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Harnessing Generative Artificial Intelligence in Computer Science Education: Pedagogical Innovation, Ethical Responsibility, and the Future of Assessment

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Abstract

Artificial Intelligence (AI), particularly Generative AI (GenAI), is profoundly reshaping assessment practices in computer science education by enabling automation, scalability, and personalized feedback mechanisms. AI-enhanced tools facilitate adaptive testing, real-time learner support, and data-driven insights that foster deeper engagement and learning outcomes. However, the integration of AI also raises critical concerns related to academic integrity, algorithmic bias, transparency, and ethical implications of AI-driven evaluation. This theoretical paper critically examines the opportunities and complexities of GenAI-enabled assessment in CS education. Drawing on contemporary literature, pedagogical theory, and emerging use cases, the paper explores how GenAI can enhance student engagement, support equitable learning, and relieve instructional burden, while also highlighting the need for ethical safeguards and pedagogically grounded frameworks. It argues that the successful integration of GenAI depends not solely on technological capability but on deliberate, human-guided design that upholds transparency, fairness, and educational purpose. By advancing a nuanced and critically reflective perspective, this paper contributes to the evolving discourse on AI in education and provides actionable insights for educators, researchers, and policymakers seeking to harness GenAI responsibly in the future of computer science education.

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Introduction

The integration of Artificial Intelligence (AI) into computer science education marks a fundamental paradigm shift, challenging traditional instructional methodologies and reshaping the student learning experience in profound ways (Walter, 2024). Advances in AI, particularly the advent of generative AI (GenAI) models, introduce unprecedented capacities to automate complex educational processes, customize learning environments to fit diverse learner needs, and provide adaptive, real-time feedback that can accelerate skill development and deepen understanding (Ali et al., 2024; Gligorea et al., 2023; Walter, 2024). This technological advance has coincided with the rapid evolution of computer science as a discipline, where educators face the persistent challenge of maintaining curricula that reflect the latest innovations, while simultaneously addressing an increasingly heterogeneous student body that spans a wide range of prior knowledge, learning preferences, and cultural backgrounds (Kaplan & Haenlein, 2019; Prather et al., 2023).

GenAI models signify a leap beyond prior AI systems rooted largely in deterministic rules or static analytical procedures. Leveraging vast datasets and deep neural network architectures, these models exhibit emergent capabilities to simulate human-like reasoning, creativity, and problem-solving by generating natural language, code snippets, and contextual suggestions that can meaningfully augment educational interactions (Bandi et al., 2023; Gupta et al., 2024). This has catalysed a growing interest in their application across the spectrum of computer science education from providing instant and interactive feedback on students' work (Xu et al., 2023) to acting as personalized tutoring outside formal classroom hours (Sun et al., 2024).

The promise of these technologies lies not only in automation, but also, in fostering learner autonomy and critical thinking, cornerstones for success in computing disciplines, where continuous innovation and self-directed learning are essential. AI-powered chatbots and virtual assistants enable students to engage in self-paced learning, receive tailored hints, and clarify concepts in an on-demand fashion, thus supporting individual pathways through diverse and often challenging material (Akram et al., 2024). This evolving relationship between learners and AI agents, however, also raises pedagogical questions regarding the balance between technology-mediated guidance and the development of independent problem-solving capabilities (Al-Zahrani, 2024). If AI scaffolding is too prescriptive, it risks fostering dependency. On the other hand, however, insufficient support may lead to frustration and disengagement.

Beyond individual learning, AI systems are transforming collaborative learning landscapes. For instance, Intelligent tutoring systems (ITS) and AI-driven peer collaboration platforms can recommend effective team formations by analysing complementary skill sets, monitor interactions to identify off-task behaviours or knowledge gaps, and offer tailored resources in real time, thereby enhancing group productivity (Graesser et al., 2018; Kovari, 2025). These innovations resonate with constructivist and socio-cultural theories of learning that emphasize interaction and social negotiation as key to deep understanding. Yet, the use of AI to mediate social learning invites ethical scrutiny. It remain as a question as how do we preserve student agency and privacy when interactions are continuously monitored and algorithmically assessed (Akgun & Greenhow, 2022; Díaz-Rodríguez et al., 2023)?

The rise of AI-driven learning analytics further empowers educators with granular, data-rich insights into students' engagement patterns, coding workflows, and conceptual progressions (Ouyang & Zhang, 2024). This shift from reactive to proactive teaching models enables timely, evidence-informed interventions, tailored curricular adjustments, and personalized feedback strategies. Nonetheless, the accumulation and use of vast amounts of learner data amplify concerns around privacy, consent, and data security (Liu et al., 2025; Williamson & Prybutok, 2024). The opacity of some AI systems' decision-making processes also raises questions about transparency and accountability in educational contexts, highlighting the need for explainable AI (XAI) solutions that foster trust among all stakeholders (Al-Zahrani, 2024; Cheong, 2024).

