |
| 22 | Pérez-Mercado et al | 2023 | ChatbotSQL: Conversational agent to support relational database query language learning | *SoftwareX* |
| 23 | Piccolo et al | 2023 | Evaluating a large language model's ability to solve programming exercises from an introductory bioinformatics course | *PLOS Computational Biology* |
| 24 | Prather et al | 2023 | "It's Weird That it Knows What I Want": Usability and Interactions with Copilot for Novice Programmers | *ACM Transactions on Computer–Human Interaction* |
| 25 | Rajala et al | 2023 | \" Call me Kiran\"–ChatGPT as a Tutoring Chatbot in a Computer Science Course | *Proceedings of the 26th International Academic Mindtrek Conference* |

| No | Author(s) | Year | Title | Published in |
|---|---|---|---|---|
| 26 | Sakib, Anik & Li | 2023 | ChatGPT in IT Education Ecosystem: Unraveling Long-Term Impacts on Job Market, Student Learning, and Ethical Practices | *Proceedings of the 24th Annual Conference on Information Technology Education* |
| 27 | Sánchez-Gordón et al | 2023 | Educating Augmented Programmers | *Computer* |
| 28 | Santos, Prasad & Becker | 2023 | Always provide context: The effects of code context on programming error message enhancement | *Proceedings of the ACM Conference on Global Computing Education* |
| 29 | Savelka et al | 2023a | Thrilled by your progress! Large language models (GPT-4) no longer struggle to pass assessments in higher education programming courses | *Proceedings of the 2023 ACM Conference on International Computing Education Research* |
| 30 | Savelka et al | 2023b | Large Language Models (GPT) Struggle to Answer Multiple-Choice Questions About Code | *Proceedings of the 15th International Conference on Computer Supported Education* |
| 31 | Shoufan | 2023 | Exploring students' perceptions of ChatGPT: Thematic analysis and follow-up survey | *IEEE Access* |
| 32 | Shue et al | 2023 | Empowering beginners in bioinformatics with ChatGPT | *Quantitative Biology* |
| 33 | Singh, Tayarani-Najaran & Yaqoob | 2023 | Exploring computer science students' perception of ChatGPT in higher education: A descriptive and correlation study | *Education Sciences* |
| 34 | Wang et al | 2023 | Exploring the Role of AI Assistants in Computer Science Education: Methods, Implications, and Instructor Perspectives | *2023 IEEE Symposium on Visual Languages and Human-Centric Computing (VL/HCC)* |
| 35 | Wermelinger | 2023 | Using github copilot to solve simple programming problems | *Proceedings of the 54th ACM Technical Symposium on Computer Science Education* |
| 36 | Wieser et al | 2023 | Investigating the Role of ChatGPT in Supporting Text-Based Programming Education for Students and Teachers | *International Conference on Informatics in Schools: Situation, Evolution, and Perspectives* |
| 37 | Xie, Wu & Chakravarty | 2023 | AI meets AI: Artificial Intelligence and Academic Integrity-A Survey on Mitigating AI-Assisted Cheating in Computing Education | *Proceedings of the 24th Annual Conference on Information Technology Education* |
| 38 | Yilmaz & Yilmaz | 2023 | The effect of generative artificial intelligence (AI)-based tool use on students' computational thinking skills, programming self-efficacy and motivation | *Computers and Education: Artificial Intelligence* |
| 39 | Zastudil et al | 2023 | Generative ai in computing education: Perspectives of students and instructors | *2023 IEEE Frontiers in Education Conference (FIE)* |
| 40 | Zheng | 2023 | ChatGPT for teaching and learning: An experience from data science education (Aboalela, 2024) | *Proceedings of the 24th Annual Conference on Information Technology Education* |
| 41 | Aboalela | 2024 | Harnessing Technology to Achieve the Highest Quality in the Academic Program of University Studies | *International Journal of Advanced Computer Science and Applications* |

