

Generative AI in Higher Education: A Systematic Review with Emphasis on Programming and Computer Science Education

Abdulaziz Saidu Yalwa¹, Mohd Shahizan Othman², Lizawati Mi Yusuf³, Muteb Sinhat Almarshadi⁴
Faculty of Computing, Universiti Teknologi Malaysia, Skudai, Johor Bahru, Malaysia^{1, 2, 3}
Department of Computer Sciences and Human Studies, Shaqra University, Shaqra, Kingdom of Saudi Arabia⁴

Abstract—Generative Artificial Intelligence (GenAI) is rapidly reshaping teaching and learning in higher education, particularly in programming and computer science education, where tools such as ChatGPT and GitHub Copilot are increasingly used for code generation, debugging, conceptual explanation, and personalised learning support. Despite this growing use, the literature remains fragmented, with limited synthesis across educational outcomes, adoption contexts, user perceptions, and factors influencing sustained use. To address this gap, this study conducts a systematic literature review following PRISMA 2020 guidelines. The review draws on a dataset of 60 empirical studies published between 2022 and 2025 and retrieved from major academic databases. The selected studies were analysed using a mixed synthesis approach that combines descriptive mapping with thematic analysis. The synthesis shows that GenAI can improve coding support, debugging efficiency, conceptual understanding, and student engagement, especially in programming-related learning contexts; however, adoption remains uneven across regions, institutions, and course settings, while concerns related to academic integrity, over-reliance, reliability, and unequal access persist. By integrating findings across learning outcomes, adoption patterns, user perceptions, and continuance-related factors, this review provides a more structured understanding of GenAI use in higher education, with particular emphasis on programming and computer science education. The study highlights the need for AI literacy, ethical governance, and inclusive institutional support to enable more responsible and sustainable GenAI integration.

Keywords—Generative artificial intelligence; higher education; programming education; computer science education; continuance intention; technology acceptance model; expectation–confirmation model; PRISMA; systematic literature review

I. INTRODUCTION

Generative Artificial Intelligence (GenAI) has emerged as a transformative technology across multiple domains, including education, healthcare, finance, and software development[1]. In the context of higher education, particularly in programming and computer science education, GenAI tools such as ChatGPT and GitHub Copilot are increasingly used to support code generation, debugging, and real-time explanation of programming concepts[2], [3], [4], [5], [6], [7]. More broadly, higher education studies also report positive perceptions of usefulness, engagement, and instructional support [1], [8], [9]. These tools provide interactive and personalised learning experiences, which are especially beneficial for novice learners who often struggle with syntax, algorithmic thinking, and debugging processes.

The rapid adoption of GenAI has raised concerns regarding the reliability of AI-generated outputs, risks to academic integrity, and students' over-reliance on automated solutions [10]. Although several studies report improvements in coding accuracy, engagement, and motivation, issues such as incorrect code generation, misuse in assessments, and unequal access across institutions remain critical [3]. These challenges highlight that the integration of GenAI is not purely a technological issue but also a pedagogical and ethical concern.

Despite the growing body of research on GenAI in education, existing studies remain fragmented and predominantly focused on short-term learning outcomes. Limited attention has been given to the sustained use of these technologies in higher education, particularly in programming and computer science education. However, the long-term educational value of GenAI depends on whether students and educators continue to use these tools effectively over time. This concept, known as continuance intention, is explained through established models such as the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), and the Expectation–Confirmation Model (ECM), which link perceived usefulness, satisfaction, and behavioural intention to continued technology use [11].

Unlike previous reviews, this study integrates continuance intention theory with empirical evidence to provide a more comprehensive understanding of sustained GenAI use in higher education, particularly in programming and computer science education. By combining theoretical perspectives with observed educational outcomes, this study aims to bridge the gap between initial adoption and long-term utilisation of GenAI tools.

To address the lack of consolidated evidence, this study conducts a systematic literature review following PRISMA 2020 guidelines. The review synthesises findings from 60 empirical studies published between 2022 and 2025, focusing on learning outcomes, adoption contexts, user perceptions, and pedagogical challenges. Furthermore, the study develops a conceptual framework linking adoption conditions, usage mechanisms, educational outcomes, and associated challenges. By providing a structured and comprehensive synthesis, this research offers practical insights into the responsible and sustainable integration of GenAI in programming education.

While the review is anchored in programming and computer science education, it also draws on broader higher education studies that provide relevant empirical evidence on adoption,

governance, user perceptions, and sustained use conditions surrounding GenAI integration.

II. RESEARCH BACKGROUND

Higher education is increasingly being shaped by digital technologies that support more interactive, flexible, and student-centered forms of learning. Within this broader context, programming and computer science education remain especially important because they aim to develop not only coding proficiency but also computational thinking, problem-solving, and algorithmic reasoning required for real-world application [12]. In response to evolving technological demands, teaching in these fields has progressively shifted toward active and experiential learning approaches that emphasise hands-on practice, timely feedback, and applied problem-solving.

Against this background, Generative Artificial Intelligence (GenAI) has emerged as a significant development in higher education, with particularly strong relevance for programming and computer science education. Tools such as ChatGPT and GitHub Copilot support code generation, debugging, conceptual explanation, and real-time assistance during learning tasks [4], [13], [14]. These capabilities make learning more adaptive and personalised, especially for novice programmers who often benefit from continuous guidance, immediate feedback, and opportunities to explore alternative coding approaches. As a result, GenAI is increasingly being viewed as a flexible instructional support tool that can enhance coding efficiency, conceptual understanding, collaboration, and learner engagement while complementing more traditional teaching methods [1], [8].

However, the integration of GenAI also introduces important pedagogical, ethical, and institutional challenges. Concerns have been raised about over-reliance on AI-generated solutions, inaccuracies in generated outputs, and issues related to academic integrity and fairness [15], [16]. In addition, differences in infrastructure, access, and institutional readiness contribute to uneven adoption across educational settings and regions [17]. These issues show that GenAI is not only a technical development but also one that must be understood through pedagogical, ethical, and institutional perspectives.

Beyond initial adoption, the continued use of GenAI has become an important issue in higher education, particularly in programming and computer science education [18]. Continuance intention provides a useful lens for understanding whether students and lecturers remain willing to use GenAI tools over time. In this regard, the Expectation–Confirmation Model (ECM) highlights the importance of satisfaction and perceived usefulness in shaping continued engagement [11]. Although this perspective is increasingly relevant, much of the existing literature still focuses on short-term outcomes rather than the conditions that support sustained and responsible use.

Despite the growing number of studies on GenAI in higher education, particularly in programming and computer science education, the literature remains fragmented and lacks a sufficiently integrated perspective. Many studies focus on immediate educational outcomes, while giving less attention to sustained use, contextual variation, and the interaction of technological, pedagogical, and ethical factors. This study addresses these gaps by providing a systematic synthesis of empirical evidence,

integrating continuance-related perspectives, and developing a more connected understanding of how GenAI is being adopted, experienced, and sustained in educational contexts.

A. Challenges and Ethical Concerns of GenAI Integration

Even with its potential, the integration of GenAI introduces several challenges. One major concern is over-reliance on AI-generated solutions, which may limit the development of independent problem-solving skills among students [12]. In addition, inaccuracies in generated outputs can mislead learners, particularly those with limited programming experience.

Academic integrity is another critical issue, as AI-generated code can be difficult to distinguish from students' original work, raising concerns about assessment validity and fairness. Furthermore, disparities in infrastructure, access to advanced tools, and institutional readiness contribute to uneven adoption across regions and educational contexts [13].

These challenges highlight that the integration of GenAI is not purely a technical issue but also involves ethical, pedagogical, and institutional dimensions that must be addressed to ensure responsible use.

B. Continuance Intention and Sustained Educational Use of GenAI

Beyond initial adoption by [14], sustained use of GenAI remains a critical issue in higher education, particularly in programming and computer science education. Continuance intention explains users' willingness to continue using a technology after initial adoption and is commonly modelled using the Expectation–Confirmation Model (ECM) [16]. According to ECM, continued use is influenced by satisfaction, perceived usefulness, and confirmation of expectations.

While models such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) explain initial adoption behaviour [19] ECM provides a stronger theoretical basis for understanding post-adoption continuance. In the context of GenAI, continuance intention reflects the extent to which students and lecturers are willing to repeatedly use tools such as ChatGPT and GitHub Copilot for learning and instructional purposes.

Empirical evidence suggests that factors such as perceived usefulness, trust, satisfaction, and ethical awareness play important roles in shaping sustained engagement. Therefore, continuance intention provides a critical lens for analysing the long-term integration of GenAI in programming education.

C. Benefits and Educational Capabilities of GenAI

GenAI tools provide scalable support for programming education through automated code generation, debugging assistance, and real-time explanation of programming concepts [8]. By analysing user inputs and coding patterns, these tools deliver adaptive feedback and personalised learning support that enhances engagement, coding efficiency, and conceptual understanding [1].