Moreover, the broad adoption of AI in education introduces complex ethical concerns. Academic integrity is threatened by the ease with which students might misuse GenAI tools to produce assignments or codes without genuine comprehension, potentially undermining learning outcomes and devaluing credential authenticity (Nikolic et al., 2023; Yang & Xin, 2022). In parallel, the datasets used to train AI models often reflect historical and societal biases, risking perpetuation or amplification of inequities in assessment and feedback (Akgun & Greenhow, 2022; Borenstein & Howard, 2021). Equity concerns extend further to disparities in access to AI-enhanced learning tools, potentially exacerbating existing digital divides among students from different socio-economic or geographical backgrounds (Chan, 2023).

In response to these multifaceted opportunities and challenges, this paper undertakes a critical examination of AI's reshaping influence on computer science education, with a particular focus on AI's role in personalizing learning, innovating assessment practices, and navigating evolving ethical landscapes. By synthesizing empirical research, theoretical frameworks, and illustrative case studies, it aims to provide educators, researchers, and policymakers with a comprehensive understanding of AI's potential, risks, and best practices in this rapidly changing domain. The discussion further integrates contemporary pedagogical models which prioritize learner autonomy, self-reflection, and lifelong learning, aligning with AI's capacity to foster self-directed educational journeys (Divasón et al., 2023; Hazzan & Erez, 2024).

Ultimately, this paper aims to advance evidence-based strategies and conceptual frameworks that support the responsible, equitable, and effective harnessing of AI technologies in computer science education, ensuring that AI enhances rather than replaces the human elements central to meaningful learning.

AI in Personalised Learning and Assessment

AI technologies have already demonstrated significant potential to personalize learning in computer science education. By leveraging AI-powered tools, educators can dynamically adapt instructional content, automate individualized feedback, and implement assessment mechanisms that respond to student-specific learning trajectories (Luckin et al., 2022; Tan et al., 2025). These affordances are particularly relevant in disciplines like computer science, where mastering complex skills such as algorithm design, debugging, and abstraction requires iterative practice and timely intervention (Logacheva et al., 2024; Rasul et al., 2023). Key examples of AI applications in personalized learning and assessment are summarized in Table 1.

Table 1

Examples of AI Applications in Assessment

AI Application in Assessment	Key Benefits
Personalized Learning & Feedback	Adapts content to student-specific learning trajectories; provides individualized feedback; supports mastery-based learning
Automated Code Analysis & Debugging	Detects errors, suggests corrections, scaffolds code quality
Scalability & Flexibility	Handles diverse inputs at scale; reduces manual authoring; supports multiple domains
Dynamic Error Handling & Iterative Feedback	Responds to unseen submissions; facilitates rapid revision cycles; encourages iterative learning
Collaborative Learning Support	Forms peer groups based on complementary skills; tracks collaboration dynamics; nudges learning interactions
Gamification & Experiential Learning	Engages students through immersive environments; fosters conceptual understanding and skill transfer
Learning Analytics & Proactive Interventions	Provides granular insights on engagement, problem-solving, and mastery; supports timely instructor interventions

Generative AI tools such as Codex, ChatGPT, and GitHub Copilot can generate varied programming exercises, detect errors in student code, and provide real-time feedback. For example, researchers using Codex showed that it could automatically generate programming exercises including solutions and test cases, and that instructors can influence both the programming concepts and contextual themes simply by supplying keywords (Sarsa et al., 2022). Further, studies of ChatGPT/GPT-4 in programming-education contexts show that the models can produce feedback aligned with human tutors' commentary, recognising logic errors, suggesting diagnostic hints, and guiding learner revisions (Phung et al., 2023). At the same time, tools like GitHub Copilot facilitate real-time code suggestions and review, enabling rapid iteration and scaffolding of code quality and correctness (Kohen-Vacs et al., 2025). These approaches support a mastery-based learning approach in which students can iteratively improve their understanding and skills with tailored scaffolding (Busropan, 2024; Franklin, 2025). Moreover, GenAI systems can adjust difficulty levels automatically, diagnose misconceptions, and offer hints or explanations, thus mimicking the personalized attention typically only available through one-on-one human tutoring (Sun et al., 2024; Xu et al., 2023). Such responsiveness has the potential to democratize quality education by extending individualized support to larger, more diverse cohorts.