| No | Author(s) | Year | Title | Published in |
|---|---|---|---|---|
| 42 | Abrahamsson et al | 2024 | ChatGPT as a Fullstack Web Developer-Early Results | *International Conference on Agile Software Development* |
| 43 | Aggrawal & Magana | 2024 | Teamwork Conflict Management Training and Conflict Resolution Practice via Large Language Models | *Future Internet* |
| 44 | Agrawal et al | 2024 | CyberQ: Generating Questions and Answers for Cybersecurity Education Using Knowledge Graph-Augmented LLMs | *Proceedings of the AAAI Conference on Artificial Intelligence* |
| 45 | Ahmad et al | 2024 | Data-driven artificial intelligence in education: A comprehensive review | *IEEE Transactions on Learning Technologies* |
| 46 | Al-Hossami et al | 2024 | Can language models employ the socratic method? experiments with code debugging | *Proceedings of the 55th ACM Technical Symposium on Computer Science Education* |
| 47 | Alshammari & Alshammari | 2024 | Factors Affecting the Adoption and Use of ChatGPT in Higher Education | *International Journal of Information and Communication Technology Education (IJICTE)* |
| 48 | Amoozadeh et al | 2024 | Trust in Generative AI among students: An exploratory study | *Proceedings of the 55th ACM Technical Symposium on Computer Science Education* |
| 49 | Azaiz, Kiesler & Strickroth | 2024 | Feedback-Generation for Programming Exercises With GPT-4 | *Proceedings of the 2024 on Innovation and Technology in Computer Science Education* |
| 50 | Azaria, Azoulay & Reches | 2024 | ChatGPT is a remarkable tool—for experts | *Data Intelligence* |
| 51 | Azoulay, Hirst & Reches | 2024 | Academia and Industry Synergy: Addressing Integrity Challenge in Programming Education | *ICAART* |
| 52 | Baalsrud Hauge & Jeong | 2024 | Does the Improvement in AI Tools Necessitate a Different Approach to Engineering Education? | *In 11th Swedish Production Symposium, SPS2024* |
| 53 | Barambones et al | 2024 | ChatGPT for learning HCI techniques: A Case Study on Interviews for Personas | *IEEE Transactions on Learning Technologies* |
| 54 | Bassner, Frankford & Krusche | 2024 | Iris: An ai-driven virtual tutor for computer science education | *Proceedings of the 2024 on Innovation and Technology in Computer Science Education* |
| 55 | Bernstein et al | 2024 | "Like a Nesting Doll": Analyzing Recursion Analogies Generated by CS Students Using Large Language Models | *Proceedings of the 2024 on Innovation and Technology in Computer Science Education* |
| 56 | Bobadilla et al | 2024 | SOBO: A Feedback Bot to Nudge Code Quality in Programming Courses | *IEEE Software* |
| 57 | Budhiraja et al | 2024 | "It's not like Jarvis, but it's pretty close!"-Examining ChatGPT's Usage among Undergraduate Students in Computer Science | *Proceedings of the 26th Australasian Computing Education Conference* |
| 58 | Cambaz & Zhang | 2024 | Use of AI-driven Code Generation Models in Teaching and Learning Programming: a Systematic Literature Review | *Proceedings of the 55th ACM Technical Symposium on Computer Science Education* |
| 59 | Canedo et al | 2024 | Teaching practice using chatgpt in higher education | *Proceedings of the 26th International Conference on Enterprise Information Systems* |

