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Integrating GAI tools and scaffolding-based learning to enhance learning outcomes in English-medium programming courses

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Abstract: This study explores the impact of integrating Generative AI (GAI) educational tools, such as Kahoot!, Slido, Notebook LM, and Visual Studio Code, with scaffolding-based learning in English-medium programming courses for first-year university students. The research aims to assess whether this hybrid teaching approach enhances students' learning outcomes, engagement, and learning continuity. A quasi-experimental design was employed, dividing participants into two groups: a control group utilizing traditional scaffolding methods and an experimental group integrating GAI tools alongside scaffolding techniques. Evaluation metrics included coursework performance, final project scores, student feedback surveys, and post-course learning continuation. The findings indicate that the experimental group outperformed the control group in programming achievements, exhibited higher satisfaction and engagement levels, and showed a greater propensity for continued learning. The key conclusion is that incorporating interactive digital tools and AI-assisted scaffolding mitigates learning barriers in English-taught programming courses, enhances student performance and confidence, and fosters long-term learning motivation. The study concludes with recommendations for future research, including expanding the sample size and analyzing long-term effects, while emphasizing the practical implications of this approach in bilingual education settings.
Keywords: *Generative AI in education, English-medium instruction, Programming education, Scaffolding-based learning.*

1. Introduction

With the rapid development of generative artificial intelligence (Generative AI, or GAI) tools, the field of education is increasingly exploring how such technologies can be applied to enhance teaching and learning outcomes (Yang, Hsu, & Wu, 2025; Zhu, Memarian, & Doleck, 2025). This trend is particularly evident in English-medium instruction (EMI) programming courses, where students not only grapple with complex programming concepts but also face language barriers. Research has shown that students learning programming in English often encounter significant challenges due to limited language proficiency (Patil, 2020; Zhu et al., 2025). Directly enhancing English skills is a long-term endeavor, and while switching to native language instruction may ease comprehension, it could hinder students' future competitiveness in an international context. Thus, with the growing prevalence of EMI courses in higher education, it is imperative to explore innovative strategies to improve learning outcomes.

Scaffolding-based learning emphasizes timely support and guidance from instructors, gradually withdrawing this assistance as students develop independent problem-solving skills. This concept, which originates from Vygotsky's theory of the Zone of Proximal Development (ZPD), highlights the role of knowledgeable guidance in enabling learners to achieve tasks beyond their current abilities (Wood, Bruner, & Ross, 1976). In programming education, scaffolding is typically implemented through problem decomposition, cues, and illustrative examples to reduce cognitive load and help students overcome learning challenges. On the other hand, GAI tools (such as ChatGPT, GitHub Copilot, and

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others) can offer real-time content generation and interactive assistance. Such tools are envisioned as a new kind of "knowledgeable other" that can provide personalized guidance and support. This study examines the integration of GAI tools with scaffolding strategies in EMI programming courses to alleviate language-related obstacles, enhance comprehension, and foster effective learning.

The primary aim of this research is to investigate the impact of integrating GAI tools with scaffolding-based learning on student outcomes in an English-medium programming course. Specifically, the study addresses the following questions: (1) Learning Outcomes: How do traditional scaffolding and GAI-assisted scaffolding compare in terms of classroom performance and final project scores? (2) Student Engagement: Does the integration of GAI tools enhance students' satisfaction and engagement levels? (3) Continued Learning: Can this hybrid approach promote autonomous, long-term learning behaviors after the course? The answers to these questions are intended to provide empirical evidence for optimizing programming education in bilingual contexts.

2.Literature Review

2.1. GAI Tools in Educational Settings

In recent years, the application of generative AI in education has surged. GAI models—especially large language models like ChatGPT—are capable of generating coherent text, code, or multimodal content based on prompts, making them promising intelligent tutoring assistants (Yang et al., 2025; Zhu et al., 2025). Studies have demonstrated that AI-driven learning platforms can scaffold students' learning by breaking down complex problems into manageable steps, aligning with the principles of educational scaffolding (Yang et al., 2025). By providing immediate feedback and targeted cues, these models can help learners gradually build knowledge while reducing cognitive overload. For instance, one survey among university students found that AI tutoring tools embedded within learning systems boosted students' confidence in asking questions and deepening their exploration of course materials (Mowreader, 2025). Moreover, instructors have noted that after incorporating AI support, students showed improved comprehension and better preparation for classes, thereby reducing the frequency of requests for assistance (Mowreader, 2025). Notably, about one-quarter of the students reported that over time they relied less on the AI tool as their own problem-solving skills improved. These findings suggest that when properly integrated, GAI tools can promote autonomous learning and enhance overall academic performance. However, the effectiveness of such integration hinges on sound instructional design; without proper guidance, simply providing answers may counteract learning benefits (Yang et al., 2025).

