AI IN PROGRAMMING EDUCATION: ADAPTIVE LEARNING SYSTEMS VS. TRADITIONAL TEACHING MODELS

by

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AI in programming education: adaptive learning systems vs. traditional teaching models

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Abstract

Artificial Intelligence (AI) is reshaping programming education through adaptive learning systems that personalize content, offer immediate feedback, and support self-paced learning. In contrast, traditional teaching models emphasize structured instruction, direct supervision, and collaborative learning. This narrative literature review examines key themes, including student engagement, academic performance, educator perceptions, and implementation challenges. While AI enhances engagement through personalized pathways, it lacks the hands-on mentorship and social interaction of traditional methods. Adoption challenges include technical barriers, educator resistance, ethical concerns, and financial constraints related to scalability. A hybrid learning model integrating AI adaptability with human instruction presents a balanced solution. This study offers insights for educators, researchers, and decision-makers, addressing implementation barriers, ethical considerations, and future research directions.

Keywords: Artificial Intelligence in Education, Adaptive Learning Systems, Traditional Teaching Models, Programming Education, Hybrid Learning Approaches

Introduction

Background

Artificial Intelligence is reshaping programming education through adaptive learning systems that personalize instruction, provide immediate feedback, and support diverse learning needs (Dutta et al., 2024; Ezzaim et al., 2024). While AI promotes flexibility and efficiency, traditional teaching models remain vital for offering structured guidance, direct supervision, and collaborative learning (Bagai & Mane, 2023). Although AI systems enable adaptable learning pathways and personalized progress tracking (Zhai et al., 2021), concerns persist regarding reduced mentorship, limited social interaction, and over-reliance on automated feedback (Becker et al., 2022). Adoption is further complicated by technical challenges like software reliability, curriculum integration, algorithmic biases (Cheng & Wang, 2023), and ethical concerns related to privacy and data security (Eden et al., 2024). Educator resistance and financial constraints, specifically in underfunded institutions (Ma et al., 2024), also limit seamless integration. This narrative literature review explores key factors, including student engagement, academic performance, educator perceptions, and implementation challenges. It also examines the potential of hybrid learning models that integrate AI with human instruction, aiming to enhance educational outcomes while addressing key barriers and ethical concerns.

Problem Statement

Despite the growing use of AI-driven adaptive learning systems in programming education, there is limited understanding of how these systems compare to traditional teaching models in terms of student engagement, learning outcomes, and accessibility (Ezzaim et al., 2024). Challenges include reduced instructor guidance, over-reliance on automation, and limited opportunities for collaborative learning (Becker et al., 2022). Educators face difficulties with curriculum integration, software reliability, and addressing algorithmic biases (Cheng & Wang, 2023). Broader concerns include data privacy, security, and the financial burden of implementing AI systems, especially in underfunded institutions (Eden et al., 2024; Ma et al., 2024). Addressing these challenges is essential to ensure that AI complements and enhances traditional teaching models.

Purpose of the Study

The purpose of this study is to critically analyze and synthesize existing research on AI-driven adaptive learning systems and traditional teaching models in programming education. It aims to evaluate the strengths and limitations of each approach by examining student engagement, academic performance, educator perceptions, and implementation challenges. Findings will inform curriculum development and pedagogical strategies, emphasizing solutions that address both technical and ethical challenges. Additionally, this research will explore the feasibility and effectiveness of hybrid learning models that combine AI adaptability with human instruction. The goal is to provide practical recommendations for enhancing educational effectiveness, supporting educator adoption, and ensuring equitable access while addressing broader concerns about sustainability and ethical concerns in diverse educational contexts.

Research Questions

RQ1: How do AI-driven adaptive learning systems influence student engagement and performance in programming education compared to traditional teaching models?

RQ2: What are educators' perceptions regarding the effectiveness and implementation of AI-powered adaptive learning systems compared to traditional teaching models in programming education.

RQ3: What challenges and limitations are associated with adopting AI-driven adaptive learning systems in programming education, specifically:

- Technical challenges: How do software reliability, system integration, and algorithmic biases impact implementation?
- Educator resistance: How do concerns over loss of instructional control and the need for extensive training affect AI adoption?
- Privacy and ethical concerns: What are the risks associated with student data privacy, security, and algorithmic fairness?

Research Objectives

This study analyzes AI-driven adaptive learning systems in programming education, comparing their effectiveness to traditional models through a narrative literature review. It examines AI's impact on student engagement, academic performance, and educators' perceptions of effectiveness, implementation, and instructional practices. Key adoption barriers include technical limitations, educator resistance, ethical concerns, and financial and scalability challenges, specifically in underfunded institutions. The study also explores the feasibility of a hybrid learning model that integrates AI adaptability with human instruction to enhance outcomes while addressing implementation barriers and ensuring equitable access.

Review of the Literature

Introduction

The integration of AI into programming education presents both opportunities and challenges compared to traditional teaching models. Traditional approaches emphasize structured engagement, hands-on learning, and direct instructor guidance, while AI-driven adaptive systems offer personalized instruction, real-time feedback, and scalability. As educational institutions adopt AI technologies, understanding their impact on student engagement, academic performance, educator perceptions, and implementation challenges is essential. This narrative literature review examines these four thematic areas, providing an in-depth analysis of AI's strengths and limitations. The findings aim to inform the development of hybrid learning models that integrate AI adaptability with human instruction, enhancing learning outcomes while addressing implementation barriers.