In addition, GenAI supports exploration and collaborative learning by allowing students to experiment with different coding approaches and interact with intelligent systems that simulate real-world development practices. These capabilities

position GenAI as a flexible and learner-centered support system that complements traditional teaching methods.

D. Summary of Research Gaps

Despite the increasing number of studies on GenAI in higher education, particularly in programming and computer science education, the literature remains fragmented and lacks a unified perspective. Existing research primarily focuses on short-term learning outcomes, with limited attention to sustained use and long-term educational impact.

Moreover, theoretical integration remains insufficient, as many studies do not explicitly connect empirical findings with established technology adoption models such as ECM, TAM, and UTAUT. In addition, challenges related to ethics, pedagogy, and infrastructure are often discussed in isolation rather than as interconnected factors.

This study addresses these gaps by providing a systematic synthesis of empirical evidence, integrating continuance intention theory, and developing a conceptual framework that links adoption contexts, usage mechanisms, outcomes, and challenges for sustainable GenAI integration in higher education, particularly in programming education.

III. METHODOLOGY

This study adopts a systematic literature review (SLR) approach to synthesise empirical evidence on the use of Generative Artificial Intelligence (GenAI) in higher education, with particular emphasis on programming and computer science education. The review follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) guidelines to ensure methodological transparency, reproducibility, and systematic reporting of the review process [20].

The overall procedure consists of the following structured stages:

- Definition of research objectives and research questions
- Development of a review protocol, including search strategy and selection criteria.
- Systematic literature search across multiple academic databases.
- Screening and selection of relevant studies based on pre-defined criteria.
- Data extraction using a structured framework.
- Quality assessment of selected studies; and
- Thematic synthesis and analysis of findings.

This structured methodology ensures a transparent and replicable review process suitable for high-quality academic research.

A. Research Questions

To structure the analysis and ensure a focused investigation, this systematic literature review is guided by the following research questions.

- RQ1. How do GenAI tools influence learning outcomes in higher education, particularly in programming and computer science education, including code correctness, debugging efficiency, conceptual understanding, and student engagement?
- RQ2. What differences exist in GenAI adoption across countries, institutions, course levels, and access conditions such as infrastructure, policies, and licensing availability?
- RQ3. What are the perceptions of students and lecturers toward GenAI in higher education, particularly in programming and computer science education, and which factors influence their continued intention to use these technologies?
- RQ4. What pedagogical, ethical, and academic integrity challenges arise from integrating GenAI into higher education, particularly in programming and computer science education, and what mitigation strategies have been proposed?

B. Review Protocol Design

To ensure the review is conducted in a systematic and reliable way, a review protocol was prepared before starting the data collection. This protocol served as a guide for the entire review process and helped to reduce possible bias.

It clearly defined the search strategy, including the keywords and Boolean combinations used to retrieve relevant studies. It also specified the selection of appropriate academic databases and established the inclusion and exclusion criteria to determine which studies should be considered.

In addition, the protocol outlined how data would be extracted from the selected studies in a consistent manner. A quality assessment approach was also included to evaluate the strength and relevance of each study. Furthermore, the protocol described how the collected data would be analysed and organised to ensure a clear and structured synthesis of the findings.

Overall, this protocol improves the consistency, transparency, and reliability of the review, making it easier for the process to be understood and replicated.

C. Data Sources and Search Strategy

A comprehensive literature search was conducted across Scopus, Web of Science, IEEE Xplore, and SpringerLink. These databases were selected because they index high-quality peer-reviewed research across computer science, education, and educational technology disciplines. The search included studies published between January 2022 and September 2025, reflecting the recent emergence and rapid development of GenAI in higher education.

The following Boolean search string was applied across the databases, with minor formatting adjustments where required by database syntax: ("Generative Artificial Intelligence" OR "GenAI" OR "ChatGPT" OR "GitHub Copilot") AND ("higher education" OR "university" OR "college") AND ("programming" OR "computer science" OR "coding").

This search strategy was designed to prioritise empirical studies on the use, adoption, and educational impact of GenAI in programming and computer science education within higher education. Relevant higher education studies outside strictly programming-specific contexts were also retained during screening where they provided direct insight into adoption conditions, user perceptions, policy environments, ethical concerns, or sustained use factors relevant to GenAI integration.

D. Inclusion and Exclusion Criteria

To ensure the relevance and quality of the selected studies, clear inclusion and exclusion criteria were defined before the screening process. Only studies that reported empirical findings on the use of Generative Artificial Intelligence (GenAI) in programming or computer science education were considered. The review focused specifically on studies involving higher education students or lecturers, as this aligns with the scope of the study.

Although this review primarily focuses on programming and computer science education, a small number of broader higher education studies were included when they provided empirical evidence directly relevant to GenAI adoption, user perceptions, governance, institutional policies, ethical considerations, or sustained use. These studies were retained because they offer insights into contextual and continuance-related factors that inform the integration of GenAI in programming-focused learning environments.

In addition, only articles published in peer-reviewed journals or conference proceedings between 2022 and 2025 were included, reflecting the recent and rapidly evolving nature of GenAI in education. To maintain consistency and clarity in analysis, only studies published in English were considered.

On the other hand, studies were excluded if they did not meet these criteria. This includes publications such as editorials, opinion papers, conceptual papers, and review articles, as they do not provide primary empirical evidence. Studies published outside the selected time frame or those not directly related to GenAI use in higher education, particularly in programming and computer science education, were also excluded.

These criteria helped to narrow the literature to relevant and high-quality studies, ensuring that the review is focused, consistent, and academically robust.

E. Screening Process

The database search initially identified 3,160 records. After removing 956 duplicates, 2,204 unique records remained for screening. Title and abstract screening excluded 2,100 records that did not meet the study criteria. The remaining 104 articles were assessed through full-text review, resulting in 60 studies that satisfied the inclusion criteria and were retained for the final synthesis. The complete screening process is presented in the PRISMA flow diagram Fig. 1.

F. Data Extraction and Review Reliability

To ensure consistency and transparency in the review process, a structured data extraction form was developed for all selected studies. This form was designed to systematically capture relevant information from each article in a clear and organized manner.

The extracted data included key bibliographic information, as well as important analytical details such as the study context, research design, sample characteristics, and the types of GenAI tools used. In addition, information related to learning outcomes, user perceptions, reported challenges, and proposed mitigation strategies was collected to support a comprehensive analysis.

To improve the reliability of the data extraction process, two researchers independently reviewed the extracted information. Any differences in interpretation or classification were discussed and resolved collaboratively. This approach helped to reduce bias and ensure consistency in the analysis [21].

Furthermore, the reporting of the review process was guided by the PRISMA 2020 framework, which supports transparency and allows the review procedure to be clearly understood and replicated.

G. Quality Assessment

To ensure the credibility and methodological rigor of the selected studies, a structured quality assessment was carried out using a checklist adapted from the Critical Appraisal Skills Programme (CASP), which is commonly used in systematic reviews across interdisciplinary research [5].

The assessment focused on five key aspects: the clarity of the research objectives, relevance to the study focus, methodological rigor, contribution to theory or practice, and transparency in reporting limitations. Each study was evaluated using a binary scoring system (0–1) for each criterion, resulting in a maximum possible score of 5. To maintain a consistent quality standard, only studies with a minimum score of 3 were included in the final analysis.

To improve reliability and reduce subjective bias, the quality assessment was conducted independently by two reviewers. Any differences in scoring were discussed and resolved collaboratively, and where necessary, a third reviewer was consulted to reach a final decision. This process helped to ensure consistency and strengthen the reliability of the evaluation.

The quality assessment played an important role in filtering out studies with unclear objectives, weak methodology, or limited relevance to GenAI in higher education, particularly in programming and computer science education. As a result, the final set of studies included in this review consists of high-quality research that provides meaningful insights into the adoption, impact, sustained use, and pedagogical implications of Generative Artificial Intelligence in higher education, particularly in programming and computer science education.

H. Coding and Thematic Analysis Approach

A mixed synthesis approach, combining both qualitative and quantitative content analysis, was employed to analyse the selected studies, allowing a comprehensive examination of both descriptive trends and deeper thematic patterns within the literature. The coding process was conducted in two stages to ensure reliability and transparency. First, descriptive coding classified each study according to publication year, country or region, publication source, course level, GenAI tool, research design, and participant group. Second, analytical coding identified themes directly aligned with the research questions, including learning outcomes, debugging support, conceptual understanding,

adoption conditions, user perceptions, continuance intention, academic integrity, ethical concerns, and mitigation strategies. For example, studies reporting improvements in code accuracy or debugging efficiency were coded under “learning outcomes,” while studies discussing trust, satisfaction, or continued use were coded under “continuance intention.”