| No | Author(s) | Year | Title | Published in |
|---|---|---|---|---|
| 60 | Cipriano & Alves | 2024 | LLMs Still Can't Avoid Instanceof: An Investigation Into GPT-3.5, GPT-4 and Bard's Capacity to Handle Object-Oriented Programming Assignments | *Proceedings of the 46th International Conference on Software Engineering: Software Engineering Education and Training* |
| 61 | del Carpio Gutierrez, Denny & Luxton-Reilly | 2024 | Automating Personalized Parsons Problems with Customized Contexts and Concepts | *Proceedings of the 2024 on Innovation and Technology in Computer Science Education* |
| 62 | Denny et al | 2024a | Prompt Problems: A new programming exercise for the generative AI era | *Proceedings of the 55th ACM Technical Symposium on Computer Science Education* |
| 63 | Denny et al | 2024b | Desirable characteristics for ai teaching assistants in programming education | *Proceedings of the 2024 on Innovation and Technology in Computer Science Education* |
| 64 | Denny et al | 2024c | Computing education in the era of generative AI | *Communications of the ACM* |
| 65 | Doughty et al | 2024 | A comparative study of AI-generated (GPT-4) and human-crafted MCQs in programming education | *Proceedings of the 26th Australasian Computing Education Conference* |
| 66 | Du et al | 2024 | Harnessing large language models to auto-evaluate the student project reports | *Computers and Education: Artificial Intelligence* |
| 67 | Dunder et al | 2024 | Kattis vs ChatGPT: Assessment and evaluation of programming tasks in the age of artificial intelligence | *Proceedings of the 14th Learning Analytics and Knowledge Conference* |
| 68 | Estévez-Ayres et al | 2024 | Evaluation of LLM Tools for Feedback Generation in a Course on Concurrent Programming | *International Journal of Artificial Intelligence in Education* |
| 69 | Fernandez & Cornell | 2024 | CS1 with a Side of AI: Teaching Software Verification for Secure Code in the Era of Generative AI | *Proceedings of the 55th ACM Technical Symposium on Computer Science Education* |
| 70 | Frankford et al | 2024 | AI-Tutoring in Software Engineering Education | *Proceedings of the 46th International Conference on Software Engineering: Software Engineering Education and Training* |
| 71 | Garg & Rajendran | 2024 | The Impact of Structured Prompt-Driven Generative AI on Learning Data Analysis in Engineering Students | *CSEDU* |
| 72 | Glynn et al | 2024 | CAET: Code Analysis and Education Tutor | *Proceedings of the 55th ACM Technical Symposium on Computer Science Education* |
| 73 | Grande, Kiesler & Francisco | 2024 | Student Perspectives on Using a Large Language Model (LLM) for an Assignment on Professional Ethics | *Proceedings of the 2024 on Innovation and Technology in Computer Science Education* |
| 74 | Grévisse, Pavlou & Schneider | 2024 | Docimological Quality Analysis of LLM-Generated Multiple Choice Questions in Computer Science and Medicine | *SN Computer Science* |
| 75 | Groothuijsen et al | 2024 | AI chatbots in programming education: students' use in a scientific computing course and consequences for learning | *Computers and Education: Artificial Intelligence* |
| 76 | Hang, Tan & Yu | 2024 | MCQGen: A Large Language Model-Driven MCQ Generator for Personalized Learning | *IEEE Access* |

| No | Author(s) | Year | Title | Published in |
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| 77 | Haindl & Weinberger | 2024 | Students' Experiences of Using ChatGPT in an Undergraduate Programming Course | *IEEE Access* |
| 78 | Hou et al | 2024a | Codetailor: Llm-powered personalized parsons puzzles for engaging support while learning programming | *Proceedings of the Eleventh ACM Conference on Learning@ Scale* |
| 79 | Hou et al | 2024b | More robots are coming: large multimodal models (ChatGPT) can solve visually diverse images of Parsons problems | *Proceedings of the 26th Australasian Computing Education Conference* |
| 80 | Hou et al | 2024c | The Effects of Generative AI on Computing Students' Help-Seeking Preferences | *Proceedings of the 26th Australasian Computing Education Conference* |
| 81 | Huesca et al | 2024 | Effectiveness of Using ChatGPT as a Tool to Strengthen Benefits of the Flipped Learning Strategy | *Education Sciences* |
| 82 | Humble et al | 2024 | Cheaters or ai-enhanced learners: Consequences of chatgpt for programming education | *Electronic Journal of e-Learning* |
| 83 | Husain | 2024 | Potentials of ChatGPT in Computer Programming: Insights from Programming Instructors | *Journal of Information Technology Education: Research* |
| 84 | Ishizue et al | 2024 | Improved Program Repair Methods using Refactoring with GPT Models | *Proceedings of the 55th ACM Technical Symposium on Computer Science Education* |
| 85 | Jin et al | 2024 | Teach AI How to Code: Using Large Language Models as Teachable Agents for Programming Education | *Proceedings of the CHI Conference on Human Factors in Computing Systems* |
| 86 | Jordan, Ly & Soosai Raj | 2024 | Need a Programming Exercise Generated in Your Native Language? ChatGPT's Got Your Back: Automatic Generation of Non-English Programming Exercises Using OpenAI GPT-3.5 | *Proceedings of the 55th ACM Technical Symposium on Computer Science Education* |
| 87 | Joshi et al | 2024 | ChatGPT in the Classroom: An Analysis of Its Strengths and Weaknesses for Solving Undergraduate Computer Science Questions | *Proceedings of the 55th ACM Technical Symposium on Computer Science Education* |
| 88 | Jošt, Taneski & Karakatič | 2024 | The Impact of Large Language Models on Programming Education and Student Learning Outcomes | *Applied Sciences* |
| 89 | Kimmel et al | 2024 | Enhancing Programming Error Messages in Real Time with Generative AI | *Extended Abstracts of the CHI Conference on Human Factors in Computing Systems* |
| 90 | Kizilcec et al | 2024 | Perceived impact of generative AI on assessments: Comparing educator and student perspectives in Australia, Cyprus, and the United States | *Computers and Education: Artificial Intelligence* |
| 91 | Kosar et al | 2024 | Computer Science Education in ChatGPT Era: Experiences from an Experiment in a Programming Course for Novice Programmers | *Mathematics* |