Traditional Approaches to Student Engagement

Traditional programming education emphasizes structured engagement through instructor-led lectures, hands-on coding exercises, and collaborative discussions. Instructors facilitate active learning by guiding students through live coding, peer programming, and structured problem-solving activities (Carbonaro, 2019; Su et al., 2017). This approach promotes deeper learning by encouraging students to actively engage with coding challenges, develop problem-solving skills, and enhance conceptual understanding (Handur et al., 2016; Munna & Kalam, 2021). Collaborative discussions and peer learning further reinforce critical thinking and social interaction (Miao et al., 2022). However, large class sizes and time constraints can limit personalized feedback, while standardized curricula may hinder adaptability for students needing additional practice (Almusaed et al., 2023; Mirata et al., 2020).

AI-Driven Learning and Student Engagement

AI-driven adaptive learning platforms enhance engagement through personalized instruction, real-time feedback, and gamification (El-Sabagh, 2021; Troussas et al., 2021). These AI programs adjust content based on student progress, helping learners remain appropriately challenged (Goel, 2020). For example, Harvard's CS50 Duck AI tutor provided 24/7 debugging support, code explanations, and style suggestions to over 211,000 students, with 75% frequently using the tutor and 94% finding it effective in improving engagement (Liu et al., 2025). Platforms like Blackboard, Moodle, Coursera, and edX further support engagement through AI-driven features like automated grading and chatbot assistance (Saqr et al., 2024). These platforms help instructors identify disengaged learners and adjust instructional delivery in real-time, enhancing personalized support (Saqr et al., 2024). However, reduced opportunities for peer collaboration and instructor feedback raise concerns about over-reliance on AI, which can lead to shallow learning experiences (Becker et al., 2022; Ouyang & Zhang, 2024).

Engagement in Hybrid Learning Models

Hybrid models that combine AI personalization with instructor-led collaboration offer a balanced approach. Almusaed et al. (2023) found that students in hybrid environments, where AI-generated feedback was supplemented by instructor-facilitated discussions, reported higher engagement and improved conceptual understanding. These models leverage AI for adaptive content delivery while retaining human mentorship for collaborative problem-solving and guidance (Handur et al., 2016; Munna & Kalam, 2021). Educators can utilize AI-driven analytics to identify disengaged learners and provide targeted interventions, reducing over-reliance on AI-generated feedback (Eden et al., 2024). Hybrid approaches ensure that students benefit from both personalized AI instruction and the depth of traditional engagement (Miao et al., 2022). The key findings and challenges related to student engagement are presented in Table 1.

Table 1: Student Engagement in Programming Education

Theme	Sub-Category	Findings	Supporting Studies	Implications	Implementation Challenges
Traditional Teaching Models	Instructor-led Engagement	Hands-on learning, instructor mentorship, and structured problem-solving promote deeper engagement but lack adaptability to individual learning needs.	(Bagai & Mane, 2023; Carbonaro, 2019; Cheng & Wang, 2023)	Encourages collaborative learning but may not scale well in large classrooms.	Difficulty in personalizing instruction in large classes.
AI-Driven Adaptive Learning	Personalized Feedback	AI enables personalized study paths, gamification, and real-time feedback but limits peer collaboration and hands-on engagement.	(El-Sabagh, 2021; Liu et al., 2025; Saqr et al., 2024)	Provides flexibility but risks reduced critical thinking and social learning opportunities.	High technical requirements, lack of peer interaction, and dependency on technology.
Hybrid Learning	Blended Engagement	Combines AI efficiency with instructor-led collaboration, improving engagement and retention.	(Almusaed et al., 2023; Handur et al., 2016; Miao et al., 2022)	Maximizes benefits of both models, allowing adaptability and mentorship.	Complexity in blending AI tools with traditional teaching, requiring balanced

Analysis of Student Engagement

Traditional instruction excels in fostering engagement through structured collaboration and immediate feedback, promoting critical thinking and deeper learning (Carbonaro, 2019; Miao et al., 2022). However, limitations in scalability and adaptability restrict its ability to offer personalized instruction (Mirata et al., 2020).

AI-driven platforms enhance engagement by providing self-paced, personalized learning experiences and instant feedback, allowing students to progress at their own speed (Goel, 2020; Liu et al., 2025). Yet, the absence of human interaction and social collaboration may lead to surface-level learning and over-reliance on automated suggestions (Ouyang & Zhang, 2024).

Hybrid models address these limitations by integrating AI's adaptability with instructor mentorship and peer collaboration (Almusaed et al., 2023; Eden et al., 2024). These models offer both personalized feedback and deeper, socially interactive learning experiences. However, their success depends on balancing AI's efficiency with meaningful human oversight. Over-reliance on AI risks shallow engagement, while excessive instructor control may reduce the flexibility and scalability of AI platforms (Miao et al., 2022).

Future Implications of Student Engagement

To refine hybrid engagement models, future research should explore strategies that balance AI-driven personalization with instructor-led collaboration, ensuring that students receive both adaptive content and critical mentorship. Research is also needed to develop AI systems that promote critical thinking while minimizing over-reliance on automated feedback. Additionally, AI platforms should incorporate features that encourage group discussions and peer collaboration, ensuring that the social dimensions of learning are preserved (Becker et al., 2022; Saqr et al., 2024). Addressing these considerations will be essential for developing hybrid models that enhance engagement while maintaining the depth and social benefits inherent in traditional education.

Research Gaps in Student Engagement

Current research lacks sufficient depth of how traditional engagement strategies can be enhanced with AI-driven adaptive technologies (Almusaed et al., 2023; Zhai et al., 2021). Limited studies have examined how students transition between AI-driven and instructor-led learning, specifically concerning how these transitions affect long-term engagement and learning outcomes (Ma et al., 2024; Tetzlaff et al., 2021). Future research should focus on refining hybrid models to ensure they balance technological efficiency with meaningful human mentorship and social learning experiences.