To ensure consistency, a random subset of 20 articles was independently coded by two reviewers, achieving an inter-rater agreement of over 94%. Any disagreements in coding were discussed until consensus was reached. This dual coding strategy enabled the review to capture both the breadth of adoption patterns and the depth of thematic insights, providing a well-rounded understanding of the role of GenAI in higher education, particularly in programming and computer science education.

IV. FINDINGS

This section presents the thematic findings of the review based on the synthesis of 60 empirical studies examining the use of Generative Artificial Intelligence (GenAI) in higher education, with particular emphasis on programming and computer science education. The reviewed studies comprised quantitative, qualitative, and mixed-method designs, enabling a comprehensive synthesis of adoption patterns, user perceptions, and educational outcomes associated with GenAI use in higher education, particularly in programming contexts.

A. Impact on Learning Outcomes and Engagement

The reviewed studies consistently indicate that GenAI tools are increasingly used in higher education, particularly in programming and computer science education, to support code generation, debugging, and personalised learning assistance. Most studies indicate that these tools contribute positively to student learning outcomes by improving coding accuracy, accelerating debugging processes, and increasing learners’ confidence in programming tasks [4]. In addition, GenAI-supported feedback systems provide real-time guidance that helps reduce frustration and sustain student engagement when addressing complex programming concepts [22], [23]. Adaptive features further enable students to progress at their own pace while addressing individual knowledge gaps [6].

Beyond individual performance gains, studies highlight the role of GenAI in supporting collaborative and reflective learning. The use of AI tools in group programming activities has been shown to stimulate peer discussion, collaborative debugging, and critical reflection on AI-generated outputs, thereby strengthening both cognitive and social aspects of programming education [10], [24]. In addition, personalised feedback mechanisms may help reduce performance disparities between students with different levels of programming proficiency [6].

However, the effectiveness of GenAI tools varies across platforms, programming tasks, and instructional contexts. Comparative studies show that the accuracy and usefulness of tools depend on the complexity of the coding problem and the level of student expertise [2]. Many studies report improvements in motivation and engagement; evidence regarding consistent improvements in academic performance remains mixed [8]. Some research also indicates that GenAI tools may struggle with complex coding problems, highlighting the need for educators to

critically guide students in evaluating and adapting AI-generated solutions [25].

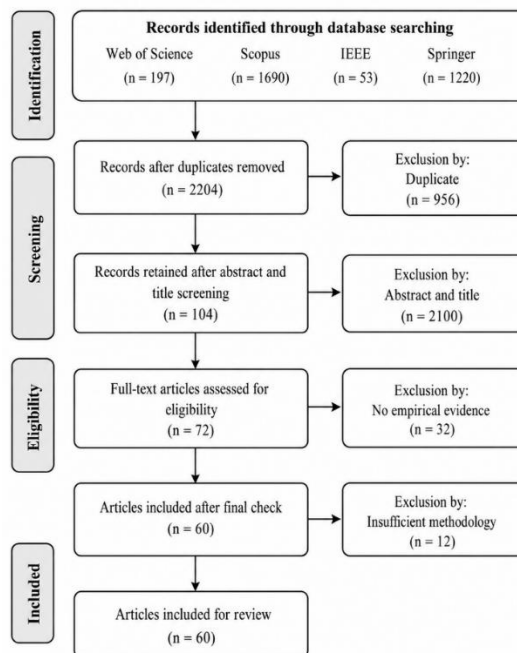


Fig. 1. PRISMA 2020 flow diagram illustrating the study selection process.

The surge in publications coincides with the emergence of large language model-based systems such as ChatGPT and GitHub Copilot, which have significantly accelerated experimentation with AI-assisted programming learning. No empirical studies were identified in 2022, reflecting the late emergence of GenAI research following the release of ChatGPT in late 2022. The zero count for 2022 reflects the fact that mainstream pedagogical research into generative AI was catalyzed by the release of ChatGPT in November 2022, meaning that the first wave of empirical findings did not reach publication until 2023. Followed by 6 in 2023 and 22 in 2024, reflecting a substantial increase in scholarly attention. By 2025, an additional 32 studies had already been reported, suggesting that research on GenAI in higher education, particularly in programming and computer science education, continues to expand rapidly, as shown in Fig. 2.

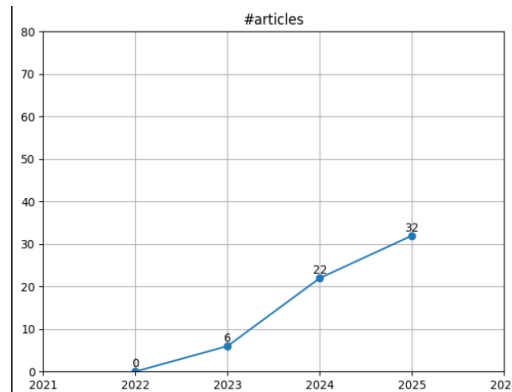


Fig. 2. Year-wise distribution of publications on GenAI in programming education (2022-2025).

B. Contexts of Adoption and Equity

The reviewed studies reveal notable disparities in the adoption of Generative Artificial Intelligence (GenAI) across course levels, institutions, and geographical contexts. Although many studies examine GenAI use in higher education broadly, fewer focus on specific domains within computer science education.

Introductory programming (CS1) emerges as the most common context of application, with 12 studies (20%) reporting the use of GenAI tools to support beginners in learning fundamental coding skills. Advanced programming and software engineering courses account for 10 studies (16.6%), while algorithms and data structures are addressed in 8 studies (13.3%). In addition, 18 studies (30%) investigate GenAI adoption in higher education settings without specifying a particular programming domain.

These patterns suggest that GenAI tools are currently used most extensively in introductory programming environments, where real-time guidance can assist students in addressing syntax errors, debugging tasks, and foundational programming concepts. The distribution of studies across computer science domains is illustrated in Fig. 3, highlighting the concentration of GenAI applications at early stages of programming education.

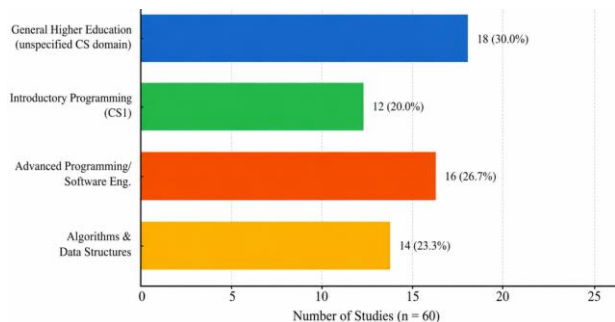


Fig. 3. Distribution of reviewed studies across computer science domains.

Regional disparities were also evident across the reviewed studies. Higher levels of GenAI adoption were reported in countries such as China, the United States, and Australia, where strong institutional support, technological infrastructure, and access to AI tools have enabled early integration into programming education [1], [39], [9]. In contrast, studies from Africa and South Asia highlight barriers related to limited infrastructure, policy readiness, and access to AI resources, which constrain the equitable adoption of GenAI in higher education [26], [27]. These findings suggest that institutional capacity and resource availability play an important role in shaping the global diffusion of GenAI in programming education. As illustrated in Fig. 4, China accounts for the largest share of studies (12 studies, approximately 20%), indicating its leading position in research and implementation within this domain.

The findings indicate that although the adoption of GenAI in programming education is expanding, it remains concentrated in introductory course levels and technologically advanced regions. This uneven distribution highlights potential disparities in access and implementation across institutions and regions. If resource-limited contexts are not adequately supported, the diffusion of GenAI may further widen existing global inequalities in computing education. Ensuring equitable access to

technological infrastructure, policy support, and digital literacy therefore remains essential for the sustainable and inclusive integration of GenAI in programming education.

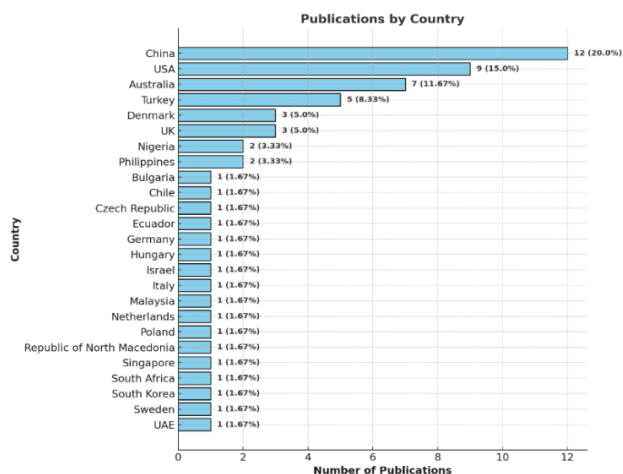


Fig. 4. Geographic distribution of reviewed studies by country.