| No | Author(s) | Year | Title | Published in |
|---|---|---|---|---|
| 92 | Koutcheme et al | 2024 | Open Source Language Models Can Provide Feedback: Evaluating LLMs' Ability to Help Students Using GPT-4-As-A-Judge | *Proceedings of the 2024 on Innovation and Technology in Computer Science Education* |
| 93 | Kozov, Ivanova & Atanasova | 2024 | Practical Application of AI and Large Language Models in Software Engineering Education | *International Journal of Advanced Computer Science & Applications* |
| 94 | Kuramitsu et al | 2024 | Training AI Model that Suggests Python Code from Student Requests in Natural Language | *Journal of Information Processing* |
| 95 | Lehtinen, Koutcheme & Hellas | 2024 | Let's Ask AI About Their Programs: Exploring ChatGPT's Answers To Program Comprehension Questions | *Proceedings of the 46th International Conference on Software Engineering: Software Engineering Education and Training* |
| 96 | Liao et al | 2024 | Scaffolding Computational Thinking with ChatGPT | *IEEE Transactions on Learning Technologies* |
| 97 | Lin et al | 2024 | DNA of learning behaviors: A novel approach of learning performance prediction by NLP | *Computers and Education: Artificial Intelligence* |
| 98 | Ling & Afzaal | 2024 | Automatic question–answer pairs generation using pre-trained large language models in higher education | *Computers and Education: Artificial Intelligence* |
| 99 | Lyu et al | 2024 | Evaluating the effectiveness of llms in introductory computer science education: A semester-long field study | *Proceedings of the Eleventh ACM Conference on Learning@ Scale* |
| 100 | MacNeil et al | 2024 | Decoding logic errors: a comparative study on bug detection by students and large language models | *Proceedings of the 26th Australasian Computing Education Conference* |
| 101 | Nguyen & Allan | 2024 | Using GPT-4 to Provide Tiered, Formative Code Feedback | *Proceedings of the 55th ACM Technical Symposium on Computer Science Education* |
| 102 | Nguyen et al | 2024a | How Beginning Programmers and Code LLMs (Mis) read Each Other | *Proceedings of the CHI Conference on Human Factors in Computing Systems* |
| 103 | Nguyen et al | 2024b | GPTSniffer: A CodeBERT-based classifier to detect source code written by ChatGPT | *Journal of Systems and Software* |
| 104 | Nikolic et al | 2024 | ChatGPT, Copilot, Gemini, SciSpace and Wolfram versus higher education assessments: an updated multi-institutional study of the academic integrity impacts of Generative Artificial Intelligence (GenAI) on assessment, teaching and learning in engineering | *Australasian Journal of Engineering Education* |
| 105 | Nizamudeen et al | 2024 | Investigating the Impact of Code Generation Tools (ChatGPT & Github CoPilot) on Programming Education | *CSEDU* |
| 106 | Ouhbi | 2024 | Bridging the Theory–Practice Gap in a Maintenance Programming Course: An Experience Report | *Proceedings of the 46th International Conference on Software Engineering: Software Engineering Education and Training* |