Traditional Approaches to Academic Performance

Traditional programming instruction follows a structured, sequential approach, ensuring students master foundational concepts before advancing to complex logic (Goel, 2020). Instructor-led environments provide direct feedback, personalized mentorship, and structured debugging sessions that promote deeper conceptual understanding (Seeling, 2016; Sheakley et al., 2019). Techniques such as active recall through whiteboard discussions and collaborative problem-solving reinforce long-term retention (Munna & Kalam, 2021). Scaffolding further supports learning by introducing complex concepts gradually (Bliss et al., 1996; Puntambekar, 2022). This approach not only helps students solve programming challenges but also strengthens logical reasoning skills essential for long-term proficiency (Miao et al., 2022). However, traditional teaching faces scalability limitations. Large class sizes and time constraints often prevent instructors from personalizing instruction to meet individual needs (Mirata et al., 2020). Students who struggle with the pace of instruction may find it challenging to keep up, specifically in standardized curriculum environments (Tetzlaff et al., 2021). This lack of adaptability can hinder students who require additional practice before advancing to complex concepts.

AI-Driven Learning and Academic Performance

AI-driven learning systems enhance performance by adapting instruction to individual progress and providing real-time feedback (El-Sabagh, 2021; Goel, 2020). Tools like automated debugging assistants and interactive coding exercises enable students to identify and correct errors in real-time, reinforcing problem-solving skills (Cheng & Wang, 2023). Harvard's CS50 Duck AI tutor, used by over 211,000 students, demonstrated improved learning efficiency, with 75% of students frequently using it and 94% finding it effective (Liu et al., 2025). However, concerns arise about over-reliance on AI-generated solutions, reducing problem-solving autonomy (Liu et al., 2025). To mitigate this, Harvard integrated teaching assistants to review AI responses, ensuring pedagogical quality (Liu et al., 2025). While AI enhances short-term performance, it may hinder deep learning and retention, especially if students become overly dependent on automated hints (Cambaz & Zhang, 2024; Cody et al., 2022; Lu, 2021). AI systems also lack structured scaffolding, which is critical for guiding students through complex concepts (Puntambekar, 2022).

Hybrid Models for Optimal Learning Outcomes

Hybrid learning models that integrate AI-driven feedback with instructor-led support offer a balanced approach. Almusaed et al. (2023) found that students engaged in AI-generated coding challenges, supplemented by instructor walkthroughs, achieved higher final exam scores and improved conceptual understanding. Similarly, platforms like Coursera and edX have successfully piloted hybrid courses where AI analytics help instructors tailor interventions, ensuring that struggling students receive immediate feedback and follow-up instruction (Saqr et al., 2024). These models capitalize on AI's efficiency in delivering personalized feedback while preserving human depth through mentorship (Becker et al., 2022). Educators can utilize AI-generated analytics to track performance trends, enabling timely interventions for students who fall behind (Tetzlaff et al., 2021). Additionally, hybrid models promote critical thinking by encouraging students to validate AI feedback through instructor-led discussions and problem-solving exercises (Handur et al., 2016). However, the balance between AI autonomy and instructor guidance requires refinement. While AI facilitates immediate problem-solving, instructor involvement is crucial for reinforcing higher-order reasoning and conceptual depth (Puntambekar, 2022). Hybrid models must be designed to ensure AI feedback complements, rather than replaces, deep learning facilitated by human instruction. The key findings and challenges related to academic performance are presented in Table 2.

Table 2: Academic Performance in Programming Education

Theme	Sub-Category	Findings	Supporting Studies	Implications	Challenges
Academic Performance	Conceptual Understanding	Structured exercises and instructor guidance improve conceptual understanding and long-term retention but struggle with scalability.	(Bliss et al., 1996; Seeling, 2016; Sheakley et al., 2019)	Supports strong conceptual foundations but may not accommodate diverse pacing needs.	Limited personalized support in large classrooms.
Academic Performance	Immediate Feedback	AI provides instant feedback and adapts to learning speeds, but over-reliance on automated hints can hinder independent problem-solving.	(Cambaz & Zhang, 2024; Crawford et al., 2024; Goel, 2020)	Increases efficiency but may reduce deep learning and critical thinking development.	Dependency on AI may weaken independent learning and long-term retention.
Academic Performance	Blended Assessment	AI tools enhance efficiency, while instructor intervention ensures deeper learning and problem-solving development.	(Almusaed et al., 2023; Becker et al., 2022)	Balances efficiency with conceptual depth, ensuring better retention and learning outcomes.	Requires coordination between AI systems and instructor feedback.

Analysis of Academic Performance

Traditional instruction fosters conceptual depth and critical thinking but struggles with scalability and personalization (Mirata et al., 2020). It excels in providing structured mentorship, scaffolding, and real-time feedback, which are essential for long-term retention (Munna & Kalam, 2021; Seeling, 2016).

AI-driven systems enhance immediate learning outcomes through adaptive, real-time feedback but risk reducing problem-solving autonomy and deep learning (Cambaz & Zhang, 2024; Goel, 2020). The absence of structured scaffolding in AI models may lead to shallow learning experiences if students rely too heavily on automated hints (Puntambekar, 2022).

Hybrid models mitigate these challenges by combining AI adaptability with structured mentorship, enhancing both short-term performance and long-term retention (Almusaed et al., 2023; Eden et al., 2024). Successful hybrid designs encourage students to engage with AI-generated feedback while validating solutions through instructor-led discussions. However, achieving this balance requires ongoing refinement to ensure AI tools promote, rather than hinder, deeper learning (Becker et al., 2022).