C. Students' and Lecturers' GenAI Perceptions and Continuance of Use

Most reviewed studies report that students hold generally positive perceptions of GenAI tools, describing them as supportive resources that reduce frustration and make programming tasks more engaging see Fig. 5. Students frequently highlight the usefulness of tools such as ChatGPT and GitHub Copilot in clarifying difficult programming concepts, assisting with debugging, and strengthening confidence in coding abilities [26]. These findings suggest that learners perceive GenAI not merely as a convenience but as a learning aid that supports persistence and self-efficacy in programming education.

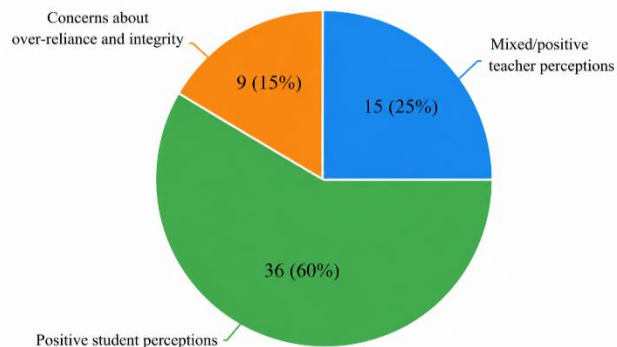


Fig. 5. Comparison of students' and lecturers' perceptions of GenAI use.

Lecturers, however, express more cautious and divided perspectives. Some acknowledge that GenAI can improve instructional efficiency by assisting with automated feedback and assessment processes [1]. Others raise concerns related to academic integrity, fairness in assessment, and the potential for students to become overly dependent on AI-generated solutions [28]. Questions about the reliability of AI-generated code further contribute to this caution, as inaccuracies or hidden errors may affect trust in GenAI for complex or high-stakes programming tasks [2].

These findings reveal a perceptual gap between students and lecturers. While students tend to view GenAI as an empowering learning tool and show strong willingness to continue using it, lecturers often weigh its efficiency benefits against concerns related to trust, originality, and long-term learning outcomes. This divergence suggests that continuance intention is influenced not only by perceived usefulness but also by factors such as trust, ethical considerations, and the pedagogical frameworks established by educators.

D. Pedagogical and Integrity Challenges

The review identified several challenges that complicate the integration of GenAI into programming education, particularly regarding tool reliability and academic integrity. A recurring concern is the accuracy of AI-generated code. Although tools such as ChatGPT can quickly generate functional code snippets, studies report that the outputs may contain logical or syntactic errors that novice learners often struggle to detect [2]. Such limitations can mislead students and highlight the need for critical evaluation of AI-generated solutions. In addition, excessive reliance on GenAI tools may reduce opportunities for students to develop independent debugging and problem-solving skills, raising questions about their long-term pedagogical impact [12].

Academic integrity represents another major challenge. Several studies indicate that GenAI tools can be misused to bypass programming assessments, blurring the boundary between authentic student work and AI-assisted outputs [29]. This creates concerns about fairness, transparency, and the validity of assessment when AI-generated code becomes difficult to distinguish from student submissions [59]. These issues highlight the importance of establishing clear institutional policies and pedagogical guidelines to ensure responsible use of GenAI in programming courses.

Finally, the findings indicate that the integration of GenAI in higher education, particularly in programming and computer science education, is expanding rapidly but remains uneven across institutional contexts and geographical regions. While many studies highlight improvements in coding support, debugging efficiency, and learner engagement, concerns regarding academic integrity, over-reliance on AI-generated solutions, and unequal access to technological infrastructure continue to shape how these tools are adopted in educational settings. These patterns underscore the need for pedagogically guided and ethically responsible integration of GenAI within programming curricula.

V. DISCUSSION

This section synthesises the key findings of the review, explicitly relates them to the research questions (RQ1–RQ4), and discusses their broader implications for theory, practice, and policy in higher education, with particular emphasis on programming and computer science education. It further identifies critical gaps and outlines directions for the responsible and sustainable use of GenAI in higher education.

A. Influence of GenAI on Learning Outcomes in Higher Education

In response to RQ1, which examines how GenAI tools influence programming learning outcomes, the findings consistently indicate that GenAI significantly improves code correctness,

debugging efficiency, conceptual understanding, and student engagement. This aligns with prior studies [6], [2], which report that AI-assisted programming tools enhance students' coding accuracy and reduce cognitive load during problem-solving tasks.

GenAI tools function as intelligent learning assistants, providing real-time feedback, automated code suggestions, and explanatory support that facilitate students' problem-solving processes [21]. These capabilities contribute to increased confidence and engagement, reinforcing both cognitive and affective dimensions of learning. Similar findings have been reported in [8], where students using GenAI demonstrated higher levels of motivation and deeper conceptual understanding compared to traditional learning environments.

However, the findings also reveal that these benefits are context-dependent. While performance improvements are evident, excessive reliance on AI-generated solutions may reduce active learning and limit the development of independent problem-solving skills. This concern is consistent with studies by [8] and [24], which highlight the risk of overdependence on AI tools leading to superficial learning and reduced critical thinking abilities.

This suggests that the impact of GenAI is not inherently positive but is mediated by how it is integrated into pedagogical practices. As noted in [23], effective instructional design and guided use of GenAI are essential to ensure that students engage meaningfully with learning tasks rather than passively relying on automated outputs.

B. Variability in GenAI Adoption Across Contexts

Addressing RQ2, the review reveals substantial variability in the adoption of GenAI across countries, institutions, course levels, and access conditions, including digital infrastructure, institutional policies, and licensing availability. This finding is consistent with prior studies [59], [3], which emphasize that the uptake of emerging educational technologies is highly contingent on contextual and organizational factors.

The findings suggest that GenAI adoption is uneven and shaped by a combination of technological readiness and institutional support. Institutions with well-developed digital infrastructure, stable internet access, and clearly defined policy frameworks tend to demonstrate higher levels of GenAI integration in teaching and learning practices. In contrast, resource-constrained environments face persistent barriers related to limited access, high subscription costs, and insufficient technical support. Similar patterns have been reported in [11], where disparities in infrastructure and funding significantly influenced the adoption of AI-based educational tools.

This variability reflects broader issues of digital inequality, where unequal access to GenAI tools risks reinforcing existing educational disparities between institutions and regions. As highlighted in [59], students and educators in under-resourced settings may be systematically disadvantaged, limiting their ability to benefit from AI-enhanced learning environments.

Furthermore, inconsistent or ambiguous institutional policies create uncertainty regarding acceptable use, academic integrity, and ethical boundaries, which may hinder effective and

confident adoption. This aligns with findings from [17] and [8], which indicate that the absence of clear governance frameworks often leads to cautious or restricted use of GenAI by educators.

Taken together, these findings suggest that GenAI adoption should not be viewed as a purely technological issue, but rather as a context-dependent and policy-sensitive process. Effective integration, therefore, requires not only access to technology, but also institutional readiness, clear guidelines, and equitable resource distribution, as emphasized in [17].

C. Perceptions and Continuance Intention of GenAI Use

The findings indicate that both students and lecturers perceive GenAI as a useful and efficient tool that enhances learning, problem-solving, and conceptual understanding [12], [30]. However, continuance intention is not driven by perceived usefulness alone but by interrelated factors including satisfaction, trust, motivation, and ethical alignment.

Consistent with the Expectation-Confirmation Model (ECM), satisfaction emerges as a key determinant of continued use, shaped by post-adoption experiences [31], [11]. Trust also plays a critical role, particularly when students are perceived to use GenAI responsibly and in line with academic integrity standards [18], [32].

Ethical considerations further reinforce this process, as clear guidelines and training enhance both academic integrity and trust, supporting sustainable adoption [10]. Additionally, GenAI positively influences student motivation and engagement, indirectly strengthening continuance intention [33].

The findings suggest that continuance intention differs between students and lecturers. For students, continued use is mainly shaped by perceived usefulness [30], immediate learning support, confidence in programming tasks, debugging assistance, and reduced frustration. In contrast, lecturers' continuance intention is more strongly influenced by trust, reliability of AI-generated outputs, academic integrity, assessment fairness, institutional policy, and the extent to which GenAI supports rather than weakens learning objectives. Therefore, sustainable GenAI adoption requires addressing both student learning benefits and lecturer concerns regarding responsible use.

D. Pedagogical, Ethical, and Academic Integrity Challenges

In response to RQ4, the review identifies key challenges associated with GenAI integration in programming education, including academic integrity risks, over-reliance, reliability concerns, and ethical misuse. These challenges highlight that GenAI adoption extends beyond technical benefits to important pedagogical and ethical considerations.

Academic integrity is a major concern, as GenAI can generate complete solutions, making it difficult to assess students' original work. This challenges traditional assessment practices and raises issues of fairness and authenticity, as also reported in [34].

Over-reliance on GenAI may limit the development of essential programming skills, such as problem-solving and algorithmic thinking. While GenAI improves efficiency, excessive dependence can reduce active learning, consistent with findings in [21], [6].