In contrast to traditional rule-based tutoring systems where pedagogical logic, student modelling, and feedback are scripted using production rules, constraint-based models, or model-tracing architectures, modern transformer-based large language models (LLMs) bring a fundamentally different architecture to educational assessment and feedback. Rule-based systems, such as classical intelligent tutoring systems (ITSs), offer high explainability and predictable error-handling because each decision path is explicitly coded and traceable (Létourneau et al., 2025; Noh et al., 2012). However, they suffer from limited scalability: writing, maintaining, and updating large rule sets in diverse domains (such as varied programming tasks) becomes prohibitively costly, and they struggle with open-ended student inputs or novel error patterns. By contrast, transformer-based LLM tutors operate via large-scale pre-training on vast textual and code corpora, with fine-tuning for educational tasks, enabling them to respond flexibly to broad inputs, generate scaffolded feedback, and adapt to many contexts at scale (García-Méndez et al., 2025). They also allow dynamic error-handling by recognizing patterns across previously unseen student submissions and generating explanations on the fly, facilitating rapid iteration and personalization. That said, LLM-based systems raise challenges in explainability since their internal reasoning paths are opaque and may propagate errors or hallucinations unless paired with guardrails or retrieval-augmented architectures (Kovari, 2025). In terms of scalability, transformer-based tutors clearly offer broader reach (multi-domain, minimal manual authoring) but may require substantial compute resources and ethical oversight, whereas rule-based tutors can be more lightweight but less flexible. For educational assessment in computer science, the key trade-off is between the consistent traceability and control of rule-based systems and the higher flexibility and coverage but lower transparency of LLM-based systems.

Beyond individual support, AI is reshaping collaborative learning in computer science. AI-driven platforms can form peer groups based on complementary skills, track collaboration dynamics, and provide intelligent nudges during group work. These affordances align with constructivist and socio-cultural pedagogies, emphasizing the role of interaction, dialogue, and social negotiation in deep learning (Denny et al., 2024; Graesser et al., 2018). However, they also raise questions about the algorithmic monitoring of interpersonal interactions, student privacy, and the possible reduction of complex social behaviours to quantifiable metrics (Akgun & Greenhow, 2022; Díaz-Rodríguez et al., 2023).

Gamification and immersive simulations are further extending the potential of AI in engagement and experiential learning. Virtual labs and adaptive simulations offer rich, interactive environments in which students apply theoretical knowledge to real-world problems, fostering both conceptual understanding and skill transfer (Koti et al., 2025; Yeganeh et al., 2024). While promising, the educational value of these tools depends on thoughtful design and pedagogical alignment to avoid superficial engagement or excessive cognitive load.

Crucially, the backbone of all these innovations lies in AI-driven learning analytics, which provide granular insights into student engagement, problem-solving approaches, and conceptual mastery. These analytics facilitate timely, evidence-based interventions by instructors, transforming teaching from reactive to proactive (Jin et al., 2025; Tamilarasu, 2025).

When embedded within an entangled pedagogy that sees technology, instruction, and learning as co-constitutive. AI can enable a shift from uniform, instructor-driven education to student-centered, reflective learning. However, this transformation must be critically managed. Overreliance on automation risks diminishing students' metacognitive development or reducing complex learning to surface-level performance metrics (Rear, 2019). Educators must therefore maintain a clear role in interpreting AI feedback, designing learning pathways, and mentoring students toward higher-order competencies such as ethical reasoning, creativity, and critical reflection (Luckin et al., 2022; Talha Siddiqui, 2025).

In sum, AI technologies offer unprecedented potential for personalized and scalable learning in computer science. Yet, realizing this potential demands more than technological deployment requires pedagogical vision, ethical foresight, and institutional support to ensure that these innovations enhance rather than fragment educational practice.

AI-Enhanced Computer Science Education

The integration of AI into computer science education presents a double-edged sword: it offers unprecedented educational opportunities while introducing complex ethical and pedagogical dilemmas that educators and institutions must navigate with care and foresight. These considerations are not peripheral; they are central to ensuring that AI is deployed in ways that enhance, rather than compromise, educational quality, equity, and integrity. A summary of these key considerations in the application of AI for assessment is presented in Table 2.

Academic Integrity and Assessment Authenticity

One of the most immediate concerns is academic integrity. With generative AI tools capable of producing entire codebases or discursive responses with minimal human prompting, traditional notions of authorship and originality are under strain. Students may increasingly rely on AI to complete assessments, sometimes without understanding the underlying logic or concepts, thereby diminishing genuine learning and eroding credential credibility (Nikolic et al., 2023; Yang & Xin, 2022). While plagiarism detection software has evolved, it often lags behind the sophistication of GenAI output. Therefore, reliance on detection alone is insufficient.