Future Implications of Academic Performance

Future research should explore how hybrid models can better balance AI feedback with instructor guidance to enhance both critical thinking and long-term retention. AI systems should be designed to provide scaffolded learning pathways, where feedback complexity increases alongside student proficiency (Puntambekar, 2022). Additionally, instructors should be equipped to interpret AI-generated analytics for timely interventions, ensuring deeper cognitive engagement. Research should also investigate how AI systems can prompt students to reflect on their solutions, encouraging critical thinking and reducing over-reliance on automated responses (Becker et al., 2022; Saqr et al., 2024). Finally, exploring how to integrate complex problem-solving challenges into AI platforms could enhance deeper learning in programming education.

Research Gaps in Academic Performance

Current research lacks sufficient insight into how students transition between AI-driven feedback and instructor-led reinforcement, specifically regarding how these transitions impact retention and higher-order thinking (Tetzlaff et al., 2021). There is also limited exploration of how AI systems can incorporate structured scaffolding to guide students through complex problem-solving (Puntambekar, 2022). Moreover, the role of instructors in interpreting AI analytics and designing interventions remains under-researched. Future studies should focus on how instructors can better leverage AI insights to guide deeper learning and how hybrid models can evolve to encourage sustained critical thinking.

Scalability Challenges in Traditional Teaching

Traditional programming instruction struggles with scalability, specifically in large classroom settings where providing individualized attention becomes challenging (Mirata et al., 2020). Fixed curricula limit flexibility, making it difficult to accommodate diverse learning paces (Tetzlaff et al., 2021). Additionally, manual feedback and assessment methods contribute to delays in progress tracking, especially in distance learning contexts where asynchronous coursework reduces opportunities for immediate feedback (Miao et al., 2022; Munna & Kalam, 2021). Despite these challenges, traditional instruction offers structured mentorship and interactive problem-solving experiences, which enhance engagement and conceptual understanding (Krusche & Berrezueta-Guzman, 2023). However, maintaining personalized attention in large classes remains a significant obstacle (Yan et al., 2024).

AI-Driven Approaches to Scalability

AI-driven learning platforms enhance scalability by automating grading, providing real-time feedback, and personalizing learning pathways (El-Sabagh, 2021). Machine learning algorithms assess student progress and adjust content delivery, ensuring learners receive tailored instruction (Goel, 2020). Platforms like Coursera and edX successfully leverage AI to manage large student cohorts while maintaining personalized learning experiences (Cheng & Wang, 2023). AI chatbots and virtual tutors offer on-demand assistance, allowing educators to focus on higher-order problem-solving (Mirata et al., 2020). However, AI models can struggle with curriculum integration, instructor oversight, and reliability. Misinterpretation of AI feedback and limited infrastructure pose significant barriers, especially for underfunded institutions (Almusaed et al., 2023; Yan et al., 2024).

Hybrid Models Balancing Scalability and Instructor Engagement

Hybrid models offer a balanced solution, integrating AI's scalability with instructor-led engagement. AI-driven analytics support personalized assessments, while instructors provide mentorship and critical thinking development (Becker et al., 2022). Research suggests that combining AI-based grading with instructor-led discussions enhances both efficiency and engagement (Almusaed et al., 2023). Hybrid models also address AI's limitations by ensuring human oversight for complex tasks. However, further research is needed to evaluate the long-term effectiveness of these models, specifically in balancing scalability with depth of learning (Tetzlaff et al., 2021). The key findings related to scalability in programming education are presented in Table 3.

Table 3: Scalability Challenges in Programming Education

Theme	Sub-Category	Findings	Supporting Studies	Implications	Implementation Challenges
Scalability & Challenges	Traditional Teaching Models	Instructor feedback is valuable but time-consuming; large classes hinder personalized learning.	(Mirata et al., 2020; Tetzlaff et al., 2021)	Scalability issues require balancing structured instruction with efficient feedback mechanisms.	Difficult to manage personalized learning in large cohorts.
Scalability & Challenges	AI-Driven Adaptive Learning	AI scales well by automating grading and personalized content but lacks human oversight for nuanced learning needs.	(Cheng & Wang, 2023; El-Sabagh, 2021; Yan et al., 2024)	Supports scalability but risks depersonalizing learning.	Technical issues, algorithmic biases, and lack of oversight by instructors.
Scalability & Challenges	Hybrid Learning	AI-assisted grading and analytics optimize scalability while preserving instructor oversight.	(Almusaed et al., 2023; Becker et al., 2022)	Hybrid approaches can balance efficiency and personalization.	Coordination between technology and teaching staff for balanced integration and oversight.

Analysis of Scalability in AI-Driven and Traditional Teaching Models

AI-driven systems show significant potential in improving scalability through automation and adaptive learning pathways (El-Sabagh, 2021; Goel, 2020). However, reliance on AI introduces challenges, particularly when misinterpretation of automated feedback and limited infrastructure impede learning outcomes (Yan et al., 2024). Traditional teaching models, while limited in scalability, provide deeper mentorship and engagement (Krusche & Berrezueta-Guzman, 2023). Hybrid models present a potential solution by combining AI efficiency with human oversight, though these systems require careful integration to avoid undermining depth of learning (Becker et al., 2022). The success of scalable models hinges on balancing automation with human engagement and addressing infrastructure disparities (Almusaed et al., 2023).

Future Implications for Enhancing Scalability in Programming Education

Educational institutions must focus on developing scalable AI systems that incorporate adaptive learning while ensuring accessibility for underfunded environments (Cheng & Wang, 2023). Future AI solutions should be designed to promote collaborative and critical thinking skills, supplementing automated feedback with instructor-led mentorship (Becker et al., 2022). Institutions should invest in training for educators to effectively oversee AI systems and manage their integration into curricula (Yan et al., 2024). Developing policies that support infrastructure improvements will be crucial for equitable access to AI-driven education (Almusaed et al., 2023).