Reliability issues further complicate its use, as GenAI may produce incorrect or misleading outputs. Without proper verification, this can negatively affect learning outcomes, particularly for less experienced students [6].

Ethical misuse is another critical issue, as unclear guidelines may lead to inappropriate use, including plagiarism or over-dependence on AI-generated content. This underscores the importance of ethical awareness and governance in GenAI adoption [33].

Although GenAI tools are useful for introductory programming tasks, their effectiveness is more limited in advanced programming contexts. Complex algorithmic reasoning, software architecture design, large-scale debugging, security-sensitive coding, and domain-specific optimisation tasks often require deeper human judgement. GenAI-generated code may appear syntactically correct while containing hidden logical errors, inefficient structures, or unsuitable design assumptions.

This review is also subject to temporal limitations. GenAI tools and their educational applications are evolving rapidly, and findings from earlier studies, particularly those published in 2022 and 2023, may not fully reflect the current capabilities of newer GenAI systems or recent institutional policy developments. As a result, the conclusions of this review should be interpreted as a synthesis of the available evidence within the 2022–2025 publication window rather than a final or static account of GenAI use in higher education. Therefore, GenAI should be used as a guided learning assistant rather than a replacement for independent reasoning, expert feedback, and rigorous code verification.

To address these challenges, the literature suggests redesigning assessments to focus on learning processes, promoting AI literacy, integrating GenAI within guided learning environments, and establishing clear institutional policies.

Overall, these findings indicate that addressing ethical and academic integrity concerns is essential for fostering trust and ensuring the sustainable and responsible use of GenAI in higher education.

E. Implications for Theory, Practice, and Policy

The findings of this study offer important implications across theoretical, practical, and policy dimensions. From a theoretical perspective, the results highlight the need to extend existing technology adoption models by integrating ethical and pedagogical factors, particularly in explaining continuance intention in GenAI-supported learning environments. This supports the inclusion of constructs such as trust, academic integrity, and ethical considerations beyond traditional frameworks like TAM and UTAUT [19].

From a practical perspective, educators are encouraged to adopt balanced instructional strategies that leverage the benefits of GenAI while preserving active learning, critical thinking, and independent problem-solving skills. This aligns with prior studies emphasizing guided and responsible AI integration in education [33]. Institutions should also provide adequate training, technical support, and clear usage guidelines to ensure effective and responsible student engagement with GenAI tools.

From a policy perspective, the findings underscore the need for well-defined institutional and regulatory frameworks that address academic integrity, ethical use, and data governance in AI-assisted learning environments. Clear policies are essential to reduce ambiguity, enhance trust, and support sustainable adoption of GenAI in higher education [26], [27].

F. Research Gaps and Future Directions

The review reveals several important gaps in the current literature on Generative AI in education. First, longitudinal evidence remains limited, as most studies examine immediate or short-term outcomes rather than the sustained effects of GenAI on learning performance, skill development, and academic behaviour over time. As a result, the durability of the reported benefits is still unclear. Second, contextual variation across regions, institutions, and resource environments remains insufficiently addressed. Differences in infrastructure, policy support, institutional readiness, and access conditions are likely to shape both adoption and educational effectiveness, yet these factors are rarely examined in a systematic way.

This unevenness is also reflected in the distribution of studies presented in Table I. Although the reviewed literature spans multiple countries, the evidence remains concentrated in a relatively small number of national settings, with China appearing most frequently. This pattern likely reflects stronger investment in artificial intelligence, rapid digitalisation in higher education, and a large STEM-oriented academic community capable of supporting early experimentation and sustained publication. A similar concentration is evident at the technological level, where ChatGPT overwhelmingly dominates the reviewed studies. Its accessibility, ease of use, and broad applicability to tasks such as writing, coding, explanation, and problem-solving have made it the most common platform for empirical investigation. By contrast, other tools, including Copilot, Gemini, DALL-E, and Midjourney, appear only sporadically, suggesting that the current knowledge base is still being developed around a narrow set of technological experiences. Taken together, these patterns indicate that existing findings, while valuable, may reflect the conditions of well-resourced contexts and the affordances of a single dominant platform more than the full diversity of educational realities. Table I therefore not only describes the spread of literature but also underscores the need for broader comparative work across countries, institutional settings, and GenAI tools to strengthen the robustness and transferability of future evidence.

TABLE I. SUMMARY OF THE DISTRIBUTION OF THE STUDY

SN	Author(s)	Ref.	Year	Country	Tools
1	Ivanov et al.	[35]	2024	Bulgaria	ChatGPT
2	C. K. Y. Chan & Tsi	[28]	2024	China	ChatGPT
3	Yang et al.	[36]	2025	China	ChatGPT
4	Suchanek & Kralova	[31]	2025	Czech Republic	ChatGPT
5	Tbaishat et al.	[37]	2025	UAE	ChatGPT, Copilot
6	Yilmaz Karaoglan Yilmaz	[5]	2023	Turkey	ChatGPT
7	Kohnke et al.	[38]	2023	China	ChatGPT

8	Chiu	[39]	2024	China	ChatGPT, Copilot
9	Lee et al.	[1]	2024	Australia	ChatGPT
10	Awidi	[23]	2024	Australia	ChatGPT
11	Kohnke	[40]	2024	China	ChatGPT
12	Ulla et al.	[41]	2024	Philippines	ChatGPT
13	Wang et al.	[9]	2024	USA	ChatGPT
14	Kong et al.	[34]	2024	China	ChatGPT, Sora
15	Jin et al.	[17]	2025	Australia	Midjourney
16	Huang et al.	[42]	2025	USA	ChatGPT
17	Hashmi & Bal	[43]	2024	USA	ChatGPT, DALL-E
18	Charles et al.	[44]	2025	Australia	ChatGPT, Copilot
19	Ukwandu et al.	[45]	2024	UK	ChatGPT
20	Zou et al.	[46]	2025	China	GenAI chatbot
21	Otto et al.	[25]	2025	Denmark	ChatGPT, Copilot
22	N. N. Chan et al.	[47]	2025	Malaysia	ChatGPT, Copilot
23	Gmiterek & Kotuła	[48]	2025	Poland	ChatGPT, Gemini
24	Beckman et al.	[49]	2025	Australia	ChatGPT
25	Zhao et al.	[50]	2024	China	ChatGPT
26	Ratten & Jones	[51]	2023	Australia	ChatGPT
27	Ostick et al.	[52]	2025	USA	ChatGPT, Gemini
28	Dai et al.	[53]	2023	China	ChatGPT
29	Cha et al.	[54]	2024	China	ChatGPT
30	Cho & Ofosu-Anim	[19]	2025	South Korea	ChatGPT
31	De Putter-Smits et al.	[55]	2025	Netherlands	ChatGPT
32	McDonald et al.	[56]	2025	USA	ChatGPT
33	V. C. Chan	[57]	2025	USA	ChatGPT
34	Nikolic et al.	[29]	2024	Australia	ChatGPT, Copilot
35	Bikanga Ada	[12]	2024	UK	ChatGPT
36	Llerena-Izquierdo et al.	[3]	2024	Ecuador	Gemini
37	Mellado et al.	[4]	2024	Chile	GenAI
38	Sarsam et al.	[58]	2023	UK	Bard GAI chatbot
39	Hernandez et al.	[6]	2025	Philippines	ChatGPT
40	Huynh & Aichner	[15]	2025	Italy	ChatGPT, DALL-E
41	Yakubu et al.	[26]	2025	Nigeria	ChatGPT, Copilot
42	Otto, Lavi, et al.	[59]	2025	Denmark	ChatGPT
43	Nicolajsen et al.	[60]	2024	Denmark	ChatGPT
44	Aruleba et al.	[10]	2025	South Africa	ChatGPT
45	Ren & Wu	[33]	2025	USA	ChatGPT
46	Cengiz & Peker	[61]	2025	Turkey	ChatGPT
47	Qu et al.	[62]	2024	Singapore	ChatGPT
48	Heil et al.	[63]	2025	Germany	ChatGPT

49	Kohen-Vacs et al.	[2]	2025	Israel	ChatGPT, Copilot
50	Bjelobaba et al.	[13]	2025	Sweden	ChatGPT
51	C. K. Y. Chan & Hu	[8]	2023	China	ChatGPT
52	Yusuf et al.	[27]	2024	Nigeria	ChatGPT
53	An et al.	[64]	2025	USA	ChatGPT
54	Zdravkova & Ilijoski	[65]	2025	Republic of North Macedonia	ChatGPT
55	Ursa vaş et al.	[66]	2025	Turkey	ChatGPT, Copilot
56	Fan et al.	[67]	2025	China	ChatGPT
57	Alagöz Hamzaj	[22]	2025	Turkey	ChatGPT
58	Dabis & Csáki	[68]	2024	Hungary	ChatGPT
59	Akçapınar & Sidan	[7]	2024	Turkey	ChatGPT
60	Irish et al.	[24]	2025	USA	ChatGPT, Gemini

Third, existing studies tend to examine technological, pedagogical, and ethical dimensions in isolation, resulting in fragmented insights. This highlights the need for more integrated frameworks that capture the complex interactions between these factors.