Instead, educators must reimagine assessment design to emphasize authenticity and the learning process over static outputs. In other words, rather than simply adopting reactive, ‘knee-jerk’ strategies to prevent students from using tools such as GenAI in their work, there is a need for assessment methods to evolve and incorporate the authentic, appropriate and ethical use of these tools. The permitted uses of AI and GenAI in assessments must reflect how the tools are being used in relevant industry contexts. Assessments must, therefore, call upon students to demonstrate their ability to do what such tools cannot yet do well tasks, that do require expert human input to achieve. Assessment formats that focus on creativity and process-oriented work, such as scaffolded coding journals, version-tracked submissions, and interactive oral assessments can help validate student understanding and reduce opportunities for dishonest AI use (Angeli, 2022; Krautloher, 2024). These approaches align with industry-relevant practices, and are likely to harness the potential of AI-based tools to foster students’ deep engagement with the learning content.

Some assessment redesign strategies for enhancing academic Integrity and assessment authenticity include version-controlled coding journals, interactive oral defenses, and AI-in-the-loop assessments. In version-controlled coding journals, students maintain repositories with time-stamped commits, meaningful commit messages, and reflections on changes, exposing the evolution of their work, making authorship visible, and emphasising revision and process (Guerrero-Higueras et al., 2020). Interactive oral defenses involve live or synchronous sessions in which students respond to prompts, debug code on the spot, explain their logic, or modify AI-generated code under supervision. Research into interactive oral assessment in computing education demonstrates that such approaches improve assessment validity and deter superficial AI-driven submissions (O'Riordan et al., 2025). AI-in-the-loop assessments provide students with AI-generated drafts such as code snippets or explanatory essays, that they must critique, refine, justify changes to, and reflect upon. This approach leverages AI productively while assessing higher-order thinking, self-regulation, and deep understanding (Xia et al., 2024). Together, these strategies align with industry-relevant practices and harness the potential of AI-based tools to foster meaningful engagement with learning content. More importantly, they shift the focus from simply producing correct outputs to demonstrating the ability to author, iterate, defend, and refine work, thereby preserving academic integrity and promoting authentic learning.

Table 2

Key Considerations in the Application of AI for Assessment

Key Application	Description	Practical and Pedagogical Implications
Academic Integrity & Assessment Authenticity	Risk of diminished authorship and originality due to AI-generated submissions; traditional plagiarism detection may be insufficient.	Redesign assessments to emphasize process and creativity; implement version-controlled coding journals, interactive oral defences, and AI-in-the-loop tasks to assess higher-order thinking and authentic learning.
AI Literacy	Need for students and educators to understand AI capabilities, limitations, biases, and ethical implications.	Integrate AI literacy modules into curricula; train educators for responsible tool adoption and critical evaluation of AI-generated content.
Bias, Fairness & Accountability	AI models can propagate social, cultural, or gender biases, leading to inequitable assessment outcomes.	Apply fairness-aware ML techniques (re-weighting, counterfactual fairness, differential privacy), ensure model explainability, and implement ethics-by-design frameworks with diverse stakeholder input.
Data Privacy, Surveillance & Consent	AI-driven learning analytics collect extensive behavioral and performance data, raising concerns over autonomy, consent, and transparency.	Implement GDPR-aligned consent, anonymization pipelines, opt-out provisions, and model explainability reports; clearly communicate what data is collected and its purpose.
Balancing Automation & Humanism	AI can automate grading, feedback, and resource curation but may undermine relational and transformative aspects of teaching.	Design assessments that blend automation with reflective inquiry; provide faculty development and institutional support to preserve pedagogy-centered approaches.
Equity & Access	Digital divide and AI literacy gaps can exacerbate disparities, limiting access to AI-enhanced learning.	Provide subsidized access to hardware/software, promote low-compute and open-source AI tools, design inclusive instructional practices, and conduct ongoing equity audits.

The Imperative of AI Literacy

Embedding AI literacy into computing curricula is another vital ethical strategy. Rather than positioning AI as a threat to be managed, students should be equipped to use AI responsibly and reflectively, as an assistive cognitive partner that complements human judgment rather than replacing it (Dilek et al., 2025; Zhao et al., 2022). AI literacy encompasses understanding how models are trained, recognizing their limitations and biases, and developing the ability to critically evaluate AI-generated content. For educators, AI literacy is equally crucial to ensure informed tool adoption and responsible pedagogical integration. Without this foundational knowledge, both students and faculty risk being passive consumers of technology, rather than active and ethical participants in its application.