Identifying Research Gaps in Scalability for Programming Education

There is limited research on how to optimize hybrid models for both scalability and depth of learning over the long term (Tetzlaff et al., 2021). Additionally, few studies address strategies to ensure reliable AI feedback interpretation in diverse learning environments (Yan et al., 2024). More research is needed to explore how infrastructure limitations can be overcome in underfunded institutions while maintaining high-quality educational outcomes (Cheng & Wang, 2023).

Educator Perceptions in Traditional Teaching

Educators value the control and flexibility that traditional instruction provides, allowing them to tailor lessons, provide real-time feedback, and foster critical thinking (Ezzaim et al., 2024; Srivatanakul, 2023). Instructor-led learning encourages mentorship and engagement through debugging demonstrations and collaborative exercises (Becker et al., 2022). However, scalability remains a concern, as managing large classes and providing individualized feedback is challenging (Zhai et al., 2021).

Educator Perceptions on AI Integration

Educators' perceptions of AI are mixed. While some view AI as a tool for enhancing efficiency and engagement, others worry about losing instructional control and the ethical implications of algorithmic biases (Becker et al., 2022; Eden et al., 2024). Concerns include AI's potential to limit personalized instruction, reinforce biases, and compromise data security (Zhai et al., 2021). Additionally, the technical demands of AI integration, including customization and reliability, contribute to educator hesitancy (Ezzaim et al., 2024).

Educator Perceptions on Hybrid Models

Hybrid models are generally viewed more favorably as they offer a balance between AI-driven efficiency and human-led mentorship. Educators appreciate the potential for AI to automate routine tasks while allowing them to focus on critical thinking and deeper learning strategies (Becker et al., 2022). However, concerns persist regarding the optimal balance between automation and human oversight, especially regarding ethical considerations and maintaining instructional quality (Almusaed et al., 2023). The key findings and challenges related to educator perceptions are presented in Table 4.

Table 4: Academic Perceptions in AI Integration

Theme	Sub-Category	Findings	Supporting Studies	Implications	Implementation Challenges
Educator Perceptions	Resistance to AI	Educators express concerns over loss of instructional control, data privacy, and AI biases.	(Becker et al., 2022; Eden et al., 2024; Zhai et al., 2021)	Faculty training programs are essential for AI adoption.	Lack of AI-specific training, concerns about job displacement, and AI accuracy.
Educator Perceptions	AI Integration in Teaching	Aome educators embrace AI for automating assessments but remain skeptical about its pedagogical value.	(Kaplan-Rakowski et al., 2023; Ma et al., 2024)	AI should complement, not replace, human instruction.	Resistance due to perceived loss of control over teaching processes and AI's pedagogical role.
Educator Perceptions	Hybrid Learning Acceptance	Hybrid models offer a balanced approach that allows AI to enhance rather than replace educator roles.	(Almusaed et al., 2023; Becker et al., 2022)	Effective integration requires clear strategies for balancing automation and instructor input.	Reluctance from educators to accept a new role of AI integration and ongoing chan

Analysis of Educator Perceptions

Educators appreciate the control and adaptability offered by traditional teaching methods, especially in fostering mentorship and critical thinking (Becker et al., 2022). However, scalability limitations present a challenge in larger classroom settings (Zhai et al., 2021). On the other hand, while AI systems enhance efficiency and provide scalable solutions, concerns about loss of control, ethical considerations, and the reliability of AI-generated feedback persist (Eden et al., 2024). Hybrid models offer a potential solution by allowing educators to maintain control over complex teaching tasks while leveraging AI for routine processes, though these models require careful balance (Almusaed et al., 2023).

Future Implications of Educator Perceptions

Future research should focus on developing strategies that empower educators to integrate AI systems confidently. Training programs should be designed to simplify AI adoption and equip instructors with the skills needed to interpret AI analytics and provide timely, personalized interventions (Kaplan-Rakowski et al., 2023). Institutions should also explore hybrid models that enhance, rather than diminish, educators' roles by promoting AI as a supportive tool rather than a replacement (Becker et al., 2022). Ensuring that AI systems are adaptable and reliable will be critical for long-term integration success (Eden et al., 2024).

Identifying Research Gaps in Educator Perceptions

There is limited research on how long-term exposure to AI systems impacts educator perceptions and teaching practices (Zhai et al., 2021). More studies are needed to explore effective professional development programs that ease AI integration and address technical challenges (Ma et al., 2024). Further research should also investigate strategies for reducing ethical concerns related to AI biases and ensuring that AI-driven systems enhance rather than diminish the human elements of teaching (George, 2023).

Implementation Challenges

While scalability and educator perceptions provide critical insights into the complexities of AI adoption, broader implementation challenges—ranging from technical barriers to ethical considerations—must also be addressed to ensure the successful integration of AI-driven adaptive learning systems (Cheng & Wang, 2023; Eden et al., 2024). Despite the potential benefits, several significant implementation challenges—such as technical infrastructure, algorithmic bias, and educator readiness—can hinder the successful adoption and integration of AI in educational settings (Kaplan-Rakowski et al., 2023; Ma et al., 2024). Addressing these barriers is essential to ensure equitable, effective, and sustainable AI integration (Almusaed et al., 2023; Zhai et al., 2021).

Technical Barriers in AI Implementation

AI systems depend on robust software reliability, advanced IT infrastructure, and seamless integration with existing curricula. Many institutions, specifically underfunded ones, face difficulties in maintaining and upgrading the necessary technological infrastructure, which can lead to system failures, delays in feedback, and inconsistent learning experiences (Cheng & Wang, 2023; Ma et al., 2024). Customization is also a major concern, as AI-driven platforms often require significant adjustments to align with specific institutional curricula and educational standards (Zhai et al., 2021). This customization adds to the workload for educators who must balance pedagogical goals with technological constraints.