Future research should therefore adopt interdisciplinary and mixed-method approaches to provide a more holistic understanding of GenAI use in education. In particular, studies should focus on developing unified models that incorporate technological, pedagogical, and ethical constructs to better explain sustainable and responsible GenAI adoption.

G. Towards Sustainable and Responsible GenAI Integration

Overall, the findings suggest that the integration of GenAI in programming education should move beyond a purely performance-driven approach toward a more responsibility-oriented framework. While GenAI demonstrates clear benefits in enhancing learning outcomes, its long-term value depends on how responsibly it is adopted and managed.

Sustainable integration requires a careful balance between technological capability, pedagogical alignment, ethical governance, and institutional readiness. These dimensions must work together to ensure that GenAI supports meaningful learning while preserving academic integrity, critical thinking, and educational quality.

VI. CONCLUSION AND FUTURE WORK

A. Conclusion

Generative Artificial Intelligence (GenAI) has emerged as a significant development in higher education, with particular relevance for programming and computer science education. Its growing use in educational settings has introduced new opportunities for code generation, real-time feedback, conceptual explanation, and adaptive learning support. At the same time, its integration also raises important pedagogical, ethical, and institutional challenges that are not yet fully understood.

This systematic literature review synthesised evidence from 60 empirical studies published between 2022 and 2025, providing a structured overview of GenAI use in higher education, with

particular emphasis on programming and computer science education. In relation to RQ1, the findings show that GenAI can positively influence learning outcomes by improving code correctness, debugging efficiency, conceptual understanding, and student engagement. These results suggest that GenAI functions not only as a productivity tool but also as a learning support system that can enhance the educational process.

Addressing RQ2, the review reveals considerable variation in GenAI adoption across countries, institutions, course contexts, and access conditions. These differences are shaped by disparities in infrastructure, policy frameworks, institutional readiness, and resource availability, highlighting the importance of context in shaping effective adoption. In response to RQ3, the findings indicate that both students and lecturers generally perceive GenAI positively. However, continued use is influenced by more than usefulness alone. Factors such as satisfaction, trust, motivation, and ethical alignment play an important role in shaping sustained engagement. Regarding RQ4, the review identifies major challenges related to academic integrity, over-reliance, reliability, and ethical misuse, underscoring the need for careful pedagogical design, clear institutional policies, and responsible governance.

Taken together, these findings highlight the need for a more integrated, theory-informed, and pedagogically grounded approach to GenAI adoption. Such an approach should align technological capability with educational goals, ethical responsibility, and institutional readiness in order to support more sustainable and meaningful use of GenAI in higher education, particularly in programming and computer science education.

B. Future Work

Based on the identified gaps and limitations in the literature, this review proposes several directions for future research, practice, and policy development:

1) *Longitudinal and experimental evaluation*: Future research should move beyond short-term performance measures to examine the long-term impact of GenAI on learning, cognitive development, problem-solving ability, and computational thinking. Such studies are necessary to determine whether the observed benefits of GenAI translate into sustained educational outcomes over time.

2) *Expansion into advanced programming and broader disciplinary contexts*: Further studies are needed to explore the role of GenAI in more advanced areas of programming and computer science education, including algorithms, software engineering, and complex system design. At the same time, broader higher education contexts should also be examined to understand how GenAI functions across disciplines with different learning demands.

3) *Addressing global and institutional disparities*: More research is needed to investigate how differences in infrastructure, policy frameworks, access conditions, and institutional readiness shape equitable adoption across regions, particularly in under-resourced and developing contexts.

4) *Pedagogical integration and instructor role*: Future work should examine how GenAI can be effectively embedded within teaching practice, including curriculum redesign,

instructor training, and the development of AI-supported strategies that promote responsible and meaningful learning.

5) *Evaluation of governance and academic integrity frameworks*: There is a need for empirical research that evaluates the effectiveness of institutional policies, ethical guidelines, and assessment redesign strategies in addressing academic integrity concerns and reducing misuse.

6) *Theory-driven and interdisciplinary approaches*: Future research should adopt stronger theoretical foundations by extending models such as ECM, TAM, and UTAUT, while integrating perspectives from educational theory, human-computer interaction, and ethics to develop more comprehensive and context-sensitive frameworks for GenAI in higher education.

7) *Practical implications for educators and policymakers*: For educators, the findings suggest the need to integrate GenAI through guided instructional design, AI literacy activities, assessment redesign, and critical evaluation of AI-generated outputs. For policymakers and institutional leaders, the results highlight the importance of clear academic integrity policies, equitable access to GenAI tools, staff training, ethical governance, and continuous monitoring of GenAI use in teaching and learning. These measures are essential to ensure that GenAI supports meaningful, inclusive, and responsible education.

The rapid evolution of Generative Artificial Intelligence (GenAI) is reshaping teaching and learning in higher education, with particularly important implications for programming and computer science education. Ensuring its effective and responsible integration requires more than technological advancement; it demands a coordinated effort to align pedagogy, ethical principles, and institutional governance. As this review has shown, the foundation for GenAI-supported learning has been established, but it remains incomplete and still evolving. The next phase of research and practice should therefore focus on developing sustainable, inclusive, and theory-informed frameworks that position GenAI not merely as a tool for efficiency, but as a resource for meaningful, equitable, and responsible education.