Bias, Fairness, and Accountability

Another core ethical issue lies in the propagation of algorithmic bias. GenAI tools trained on large-scale public datasets often encode existing social, cultural, and gender biases. When applied in educational contexts, particularly in high-stakes assessment, these biases can produce inequitable outcomes and reinforce systemic disparities (Borenstein & Howard, 2021). For example, feedback generated by biased models may systematically disadvantage students from underrepresented backgrounds, whether by misinterpreting code style conventions or providing less nuanced responses.

Addressing these concerns requires multifaceted interventions. At the technical level, developers can integrate fairness-aware machine learning methods, such as re-weighting samples to mitigate underrepresented groups, enforcing counterfactual fairness to ensure predictions are invariant under sensitive attributes, and applying differential privacy to protect individual student data while reducing bias amplification (Ferrara et al., 2024; Raftopoulos et al., 2025). These approaches help ensure that AI-driven assessments and feedback are more equitable and do not systematically disadvantage any group. Additionally, transparency can be enhanced through explainable AI (XAI) mechanisms that make model decisions interpretable to educators and students, facilitating trust and accountability.

At the institutional level, ethics-by-design frameworks should be adopted to ensure inclusive and accountable AI deployment, incorporating proactive auditing of AI outputs and evaluation metrics for bias detection (IEEE, 2019; UNESCO, 2021). Moreover, involving a diverse group of stakeholders including educators, technologists, ethicists, and students in the design and governance of AI systems helps ensure that multiple perspectives inform the development and implementation of these tools (Nguyen et al., 2023).

Data Privacy, Surveillance, and Consent

The application of AI-powered learning analytics introduces additional ethical concerns related to surveillance and privacy. These systems collect vast amounts of behavioural and performance data, from keystroke dynamics to forum activity and code iterations. While such data enables early interventions and customized support, it also risks constructing students as shrivelled subjects, raising questions about autonomy, consent, and trust (Alfredo et al., 2024; Selwyn, 2019). Students are often unaware of the extent to which their data is tracked and analysed, creating an opaque data environment that challenges institutional transparency.

To strengthen data governance in AI-enabled learning analytics, institutions should adopt clear protocols that operationalise the principles of transparency, data minimisation and student agency.

This includes deploying GDPR-aligned consent mechanisms that clearly inform students about what data is collected (e.g., keystrokes, IDE telemetry, revision histories, forum interactions), how it will be processed, and for what purposes (the European Parliament and of the Council, 2016). Next, anonymisation pipelines should be implemented to de-identify or pseudonymise student data before analysis, limiting the risk of re-identification while enabling meaningful insights (El Mestari et al., 2024). Institutions should also offer opt-out provisions that allow students to decline certain analytic tracking without academic penalty, thus preserving autonomy and equity (Ismail & Aloshi, 2024; Shata, 2025). Finally, the production of model explainability reports is essential. Learning analytics tools should include human-readable summaries of how models use student data, how predictions or interventions are derived, and what safeguards are in place fostering transparency and trust in an otherwise opaque system (Liu & Khalil, 2024). Together, these governance practices outline a practical, ethically grounded framework for colleges and universities to harness learning analytics responsibly.

Balancing Automation with Humanism in Pedagogy

AI's ability to automate routine educational tasks such as grading, code testing, or resource curation, can enhance instructional efficiency. However, this efficiency must not come at the cost of human-centered pedagogy. Teaching is more than the delivery of content; it involves mentorship, ethical dialogue, emotional support, and the cultivation of critical consciousness. Over-automation risks reducing educators to supervisory roles, diminishing the relational and transformative dimensions of learning (Baidoo-Anu & Ansah, 2023; Walter, 2024). Maintaining this balance requires intentional instructional design and robust faculty development programs. Educators must be supported to integrate AI in ways that reflect their pedagogical values and teaching philosophies. This includes professional learning in how to evaluate AI tools critically, facilitate ethical discussions about AI's societal implications, and design assessments that blend automation with reflective inquiry and creativity (Kohnke et al., 2025). Institutional support in the form of academic freedom, policy flexibility, and infrastructure investment is critical to sustaining this balance.

Equity and Access in an AI-Mediated Learning Environment

A final, but foundational, consideration is digital equity. The promise of AI-enhanced education will remain unevenly distributed unless institutions commit to narrowing the digital divide. Students from lower socioeconomic backgrounds, rural areas, or marginalized communities may face both hardware and software access barriers, such as unreliable internet, outdated devices, or insufficient access to commercial AI platforms, as well as AI literacy gaps, including limited prior exposure to generative AI tools or the skills required to use them effectively (Akgun & Greenhow, 2022; Chan, 2023). This dual disparity risks compounding existing inequalities in computer science education.