Addressing Algorithmic Biases in AI Systems

AI-driven systems are susceptible to algorithmic biases, which can unintentionally reinforce inequalities and negatively impact marginalized student groups. Biases can stem from training data that does not accurately represent diverse student populations, leading to skewed learning recommendations or inaccurate assessments (Eden et al., 2024; Zhai et al., 2021). These biases may result in unfair grading, misaligned learning pathways, and decreased student trust in AI systems. To mitigate this, continuous refinement of algorithms and rigorous bias detection measures are necessary to ensure fairness and inclusivity in AI-assisted learning.

Ensuring Data Privacy and Security in AI Integration

The ethical handling of student data is a significant concern in AI integration. AI platforms process large volumes of sensitive data, raising concerns about security breaches and ethical management. Institutions must comply with data privacy regulations such as GDPR and FERPA to ensure that student information is protected (Ezzaim et al., 2024; Gligorea et al., 2023). Moreover, AI-generated analytics must be handled responsibly to avoid misuse. Institutions should develop comprehensive AI governance frameworks and enforce strict data protection policies to ensure ethical data management and maintain student trust.

Overcoming Financial Barriers for AI Adoption

The financial costs associated with implementing AI-driven platforms present significant challenges, specifically for underfunded institutions. Expenses related to purchasing, maintaining, and upgrading AI systems, along with associated infrastructure, can be prohibitive (Almusaed et al., 2023; Ma et al., 2024). These financial constraints contribute to unequal access to AI-enhanced education, exacerbating educational disparities. To mitigate these challenges, policymakers and institutions should explore options such as government subsidies, grants, and open-source AI solutions to promote equitable access across diverse educational settings.

Educator Readiness for AI Integration

One of the most significant challenges in AI integration is the time and training required to implement these technologies into existing educational platforms (Lee & Perret, 2022). Many educators lack the technical expertise necessary to effectively utilize AI-driven tools, making adoption a slow and resource-intensive process (Ma et al., 2024). Faculty members must undergo extensive training to understand how AI-generated analytics function, how to interpret student progress data, and how to intervene effectively when AI systems fail to address student needs (Kaplan-Rakowski et al., 2023). Additionally, AI-driven platforms often require customization to align with institutional curricula, creating an additional workload for educators who must balance pedagogical goals with technological constraints (Zhai et al., 2021). Software reliability issues further exacerbate these challenges, as educators frequently struggle with platform malfunctions, inaccurate assessments, and limited adaptability in AI-based tools (Eden et al., 2024). These difficulties illustrate the gap between AI's potential and its practical implementation, underscoring the need for continued improvements in AI infrastructure and educator training programs. The key findings and challenges related to implementation challenges in AI integration are presented in Table 5.

Table 5: Implementation Challenges in AI Integration

Theme	Sub-Category	Findings	Supporting Studies	Implications	Implementation Challenges
Technical Barriers	Infrastructure & Customization	I systems require robust software, strong IT infrastructure, and seamless curriculum integration. Customization adds to educator workload.	(Cheng & Wang, 2023; Ma et al., 2024; Zhai et al., 2021)	Institutions must invest in reliable infrastructure and provide customization support.	High costs, system failures, and integration complexities delay adoption.
Algorithmic Biases	Equity & Fairness	AI systems can unintentionally reinforce biases, affecting marginalized groups through skewed recommendations or assessments.	(Eden et al., 2024; Zhai et al., 2021)	Continuous algorithm refinement and bias detection are necessary to ensure fair and inclusive AI learning.	Risk of reinforcing inequities, reducing trust, and creating unfair learning pathways.
Data Privacy & Security	Ethical Management	AI platforms process sensitive student data, raising privacy and ethical concerns. Institutions must comply with GDPR and FERPA regulations.	(Ezzaim et al., 2024; Gligorea et al., 2023)	Institutions should develop AI governance frameworks and strict data protection policies.	Risks of security breaches and data misuse; need for ethical and legal compliance.
Cost and Accessibility	Financial Constraints	Implementing AI systems is costly, posing accessibility challenges for underfunded institutions.	(Almusaed et al., 2023; Ma et al., 2024)	Governments and institutions should explore grants and subsidies to make AI accessible.	Financial barriers create a digital divide and hinder equal access to AI-enhanced learning.
Educator Training & Readiness	Technical Readiness	Educators often lack the technical skills required for effective AI adoption, leading to resistance and integration difficulties.	(Kaplan-Rakowski et al., 2023; Lee & Perret, 2022)	Institutions need to establish continuous professional development programs focused on AI integration.	Resistance due to lack of training, perceived complexity, and increased workload.

Analysis of Implementation Challenges

Technical barriers such as unreliable infrastructure, the need for platform customization, and integration difficulties significantly impede AI adoption (Zhai et al., 2021). Ethical concerns around algorithmic biases and data security complicate trust in AI systems (Eden et al., 2024). Financial constraints further limit accessibility, contributing to inequalities in educational opportunities (Ma et al., 2024). Educator readiness also presents a major challenge, as many instructors lack the technical expertise needed for AI adoption, resulting in hesitancy and resistance (Lee & Perret, 2022). These layered challenges highlight the complexity of successful AI implementation and underscore the need for strategic planning, strong infrastructure, and educator support systems.