REFERENCES

- [1] D. Lee et al., "The impact of generative AI on higher education learning and teaching: A study of educators' perspectives," *Comput. Educ. Artif. Intell.*, vol. 6, p. 100221, Jun. 2024, doi: 10.1016/j.caeai.2024.100221.
- [2] D. Kohen-Vacs, M. Usher, and M. Jansen, "Integrating Generative AI into Programming Education: Student Perceptions and the Challenge of Correcting AI Errors," *Int. J. Artif. Intell. Educ.*, Jul. 2025, doi: 10.1007/s40593-025-00496-4.
- [3] J. Llerena-Izquierdo, J. Mendez-Reyes, R. Ayala-Carabajo, and C. Andrade-Martinez, "Innovations in Introductory Programming Education: The Role of AI with Google Colab and Gemini," *Educ. Sci.*, vol. 14, no. 12, p. 1330, Dec. 2024, doi: 10.3390/educsci14121330.
- [4] R. Mellado, C. Cubillos, and G. Ahumada, "Effectiveness of Generative Artificial Intelligence in learning programming to higher education students," in 2024 IEEE International Conference on Automation/XXVI Congress of the Chilean Association of Automatic Control (ICA-ACCA), Santiago, Chile: IEEE, Oct. 2024, pp. 1–7. doi: 10.1109/ICA-ACCA62622.2024.10766746.
- [5] R. Yilmaz and F. G. Karaoglan Yilmaz, "The effect of generative artificial intelligence (AI)-based tool use on students' computational thinking skills, programming self-efficacy and motivation," *Comput. Educ. Artif. Intell.*, vol. 4, p. 100147, 2023, doi: 10.1016/j.caeai.2023.100147.
- [6] A. A. Hernandez, E. M. Albina, and A. R. Caballero, "Generative Artificial Intelligence for Programming Education: Enhancing Input to Outcome-Based Teaching and Learning Approaches," in 2025 Seventh International Symposium on Computer, Consumer and Control (IS3C), Taichung, Taiwan: IEEE, Jun. 2025, pp. 1–5. doi: 10.1109/IS3C65361.2025.11131023.
- [7] G. Akçapınar and E. Sidan, "AI chatbots in programming education: guiding success or encouraging plagiarism," *Discov. Artif. Intell.*, vol. 4, no. 1, p. 87, Nov. 2024, doi: 10.1007/s44163-024-00203-7.
- [8] C. K. Y. Chan and W. Hu, "Students' voices on generative AI: perceptions, benefits, and challenges in higher education," *Int. J. Educ. Technol. High. Educ.*, vol. 20, no. 1, p. 43, Jul. 2023, doi: 10.1186/s41239-023-00411-8.
- [9] H. Wang, A. Dang, Z. Wu, and S. Mac, "Generative AI in higher education: Seeing ChatGPT through universities' policies, resources, and guidelines," *Comput. Educ. Artif. Intell.*, vol. 7, p. 100326, Dec. 2024, doi: 10.1016/j.caeai.2024.100326.
- [10] K. Aruleba, I. T. Sanusi, G. Obaido, B. Ogbuokiri, and I. D. Mienye, "Beyond the Prompt: Student Strategies, Ethical Reflections, and Learning with ChatGPT in Computer Science," *Technol. Knowl. Learn.*, Aug. 2025, doi: 10.1007/s10758-025-09899-7.
- [11] M. I. Baig and E. Yadegaridehkordi, "Factors influencing academic staff satisfaction and continuous usage of generative artificial intelligence (GenAI) in higher education," *Int. J. Educ. Technol. High. Educ.*, vol. 22, no. 1, Feb. 2025, doi: 10.1186/s41239-025-00506-4.
- [12] M. Bikanga Ada, "It Helps with Crap Lecturers and Their Low Effort: Investigating Computer Science Students' Perceptions of Using ChatGPT for Learning," *Educ. Sci.*, vol. 14, no. 10, p. 1106, Oct. 2024, doi: 10.3390/educsci14101106.
- [13] S. Bjelobaba, L. Waddington, M. Perkins, T. Foltýnek, S. Bhattacharyya, and D. Weber-Wulff, "Maintaining research integrity in the age of GenAI: an analysis of ethical challenges and recommendations to researchers," *Int. J. Educ. Integr.*, vol. 21, no. 1, p. 18, Jul. 2025, doi: 10.1007/s40979-025-00191-w.
- [14] V. Venkatesh, J. Y. Thong, and X. Xu, "Unified Theory of Acceptance and Use of Technology: A Synthesis and the Road Ahead," *J. Assoc. Inf. Syst.*, vol. 17, no. 5, pp. 328–376, 2016, doi: 10.17705/1jais.00428.
- [15] M.-T. Huynh and T. Aichner, "In generative artificial intelligence we trust: unpacking determinants and outcomes for cognitive trust," *AI Soc.*, May 2025, doi: 10.1007/s00146-025-02378-8.
- [16] R. S. Pasupuleti and D. Thiyyagura, "An empirical evidence on the continuance and recommendation intention of ChatGPT among higher education students in India: An extended technology continuance theory," *Educ. Inf. Technol.*, Mar. 2024, doi: 10.1007/s10639-024-12573-7.
- [17] Y. Jin, L. Yan, V. Echeverria, D. Gašević, and R. Martinez-Maldonado, "Generative AI in higher education: A global perspective of institutional adoption policies and guidelines," *Comput. Educ. Artif. Intell.*, vol. 8, p. 100348, Jun. 2025, doi: 10.1016/j.caeai.2024.100348.
- [18] M.-L. Chiu, "Exploring user awareness and perceived usefulness of generative AI in higher education: The moderating role of trust," *Educ. Inf. Technol.*, May 2025, doi: 10.1007/s10639-025-13612-7.
- [19] C. Cho and D. Ofori-Anim, "Exploring international students' perceptions of adopting generative artificial intelligence (GenAI) technologies in learning," *Soc. Sci. Humanit. Open*, vol. 11, p. 101418, 2025, doi: 10.1016/j.ssaho.2025.101418.
- [20] M. J. Page et al., "The PRISMA 2020 statement: an updated guideline for reporting systematic reviews," *BMJ*, p. n71, Mar. 2021, doi: 10.1136/bmj.n71.
- [21] G. W. Cheung, H. D. Cooper-Thomas, R. S. Lau, and L. C. Wang, "Reporting reliability, convergent and discriminant validity with structural equation modeling: A review and best-practice recommendations," *Asia Pac. J. Manag.*, vol. 41, no. 2, pp. 745–783, Jun. 2024, doi: 10.1007/s10490-023-09871-y.
- [22] Y. Alagöz Hamzaj, "Generative AI acceptance among future educators: personality and behavioral insights," *Educ. Inf. Technol.*, Jul. 2025, doi: 10.1007/s10639-025-13678-3.

- [23] I. T. Awidi, "Comparing expert tutor evaluation of reflective essays with marking by generative artificial intelligence (AI) tool," *Comput. Educ. Artif. Intell.*, vol. 6, p. 100226, Jun. 2024, doi: 10.1016/j.caeai.2024.100226.
- [24] A. L. Irish, M. W. Gazica, and V. Becerra, "A qualitative descriptive analysis on generative artificial intelligence: bridging the gap in pedagogy to prepare students for the workplace," *Discov. Educ.*, vol. 4, no. 1, p. 48, Mar. 2025, doi: 10.1007/s44217-025-00435-4.
- [25] S. Otto, S. Ejsing-Duun, and E. Lindsay, "Disruptive tensions and emerging practices: an exploratory inquiry into student perspectives on generative Artificial Intelligence in a problem-based learning environment," *Educ. Inf. Technol.*, vol. 30, no. 13, pp. 19111–19140, Aug. 2025, doi: 10.1007/s10639-025-13533-5.
- [26] M. N. Yakubu, N. David, and N. H. Abubakar, "Students' behavioural intention to use content generative AI for learning and research: A UTAUT theoretical perspective," *Educ. Inf. Technol.*, vol. 30, no. 13, pp. 17969–17994, Aug. 2025, doi: 10.1007/s10639-025-13441-8.
- [27] A. Yusuf, N. Pervin, and M. Román-González, "Generative AI and the future of higher education: a threat to academic integrity or reformation? Evidence from multicultural perspectives," *Int. J. Educ. Technol. High. Educ.*, vol. 21, no. 1, p. 21, Mar. 2024, doi: 10.1186/s41239-024-00453-6.
- [28] C. K. Y. Chan and L. H. Y. Tsi, "Will generative AI replace teachers in higher education? A study of teacher and student perceptions," *Stud. Educ. Eval.*, vol. 83, p. 101395, Dec. 2024, doi: 10.1016/j.stueduc.2024.101395.
- [29] S. Nikolic et al., "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," *Australas. J. Eng. Educ.*, vol. 29, no. 2, pp. 126–153, Jul. 2024, doi: 10.1080/22054952.2024.2372154.
- [30] F. Deriba, I. T. Sanusi, O. O. Campbell, and S. S. Oyelere, "Computer Programming Education in the Age of Generative AI: Insights from Empirical Research," *SSRN Electron. J.*, 2024, doi: 10.2139/ssrn.4891302.
- [31] P. Suchanek and M. Kralova, "Generative artificial intelligence expectations and experiences in management education: ChatGPT use and student satisfaction," *J. Innov. Knowl.*, vol. 10, no. 5, p. 100781, Sep. 2025, doi: 10.1016/j.jik.2025.100781.
- [32] A. E. Sousa and P. Cardoso, "Use of Generative AI by Higher Education Students," *Electronics*, vol. 14, no. 7, p. 1258, Mar. 2025, doi: 10.3390/electronics14071258.
- [33] X. Ren and M. L. Wu, "Examining Teaching Competencies and Challenges While Integrating Artificial Intelligence in Higher Education," *TechTrends*, vol. 69, no. 3, pp. 519–538, May 2025, doi: 10.1007/s11528-025-01055-3.
- [34] S. C. Kong, Y. Yang, and C. Hou, "Examining teachers' behavioural intention of using generative artificial intelligence tools for teaching and learning based on the extended technology acceptance model," *Comput. Educ. Artif. Intell.*, vol. 7, p. 100328, Dec. 2024, doi: 10.1016/j.caeai.2024.100328.
- [35] S. Ivanov, M. Soliman, A. Tuomi, N. A. Alkathiri, and A. N. Al-Alawi, "Drivers of generative AI adoption in higher education through the lens of the Theory of Planned Behaviour," *Technol. Soc.*, vol. 77, Jun. 2024, doi: 10.1016/j.techsoc.2024.102521.
- [36] Y. Yang, Q. Xia, C. Liu, and T. K. F. Chiu, "The impact of TPACK on teachers' willingness to integrate generative artificial intelligence (GenAI): The moderating role of negative emotions and the buffering effects of need satisfaction," *Teach. Teach. Educ.*, vol. 154, p. 104877, Feb. 2025, doi: 10.1016/j.tate.2024.104877.
- [37] D. Tbaishat, G. Amoudi, and M. Elfadel, "Adapting teaching and learning with existing generative AI by higher education Students: Comparative study of Zayed University and King Abdulaziz University," *Comput. Educ. Artif. Intell.*, vol. 8, p. 100421, Jun. 2025, doi: 10.1016/j.caeai.2025.100421.
- [38] L. Kohnke, B. L. Moorhouse, and D. Zou, "Exploring generative artificial intelligence preparedness among university language instructors: A case study," *Comput. Educ. Artif. Intell.*, vol. 5, p. 100156, 2023, doi: 10.1016/j.caeai.2023.100156.
- [39] T. K. F. Chiu, "Future research recommendations for transforming higher education with generative AI," *Computers and Education: Artificial Intelligence*, vol. 6, Elsevier B.V., 2024, doi: 10.1016/j.caeai.2023.100197.
- [40] L. Kohnke, "Exploring EAP students' perceptions of GenAI and traditional grammar-checking tools for language learning," *Comput. Educ. Artif. Intell.*, vol. 7, p. 100279, Dec. 2024, doi: 10.1016/j.caeai.2024.100279.
- [41] M. B. Ulla, M. J. C. Advincula, C. D. S. Mombay, H. M. A. Mercullo, J. P. Nacionales, and A. D. Entino-Señorita, "How can GenAI foster an inclusive language classroom? A critical language pedagogy perspective from Philippine university teachers," *Comput. Educ. Artif. Intell.*, vol. 7, p. 100314, Dec. 2024, doi: 10.1016/j.caeai.2024.100314.
- [42] D. Huang, N. Hash, J. J. Cummings, and K. Prena, "Academic cheating with generative AI: Exploring a moral extension of the theory of planned behavior," *Comput. Educ. Artif. Intell.*, vol. 8, p. 100424, Jun. 2025, doi: 10.1016/j.caeai.2025.100424.
- [43] N. Hashmi and A. S. Bal, "Generative AI in higher education and beyond," *Bus. Horiz.*, vol. 67, no. 5, pp. 607–614, Sep. 2024, doi: 10.1016/j.bushor.2024.05.005.
- [44] K. A. Charles, A. Yousuf, H. C. Chua, S. Matthews, J. Harnett, and T. Hinton, "AI in action: Changes to student perceptions when using generative artificial intelligence for the creation of a multimedia project-based assessment," *Eur. J. Pharmacol.*, vol. 998, p. 177508, Jul. 2025, doi: 10.1016/j.ejphar.2025.177508.
- [45] E. Ukwandu, O. Omisade, K. Jones, S. Thorne, and M. Castle, "The Future of Teaching and Learning In The Context Of Emerging Artificial Intelligence Technologies," 2024, SSRN, doi: 10.2139/ssrn.4852030.
- [46] B. Zou, C. Wang, H. He, C. Li, E. Purwanto, and P. Wang, "Enhancing EFL writing with visualised GenAI feedback: A cognitive affective theory of learning perspective on revision quality, emotional response, and human-computer interaction," *Learn. Motiv.*, vol. 91, p. 102158, Aug. 2025, doi: 10.1016/j.lmot.2025.102158.
- [47] N. N. Chan et al., "Generative artificial intelligence in a VUCA world: the 'Lived Experiences' of Southeast Asian teachers' use of AI in higher education," *Int. J. Educ. Res.*, vol. 133, p. 102733, 2025, doi: 10.1016/j.ijer.2025.102733.
- [48] G. Gmiterek and S. D. Kotuła, "Generative artificial intelligence in the activities of academic libraries of public universities in Poland," *J. Acad. Librariansh.*, vol. 51, no. 3, p. 103043, May 2025, doi: 10.1016/j.acalib.2025.103043.
- [49] K. Beckman, T. Apps, S. K. Howard, C. Rogerson, A. Rogerson, and J. Tondeur, "The GenAI divide among university students: A call for action," *Internet High. Educ.*, vol. 67, p. 101036, Oct. 2025, doi: 10.1016/j.iheduc.2025.101036.
- [50] H. Zhao, B. Yuan, and Y. Song, "Employees' perception of generative artificial intelligence and the dark side of work outcomes," *J. Hosp. Tour. Manag.*, vol. 61, pp. 191–199, Dec. 2024, doi: 10.1016/j.jhtm.2024.10.007.
- [51] V. Ratten and P. Jones, "Generative artificial intelligence (ChatGPT): Implications for management educators," *Int. J. Manag. Educ.*, vol. 21, no. 3, p. 100857, Nov. 2023, doi: 10.1016/j.ijme.2023.100857.
- [52] M. Ostick, B. Mariani, and C. Lovocchio, "The use of generative artificial intelligence (AI) in nursing education," *Teach. Learn. Nurs.*, p. S1557308725001799, Jun. 2025, doi: 10.1016/j.teln.2025.05.025.
- [53] Y. Dai, A. Liu, and C. P. Lim, "Reconceptualizing ChatGPT and generative AI as a student-driven innovation in higher education," *Procedia CIRP*, vol. 119, pp. 84–90, 2023, doi: 10.1016/j.procir.2023.05.002.
- [54] Y. Cha, Y. Dai, Z. Lin, A. Liu, and C. P. Lim, "Empowering University Educators to Support Generative AI-enabled Learning: Proposing a Competency Framework," *Procedia CIRP*, vol. 128, pp. 256–261, 2024, doi: 10.1016/j.procir.2024.06.021.
- [55] L. G. A. De Putter-Smits, C. F. J. Pols, P. J. J. M. Dekkers, P. R. Runhaar, M. Timmer, and J. T. Van Der Veen, "Exploring the role of generative AI in science teacher education programs: a qualitative study," *Int. J. Educ.*