Addressing these challenges requires multi-faceted strategies. Institutions should invest in infrastructure and provide subsidized access to AI tools for students who lack resources. Promoting low-compute LLMs or models that run on modest hardware can reduce technical barriers, while the adoption of open-source generative AI tools offers cost-effective alternatives that support equitable access to AI-powered learning (Liu & Khalil, 2024). Instructional design should be inclusive, ensuring that AI-based learning and assessment tools are not mandatory unless pedagogically equivalent alternatives are available, thus preserving learner autonomy and avoiding exclusion (Bogina et al., 2022; Xivuri & Twinomurinzi, 2023). Equity also requires ongoing audits to detect and remediate disparities in AI tool usage, feedback accuracy, and student outcomes.

In sum, the responsible integration of AI in computer science education is not merely a technological challenge. It is a deeply ethical and pedagogical imperative. Academic integrity, fairness, transparency, humanism, and equity must be at the centre of AI adoption strategies. By engaging critically with these challenges and embedding ethical foresight into educational design, institutions can ensure that AI enhances rather than erodes the foundational values of learning. This work must be iterative, collaborative, and context-sensitive, requiring continued investment in research, professional development, and inclusive dialogue across disciplines and stakeholder communities.

The Need for a Pedagogically Grounded Framework

The rapid rise and proliferation of GenAI in computer science education offers transformative possibilities for assessment design, yet this surge is occurring largely in the absence of a well-established, pedagogically grounded framework to guide its implementation. This gap is not merely theoretical, it poses tangible risks to educational equity, integrity, and effectiveness. As GenAI systems become increasingly sophisticated, the allure of their automation capabilities can overshadow foundational educational concerns, leading to the premature or uncritical adoption of tools that may not align with sound pedagogical principles (Franklin, 2025; McDonald et al., 2025).

One of the most pressing issues is the potential for algorithmic bias to reinforce or deepen existing educational inequalities. Without intentional safeguards, AI tools trained on skewed or non-representative datasets may disproportionately disadvantage students from underrepresented backgrounds or those with atypical learning trajectories (Baidoo-Anu & Ansah, 2023). The automation of assessment processes particularly grading and feedback, can further exacerbate this problem by reducing complex, nuanced human learning into reductive metrics. These risks transforming rich, developmental assessments into mechanistic exercises, eroding both their validity and educational purpose (Darvishi et al., 2022; Shaik et al., 2022).

In this context, a pedagogically grounded framework must function as more than a technical scaffold. It should actively mediate the relationship between educational goals and AI applications, ensuring that the integration of GenAI tools promotes constructivist, student-centred learning rather than administrative convenience. Expanding upon constructivism, this framework could also draw on Assessment as Learning (Earl, 2012), which positions assessment as an active and reflective process through which learners monitor and direct their own learning. This approach complements the affordances of GenAI by emphasizing features such as formative feedback loops and learner agency which AI systems can enhance if designed and deployed responsibly. Similarly, understanding the continuum between formative and summative assessment models (Black & Wiliam, 2018) is critical for ensuring that AI tools serve not merely as evaluators but as facilitators of continuous learning and self-regulation.

Moreover, Critical Digital Pedagogy (Gutiérrez-Ujaque, 2024) provides a necessary ethical and socio-political lens for this framework. It calls for transparency, inclusivity, and critical engagement with technology rather than passive adoption. Within an AI-mediated context, this means interrogating whose knowledge, data, and values are embedded in these systems and how they shape the learning experience. Transparency should therefore be a foundational principle: students and educators must be able to interpret and trust the logic behind AI-generated outputs, particularly in formative contexts where feedback directly informs ongoing learning. This includes clear communication about how decisions are made, what data are used, and how outputs can be contested or corrected if inaccurate(Yan et al., 2024). Moreover, fairness must be embedded throughout all stages of AI development and deployment. This entails bias detection during dataset curation, fairness-aware modelling techniques, and routine post-deployment audits to monitor unintended consequences (Bogina et al., 2022; Busropan, 2024). These efforts should be coupled with inclusive design practices that involve students, educators, ethicists, and technologists collaboratively to ensure that diverse perspectives shape the development and governance of GenAI in education.