Future Implications of AI Implementation

To overcome implementation challenges, institutions should prioritize investments in infrastructure, especially for underfunded environments (Almusaed et al., 2023). Development of reliable, adaptable AI platforms that integrate smoothly with existing curricula will be critical (Cheng & Wang, 2023). Training programs should be established to build educators' technical skills and foster confidence in AI integration (Kaplan-Rakowski et al., 2023). Policies for ethical data management and algorithm refinement must also be developed to mitigate biases and ensure student privacy (Ezzaim et al., 2024). Collaborative efforts involving policymakers, educators, and technologists will be essential to support sustainable and equitable AI adoption.

Identifying Research Gaps in AI Implementation

There is limited research on how to develop AI systems that are both adaptable and accessible for underfunded institutions (Ma et al., 2024). More studies are needed on effective professional development models for equipping educators with the skills needed for AI integration (Lee & Perret, 2022). Additionally, research should focus on refining algorithmic fairness and data privacy strategies to enhance ethical AI adoption (Eden et al., 2024). Future studies could also explore scalable financial solutions to promote equitable access to AI-driven education (Almusaed et al., 2023).

Methodology

This study employs a narrative literature review to compare AI-driven adaptive learning systems with traditional teaching models in programming education. A narrative review was chosen over a systematic review because it allows for a broader synthesis of qualitative and mixed-methods research, providing flexibility in analyzing conceptual themes and emerging trends (Baumeister & Leary, 1997; Siddaway et al., 2019). Systematic reviews follow a strict inclusion protocol focused on quantitative data, whereas a narrative approach better captures pedagogical implications and faculty/student perceptions in AI-enhanced education (Moher et al., 2009). A structured search strategy was applied using Google Scholar, EBSCO Host, IEEE Xplore, and ACM Digital Library with search terms such as "AI-driven adaptive learning," "programming education," and "traditional teaching models." The study included peer-reviewed articles from the last ten years while excluding sources focused on K-12 education, non-programming disciplines, or opinion-based pieces (Siddaway et al., 2019). Thematic analysis was conducted using Braun and Clarke's (2006) six-step framework, categorizing findings into student engagement, academic performance, scalability and accessibility, and educator perceptions. Research validity was improved by using multiple sources and only including peer-reviewed studies. The findings provide a comprehensive synthesis of AI's impact on programming education, identifying key trends, benefits, limitations, and research gaps to inform future strategies in higher education.

Results, and Analysis

The findings from this narrative literature review reveal significant insights into how AI-driven adaptive learning systems and traditional teaching models influence programming education, specifically regarding student engagement, academic performance, scalability, and educator perceptions.

The research indicates that AI-driven adaptive learning systems significantly enhance student engagement by providing personalized instruction, real-time feedback, and adaptive learning pathways (El-Sabagh, 2021; Goel, 2020;). Platforms like Harvard's CS50 Duck AI tutor exemplify this approach by offering 24/7 support for debugging, code explanation, and style suggestions. With over 211,000 students utilizing the AI tutor and 10 million queries submitted, the system demonstrated high engagement levels, with 75% of students frequently using it and 94% finding it effective (Liu et al., 2025). AI systems also enhance scalability by accommodating large cohorts without compromising personalized instruction (Cheng & Wang, 2023). The ability to automate grading and provide instant feedback ensures that learners receive timely support, reducing dependency on instructor availability.

However, the analysis highlights critical limitations of AI-driven models. Despite their efficiency, these systems often lack the depth of social interaction, peer collaboration, and mentorship that traditional models offer (Becker et al., 2022). Students may become overly dependent on AI-generated suggestions, resulting in shallow learning and limited critical thinking development (Ouyang & Zhang, 2024). Furthermore, ethical concerns regarding algorithmic biases, data privacy, and software reliability complicate the widespread adoption of AI in education (Eden et al., 2024). These concerns are specifically pronounced in underfunded institutions, where access to advanced AI systems is limited (Almusaed et al., 2023).

In contrast, traditional teaching models excel in providing structured engagement, direct mentorship, and collaborative learning experiences (Carbonaro, 2019; Miao et al., 2022). Instructor-led discussions, live coding sessions, and peer collaboration promote deeper conceptual understanding and encourage critical thinking (Becker et al., 2022). Traditional approaches also offer the advantage of immediate feedback, allowing educators to clarify concepts in real-time and foster social learning (Miao et al., 2022). However, scalability remains a significant challenge. Large class sizes and time constraints limit the ability to provide personalized feedback, and the manual nature of grading can delay progress tracking (Mirata et al., 2020; Tetzlaff et al., 2021). Additionally, the fixed nature of traditional curricula may hinder adaptability, making it difficult to accommodate diverse learning needs.

Given these contrasting strengths and limitations, hybrid learning models emerge as a promising solution. These models leverage AI’s adaptive capabilities for routine tasks, such as automated feedback and analytics, while preserving human mentorship for more complex instructional elements (Almusaed et al., 2023). Research suggests that hybrid models enhance both engagement and performance by ensuring that students receive timely, personalized feedback while also benefiting from instructor-led discussions that foster deeper understanding (Becker et al., 2022). For instance, institutions that integrated AI-powered analytics with human intervention reported improved academic outcomes and reduced reliance on automated suggestions, promoting better critical thinking and retention (Eden et al., 2024). However, successful implementation of hybrid models requires careful planning to mitigate ethical concerns and ensure equitable access across diverse educational environments (Saqr et al., 2024).

Moreover, the findings underscore the importance of educator perceptions and training in facilitating AI adoption. While some educators view AI as a valuable tool for enhancing engagement and streamlining assessments, others express concerns about losing instructional autonomy and the potential for algorithmic biases to negatively impact learning outcomes (Zhai et al., 2021). Effective educator training programs are essential to address these concerns, equipping instructors with the skills to interpret AI-generated analytics and provide timely, meaningful interventions (Kaplan-Rakowski et al., 2023).