| No | Author(s) | Year | Title | Published in |
|---|---|---|---|---|
| 107 | Pan et al | 2024 | Assessing AI Detectors in Identifying AI-Generated Code: Implications for Education | *Proceedings of the 46th International Conference on Software Engineering: Software Engineering Education and Training* |
| 108 | Pankiewicz & Baker | 2024 | Navigating Compiler Errors with AI Assistance-A Study of GPT Hints in an Introductory Programming Course | *Proceedings of the 2024 on Innovation and Technology in Computer Science Education* |
| 109 | Phung et al | 2024 | Automating human tutor-style programming feedback: Leveraging gpt-4 tutor model for hint generation and gpt-3.5 student model for hint validation | *Proceedings of the 14th Learning Analytics and Knowledge Conference* |
| 110 | Pirzado et al | 2024 | Navigating the Pitfalls: Analyzing the Behavior of LLMs as a Coding Assistant for Computer Science Students-A Systematic Review of the Literature | *IEEE Access* |
| 111 | Poulsen et al | 2024 | Solving Proof Block Problems Using Large Language Models | *Proceedings of the 55th ACM Technical Symposium on Computer Science Education* |
| 112 | Prasad & Sane | 2024 | A Self-Regulated Learning Framework using Generative AI and its Application in CS Educational Intervention Design | *Proceedings of the 55th ACM Technical Symposium on Computer Science Education* |
| 113 | Quille et al | 2024 | Machine vs Machine: Large Language Models (LLMs) in Applied Machine Learning High-Stakes Open-Book Exams | *Revista de Educación a Distancia (RED)* |
| 114 | Richards et al | 2024 | Bob or Bot: Exploring ChatGPT's Answers to University Computer Science Assessment | *ACM Transactions on Computing Education* |
| 115 | Roest, Keuning & Jeuring | 2024 | Next-Step Hint Generation for Introductory Programming Using Large Language Models | *Proceedings of the 26th Australasian Computing Education Conference* |
| 116 | Sağlam et al | 2024 | Automated Detection of AI-Obfuscated Plagiarism in Modeling Assignments | *Proceedings of the 46th International Conference on Software Engineering: Software Engineering Education and Training* |
| 117 | Sheard et al | 2024 | Instructor Perceptions of AI Code Generation Tools-A Multi-Institutional Interview Study | *Proceedings of the 55th ACM Technical Symposium on Computer Science Education* |
| 118 | Sheese et al | 2024 | Patterns of student help-seeking when using a large language model-powered programming assistant | *Proceedings of the 26th Australasian Computing Education Conference* |
| 119 | Shen et al | 2024 | Implications of ChatGPT for Data Science Education | *Proceedings of the 55th ACM Technical Symposium on Computer Science Education* |
| 120 | Shibani et al | 2024 | Untangling Critical Interaction with AI in Students' Written Assessment | *Extended Abstracts of the CHI Conference on Human Factors in Computing Systems* |
| 121 | Silva et al | 2024 | ChatGPT: Challenges and benefits in software programming for higher education | *Sustainability* |
| 122 | Stampfl | 2024 | Revolutionising Role-Playing Games with ChatGPT | *Advances in Artificial Intelligence and Machine Learning* |

| No | Author(s) | Year | Title | Published in |
|---|---|---|---|---|
| 123 | Tang et al | 2024 | AI-Generated Programming Solutions: Impacts on Academic Integrity and Good Practices | *CSEDU* |
| 124 | Woodrow, Malik & Piech | 2024 | Ai teaches the art of elegant coding: Timely, fair, and helpful style feedback in a global course | *Proceedings of the 55th ACM Technical Symposium on Computer Science Education* |
| 125 | Xiao, Hou & Stamper | 2024 | Exploring How Multiple Levels of GPT-Generated Programming Hints Support or Disappoint Novices | *Extended Abstracts of the CHI Conference on Human Factors in Computing Systems* |
| 126 | Xu & Sheng | 2024 | Detecting AI-Generated Code Assignments Using Perplexity of Large Language Models | *Proceedings of the AAAI Conference on Artificial Intelligence* |
| 127 | Xue et al | 2024 | Does ChatGPT Help With Introductory Programming? An Experiment of Students Using ChatGPT in CS1 | *Proceedings of the 46th International Conference on Software Engineering: Software Engineering Education and Training* |
| 128 | Zeng et al | 2024 | Towards automatic boundary detection for human-ai collaborative hybrid essay in education | *Proceedings of the AAAI Conference on Artificial Intelligence* |
| 129 | Zhang et al | 2024 | Pydex: Repairing bugs in introductory python assignments using llms | *Proceedings of the ACM on Programming Languages* |

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**Availability of data and materials**
This study is based on a literature review where all collected data are published with Open Access. See Appendix 1 for full list of included papers.

## Declarations

**Competing interests**
The authors declare that they have no competing interests.

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