Crucially, human oversight must remain central. While GenAI can enhance scale and speed, it cannot replicate pedagogical intuition, empathy, or ethical discernment. Educators play a vital role in contextualizing AI-generated insights, interpreting patterns in student learning, and maintaining the relational aspects of education that AI cannot emulate. AI should serve as an augmentation, not a substitution, for human judgment (Divasón et al., 2023; Xu et al., 2023). Additionally, any guiding framework must account for the structural realities of computer science education. Large cohorts, intensive programming demands, and resource limitations place significant strain on educators. GenAI can help alleviate workload by providing scalable feedback and automated assessments, but its use must be situated within institutional strategies that support staff with adequate training, ethical guidance, and infrastructure (Azoulay et al., 2025; Sun et al., 2024). If not, the risk remains that poorly integrated AI systems may create new burdens technical, pedagogical, or ethical, rather than solving existing ones.

Finally, the framework must explicitly promote ethical and digital literacy for both students and educators. Understanding the affordances, limitations, and potential misuse of AI is foundational to navigating the emerging educational landscape. Without such competencies, institutions risk endorsing "black box" systems that undermine transparency, student trust, and academic integrity. Frameworks must therefore include not only technical and pedagogical guidelines but also mechanisms for critical reflection, co-design, and ongoing institutional learning (Kohnke et al., 2025; Walter, 2024). The responsible integration of GenAI into assessment design demands a theoretically informed, context-sensitive, and ethically attuned framework. This framework should emerge from interdisciplinary collaboration and be grounded in a commitment to educational equity, transparency, and pedagogical rigor, ensuring that the promise of AI supports, rather than compromises, the fundamental goals of higher education.

Future Directions

While the ethical and pedagogical challenges of GenAI integration are substantial, they exist alongside a growing body of evidence showcasing its transformative potential in reimagining assessment in computer science education. These emerging applications not only address longstanding limitations in feedback delivery and scalability but also enable novel pedagogical approaches that promote critical thinking, creativity, and self-directed learning.

One of the most promising developments is the use of GenAI as an intelligent tutor. Platforms such as ChatGPT, GitHub Copilot, and other code-focused large language models offer personalized support that adapts dynamically to individual learning needs. These tools provide real-time debugging assistance, suggest alternative problem-solving approaches, and deliver immediate feedback, capabilities that align with mastery learning models, where repeated practice and adaptive guidance foster deeper understanding (Leotta et al., 2024; Sun et al., 2024). By automating routine support tasks, GenAI can reduce instructor workload, allowing educators to focus on higher-order pedagogical functions such as mentorship, curriculum design, and ethical reflection. In parallel, the integration of GenAI with advanced learning analytics (LA) systems is opening new frontiers for data-driven education. AI tools such as OpenAI Codex and Whisper can process and analyse multimodal data sources, including code, audio transcripts, and collaborative dialogue. This enables more holistic insights into student learning behaviours, enabling timely interventions and tailored instructional strategies (Paiva et al., 2022; Pande & Mishra, 2023). Tools like VizChat, which provide contextualized visual analytics, are already enhancing educators' ability to interpret and act upon complex data sets (Yan et al., 2024).

Furthermore, GenAI is facilitating the design of alternative assessment formats that promote authenticity and reduce opportunities for misconduct. Interactive oral assessments, scaffolded coding journals, and collaborative simulations can shift the focus from outputs to processes, emphasizing reflection, iteration, and explanatory depth (Angeli, 2022; Krautloher, 2024). These methods not only align more closely with real-world computing practices but also resist surface-level plagiarism by requiring learners to demonstrate conceptual understanding and articulate problem-solving rationale. Despite these advances, several critical issues demand ongoing attention. As AI systems become more pervasive, the temptation to over-automate must be resisted. Educators and institutions must ensure that AI tools do not marginalize human judgment or reduce complex pedagogical decisions to algorithmic outputs. This includes safeguarding students' rights to contest AI-generated feedback, access alternative assessment pathways, and receive human support where needed (Grandel et al., 2024; Qureshi, 2023).

Moreover, educator roles must evolve in tandem with AI technologies. The shift from knowledge delivery to facilitation and ethical mediation requires new competencies in AI literacy, digital pedagogy, and interdisciplinary collaboration (Abulibdeh et al., 2024; Zhao et al., 2022). Institutions must invest in sustained professional development and supportive policies that empower educators to critically adopt and adapt AI tools in ways that align with their pedagogical values and local contexts. Future research should further explore how GenAI can support not just individual learning but broader curricular transformation. This includes investigating how AI tools influence learning outcomes over time, how students internalize feedback from AI systems, and how collaborative learning environments mediated by AI affect group dynamics and social learning. Comparative studies across institutional contexts will also be essential to identify scalable, inclusive practices that accommodate diverse learner needs.