- Res. Open, vol. 9, p. 100492, Dec. 2025, doi: 10.1016/j.ijedro.2025.100492.
- [56] N. McDonald, A. Johri, A. Ali, and A. H. Collier, "Generative artificial intelligence in higher education: Evidence from an analysis of institutional policies and guidelines," *Comput. Hum. Behav. Artif. Hum.*, vol. 3, p. 100121, Mar. 2025, doi: 10.1016/j.chbah.2025.100121.
- [57] V. C. Chan, "Integrating generative artificial intelligence in a writing intensive course for undergraduate nursing students," *J. Prof. Nurs.*, vol. 57, pp. 85–91, Mar. 2025, doi: 10.1016/j.profnurs.2025.01.003.
- [58] S. M. Sarsam, A. A. Alias, C. S. Mon, H. Al-Samarraie, and A. I. Al-Hatem, "Exploring Public Opinions Toward the Use of Generative Artificial Intelligence Chatbot in Higher Education: An Insight from Topic Modelling and Sentiment Analysis," in *2023 International Conference on Big Data, Knowledge and Control Systems Engineering (BdKCSE)*, Sofia, Bulgaria: IEEE, Nov. 2023, pp. 1–6. doi: 10.1109/BdKCSE59280.2023.10339760.
- [59] S. Otto, R. Lavi, and L. Brogaard Bertel, "Human-GenAI interaction for active learning in STEM education: State-of-the-art and future directions," *Comput. Educ.*, vol. 239, p. 105444, Dec. 2025, doi: 10.1016/j.compedu.2025.105444.
- [60] S. M. Nicolajsen, S. Nielsen, L. M. Carlsen, and C. Brabrand, "Programming education across disciplines: a nationwide study of Danish higher education," *High. Educ.*, Dec. 2024, doi: 10.1007/s10734-024-01345-4.
- [61] S. Cengiz and A. Peker, "Generative artificial intelligence acceptance and artificial intelligence anxiety among university students: the sequential mediating role of attitudes toward artificial intelligence and literacy," *Curr. Psychol.*, vol. 44, no. 9, pp. 7991–8000, May 2025, doi: 10.1007/s12144-025-07433-7.
- [62] Y. Qu, M. X. Y. Tan, and J. Wang, "Disciplinary differences in undergraduate students' engagement with generative artificial intelligence," *Smart Learn. Environ.*, vol. 11, no. 1, p. 51, Nov. 2024, doi: 10.1186/s40561-024-00341-6.
- [63] J. Heil, D. Ifenthaler, M. Cooper, M. L. Mascia, R. Conti, and M. P. Penna, "Students' perceived impact of GenAI tools on learning and assessment in higher education: the role of individual AI competence," *Smart Learn. Environ.*, vol. 12, no. 1, p. 37, May 2025, doi: 10.1186/s40561-025-00395-0.
- [64] Y. An, J. H. Yu, and S. James, "Investigating the higher education institutions' guidelines and policies regarding the use of generative AI in teaching, learning, research, and administration," *Int. J. Educ. Technol. High. Educ.*, vol. 22, no. 1, p. 10, Feb. 2025, doi: 10.1186/s41239-025-00507-3.
- [65] K. Zdravkova and B. Iljoski, "The impact of large language models on computer science student writing," *Int. J. Educ. Technol. High. Educ.*, vol. 22, no. 1, p. 32, May 2025, doi: 10.1186/s41239-025-00525-1.
- [66] Ö. F. Ursavaş, Y. Yalçın, H. İslamoğlu, E. Bakır-Yalçın, and M. Cukurova, "Rethinking the importance of social norms in generative AI adoption: investigating the acceptance and use of generative AI among higher education students," *Int. J. Educ. Technol. High. Educ.*, vol. 22, no. 1, p. 38, Jun. 2025, doi: 10.1186/s41239-025-00535-z.
- [67] L. Fan, K. Deng, and F. Liu, "Educational impacts of generative artificial intelligence on learning and performance of engineering students in China," *Sci. Rep.*, vol. 15, no. 1, p. 26521, Jul. 2025, doi: 10.1038/s41598-025-06930-w.
- [68] A. Dabis and C. Csáki, "AI and ethics: Investigating the first policy responses of higher education institutions to the challenge of generative AI," *Humanit. Soc. Sci. Commun.*, vol. 11, no. 1, p. 1006, Aug. 2024, doi: 10.1057/s41599-024-03526-z.