In conclusion, the analysis suggests that while AI systems offer substantial advantages in terms of engagement and scalability, they also pose risks related to shallow learning, ethical concerns, and educator resistance. Traditional teaching models, while strong in mentorship and critical thinking development, struggle with scalability and adaptability. Hybrid models, which integrate AI-driven efficiency with instructor-led engagement, offer the most promising approach for optimizing learning outcomes. However, further research is needed to refine these models, ensuring they balance technological efficiency with deep, meaningful learning experiences while addressing ethical and practical challenges.

Discussion of Findings

The findings of this study suggest that AI-driven adaptive learning systems enhance student engagement and scalability by providing personalized instruction, real-time feedback, and flexible learning pathways (El-Sabagh, 2021; Goel, 2020). These systems enable students to progress at their own pace, reducing the likelihood of disengagement (Cheng & Wang, 2023). AI's adaptability is specifically effective in large-class settings, where traditional teaching struggles to provide individualized attention (Mirata et al., 2020).

However, AI systems also present limitations. While they enhance immediate performance, they often lack the structured mentorship and interactive learning that traditional methods offer (Becker et al., 2022). This gap may result in shallow learning, with students over-relying on automated solutions and failing to develop critical thinking and problem-solving skills (Liu et al., 2025; Ouyang & Zhang, 2024). Traditional teaching, despite its strengths in fostering deeper conceptual understanding and social learning, faces scalability issues, especially when it comes to managing large student populations (Tetzlaff et al., 2021; Yan et al., 2024).

Hybrid models emerge as a promising solution by combining the efficiency of AI with the depth of instructor-led engagement (Almusaed et al., 2023). These models allow AI to handle routine feedback and assessments, while instructors focus on facilitating complex discussions and critical thinking activities (Becker et al., 2022). However, the successful implementation of hybrid models requires thought regarding ethical concerns, algorithmic biases, and the role of human oversight (Eden et al., 2024; Saqr et al., 2024).

Implications of Findings

The study's findings have theoretical, practical, and ethical implications for programming education. Theoretically, the research supports the integration of hybrid learning models that balance AI-driven adaptability with human instruction, ensuring that technology enhances rather than replaces the educator's role (Becker et al., 2022).

Curriculum development should prioritize adaptive models that personalize learning while maintaining opportunities for mentorship and critical thinking (Almusaed et al., 2023). Educator training programs are essential to help faculty with the skills to interpret AI-driven analytics and provide timely, informed interventions (Kaplan-Rakowski et al., 2023).

Institutions must address concerns related to data privacy, algorithmic fairness, and equitable access, specifically in underfunded institutions (Eden et al., 2024). Additionally, future strategies must ensure that AI systems are transparent and free from bias to foster ethical, inclusive learning environments (Zhai et al., 2021).

Integrating AI effectively requires thoughtful planning and resource allocation to ensure accessibility, reduce biases, and uphold instructional quality.

Conclusion

This study contributes to the understanding of AI-driven adaptive learning systems in programming education, specifically in comparison to traditional teaching models. While AI systems improve engagement and scalability through personalized learning and real-time feedback (El-Sabagh, 2021; Goel, 2020), they lack the depth of human interaction and critical mentorship inherent in traditional education (Becker et al., 2022; Liu et al., 2025).

Hybrid models offer a balanced approach, combining the strengths of both AI-driven personalization and instructor-led engagement (Almusaed et al., 2023). However, effective hybrid learning requires more analysis of ethical concerns, educator training, and curriculum integration (Eden et al., 2024).

This research contributes to the broader academic discourse by highlighting the potential of hybrid models to address current challenges in programming education, including scalability, engagement, and instructional depth. It also emphasizes the importance of ethical AI integration and calls for further research into sustainable, accessible, and effective learning solutions. This study enhances the understanding of how AI can be leveraged to support educational outcomes, while reinforcing the critical role of human oversight.

Limitations of the Study

This study is limited by its reliance on a narrative literature review, which restricts the ability to observe real-world applications and empirical data (Becker et al., 2022). The scope of the research is also confined to programming education, limiting generalizability to other disciplines. Additionally, the research is influenced by the quality and scope of the existing literature, which may include biases related to geographical regions, technological infrastructure, and cultural practices (Saqr et al., 2024).

Another limitation is the rapid evolution of AI technology, which could render some findings outdated (Cheng & Wang, 2023). Finally, the review is limited by potential publication bias, as studies reporting successful AI integrations may be overrepresented compared to studies highlighting failures.

To mitigate these limitations, future research should incorporate empirical studies, interviews with educators, and cross-disciplinary analyses to provide a more comprehensive understanding of AI's impact on education.

Recommendations for Future Research

Future research should focus on optimizing hybrid learning models to balance AI-driven scalability with human-led instruction, enhancing both engagement and deep learning outcomes (Almusaed et al., 2023).

Addressing ethical concerns is also essential, with studies needed to design AI systems that minimize biases, protect data privacy, and ensure equitable access, specifically in underfunded institutions (Eden et al., 2024).

Expanding educator training programs is critical to equip instructors with the skills to interpret AI analytics and provide effective interventions (Kaplan-Rakowski et al., 2023). Additionally, research should explore scalable strategies to improve AI accessibility in underfunded institutions without compromising learning quality (Saqr et al., 2024).

Longitudinal studies are necessary to assess how AI-driven education impacts long-term retention, critical thinking, and problem-solving skills (Cambaz & Zhang, 2024). Finally, refining strategies for transitioning between AI feedback and instructor guidance will ensure students effectively adapt and develop deeper learning skills (Becker et al., 2022).

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