In practice, AI-enhanced assessment should be implemented iteratively, with built-in mechanisms for feedback, adjustment, and ethical oversight. Pilot programs, co-design initiatives, and participatory evaluations can help institutions navigate this dynamic landscape while centring student agency and pedagogical intentionality. The goal is not simply to integrate AI but to do so in ways that enhance equity, creativity, and engagement.

The integration of established learning and assessment models can further ground GenAI-enabled approaches within coherent pedagogical theory. For instance, Bloom's Taxonomy provides a structured lens to design AI-supported assessments that move beyond lower-order cognitive skills such as recall or comprehension toward higher-order competencies like analysis, synthesis, and creation, areas where generative tools can prompt learners to explain reasoning, debug complex problems, or design novel algorithms (Anderson & Krathwohl, 2001). Similarly, Biggs' Constructive Alignment underscores the importance of aligning intended learning outcomes, teaching activities, and assessment tasks; AI-driven systems can operationalize this alignment by dynamically adapting tasks and feedback to reflect specific cognitive and skill-level goals (Biggs & Tang, 2011). Moreover, principles of heutagogy or self-determined learning, highlight how GenAI tools can empower students to take greater agency over their learning trajectories, using AI feedback to set personal goals, experiment with coding strategies, and reflect on performance (Blaschke, 2012), Embedding GenAI within these established frameworks thus reinforces pedagogical coherence, ensuring that technological innovation continues to serve educational purpose and cognitive development rather than mere automation. The future of computer science assessment lies at the intersection of human expertise and machine intelligence. GenAI presents an opportunity to move beyond efficiency and automation toward assessments that are adaptive, reflective, and deeply aligned with the goals of higher education. Achieving this vision will require sustained critical inquiry, collaborative innovation, and a principled commitment to student-centred learning.

Conclusion

The integration of GenAI into computer science education represents one of the most significant technological and pedagogical shifts in recent decades. As demonstrated throughout this paper, GenAI holds immense promise in transforming how assessments are designed, delivered, and interpreted. It offers scalable, personalized, and dynamic solutions to the longstanding challenges of large cohorts, diverse learner needs, and rapidly evolving curricular content. From intelligent tutoring systems and automated code feedback to interactive oral assessments and learning analytics dashboards, AI-powered tools are reshaping not only assessment practices but also the broader pedagogical landscape of computing education.

Yet, the adoption of GenAI must not be equated with uncritical technological optimism. This paper has underscored that along with opportunity comes responsibility. The ethical challenges posed by AI such as algorithmic bias, academic integrity, data privacy, and transparency, demand a proactive and interdisciplinary response. Without such vigilance, the automation and efficiency gains of GenAI risk reinforcing inequities, eroding trust, and displacing the human values at the core of effective education. AI cannot and should not replace the relational, contextual, and ethical dimensions of teaching and learning. Rather, it should augment educators' capacities to foster critical thinking, mentorship, and inclusivity.

The absence of a pedagogically grounded framework to guide the integration of GenAI into assessment practices further complicates these dynamics. A comprehensive framework is urgently needed, which enshrines the principles of fairness, transparency, human oversight, and educational validity. This framework must align AI tools with pedagogical theories such as constructivism, heutagogy, and entangled pedagogy, which recognize the co-constitutive relationship between technology, teaching methods, and learner agency. It must also incorporate mechanisms for participatory design, ethical governance, and continuous professional development to support educators in this evolving role. Looking ahead, the future of computer science assessment will be shaped by how educators, researchers, institutions, and policymakers collectively respond to the dual imperatives of innovation and responsibility. Professional development initiatives must prioritize AI literacy for both staff and students. Institutions must invest in digital infrastructure, inclusive policies, and mechanisms for ethical oversight. Developers must engage educators in co-creating tools that reflect real-world pedagogical needs. And researchers must continue to evaluate the long-term impact of GenAI on learning outcomes, equity, and academic culture.

This paper contributes to that ongoing discourse by highlighting both the promise and the complexity of GenAI in computer science education. It offers critical insights into how AI can be leveraged to support more authentic, engaging, and personalized assessments, while cautioning against reductionist, dehumanized models of learning. GenAI, when aligned with principled educational frameworks and driven by collaborative human judgment, has the capacity to empower, but not replace educators and learners alike. In conclusion, the challenge before us is not merely technical but philosophical and pedagogical. It is about deciding what kind of learning we want to cultivate, what values we wish to uphold, and how we envision the future of education in an AI-mediated world. GenAI offers powerful tools, but it is through deliberate, ethical, and critically informed use that these tools can truly serve education's higher purpose: not just to assess what students know, but to support who they are becoming.

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