2.2. Scaffolding-Based Learning

Scaffolding-based learning is rooted in Vygotsky's theory, which stresses the importance of providing "just enough support" within a learner's ZPD to enable the accomplishment of tasks that would otherwise be unattainable (Wood et al., 1976). By gradually removing this support as competence develops, learners eventually achieve independence in their learning. Early work by Wood et al. (1976) introduced the metaphor of "scaffolding" to describe this gradual transfer of responsibility from teacher to student. Numerous studies have confirmed the positive effects of scaffolding on learning outcomes. For example, a meta-analysis of online higher education revealed that appropriate scaffolding significantly improves student performance (Doo, Bonk, & Heo, 2020). Scaffolding not only supports cognitive domain learning but also enhances metacognitive skills and motivational factors. In practice, teachers employ techniques such as segmented instruction, guided questioning, worked examples, and timely feedback to achieve these outcomes. With the increasing integration of technology in education, digital tools and intelligent systems have begun to serve as scaffolding supports (Yang et al., 2025). Adaptive learning systems, for instance, can tailor cues and prompts based on individual student responses, while intelligent tutoring systems like Auto Tutor detect comprehension gaps and provide tailored guidance. However, one limitation of traditional scaffolding is its challenge in delivering personalized support in large classes—a gap that GAI tools are well-suited to address by acting as individualized "tutors" within the scaffolding framework.

2.3. Challenges of English-Medium Programming Courses

In EMI environments, where students' native language is not the language of instruction, the added burden of language proficiency can hinder effective learning in technical subjects like programming. Programming courses are inherently abstract and challenging; when the language of instruction is English, students must simultaneously decode technical content and navigate unfamiliar linguistic territory (Patil, 2020). For instance, a study in India highlighted that student whose first language was not English struggled significantly with programming courses taught in English (Patil, 2020). Researchers have noted that the dual challenge of understanding technical terms in a second language increases cognitive load and impedes effective learning. Traditional strategies to mitigate these challenges have included enhancing students' English proficiency and providing native language support in classrooms. However, each approach has its limitations: boosting language skills requires long-term effort, while native language support may reduce students' exposure to technical English and thus affect their international competitiveness. Literature also points to several common EMI challenges such as difficulties in lecture comprehension, limited technical vocabulary, reduced classroom participation, and a lack of confidence resulting from language barriers (Chang, 2024). In such courses, teachers must serve both as language coaches and subject-matter experts. Scaffolding is particularly crucial here, as it allows teachers to gradually guide students through key concepts while mitigating the language load. GAI tools, with their capacity for real-time language assistance, offer an attractive solution for supplementing traditional scaffolding.

2.4. Potential Benefits of Integrating GAI Tools with Scaffolding

The integration of GAI tools with scaffolding-based learning offers complementary benefits. First, GAI tools can provide personalized, on-demand support without the limitations of time and human resources. Large language models can respond to individual queries at any time and adjust the complexity of their responses based on a student's prior performance (Yang et al., 2025; Zhu et al., 2025). For instance, proactive AI teaching agents can simulate the role of an instructor by prompting students with guiding questions that help deconstruct complex topics. This interactive approach not only reinforces comprehension but also aligns with the scaffolding theory by guiding students to higher cognitive levels. Second, the use of GAI helps lower cognitive load when students face language or conceptual difficulties. When confronted with complex English texts or technical descriptions, GAI can offer immediate translations, additional examples, or visual aids that cater to various learning styles. Moreover, GAI-supported scaffolding promotes autonomous learning and self-regulation by providing a safe environment for trial and error. Empirical studies have shown that when AI tutors engage students in dialogic problem-solving, learners become more willing to ask questions and take risks without the fear of judgment (Mowreader, 2025). In the long run, as students internalize problem-solving strategies with AI support, they gradually reduce their dependence on these tools—a crucial indicator of genuine learning. Recent experimental research further underscores these advantages. For example, Yan et al. (2024) conducted a randomized controlled trial with 117 undergraduate students and found that combining active GAI tutoring with scaffolding significantly enhanced students' understanding of course material, with benefits persisting even after the intervention ended. Similarly, Ma, Wang, Zhang, Ma, and Wang (2025) reported that their DBox system—an AI-assisted scaffolding tool for algorithmic programming—yielded higher learning outcomes and improved critical thinking skills compared to traditional approaches. Collectively, these findings suggest that carefully integrating GAI tools with scaffolding strategies not only improves immediate learning outcomes in EMI programming courses but also fosters long-term, self-directed learning.

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3. Research Methods

3.1. Research Design

This study employs a quasi-experimental design conducted in a real classroom setting to compare the effects of "traditional scaffolding" versus "GAI-assisted scaffolding" on student learning outcomes. Due to practical challenges in random assignment in educational settings, two parallel sections of an introductory programming course were selected—one serving as the experimental group and the other as the control group. Both groups shared identical course content, instructor expertise, and class hours to minimize extraneous variables. The intervention spanned one academic semester (18 weeks), with pre-tests administered at the beginning to assess baseline programming knowledge and English proficiency. Post-intervention tests and data collection were conducted at the end of the semester to evaluate the effects of the instructional intervention.

3.2. Participants and Grouping

Participants were first-year students enrolled in a compulsory "Introduction to Programming (Python)" course at a technology university, totaling 60 students who were randomly assigned into two sections (30 students each). All students were native Chinese speakers with a basic background in programming and elementary English reading skills. The control group received traditional scaffolding-based instruction, while the experimental group experienced the same scaffolding framework augmented by GAI tools. To minimize expectancy effects, students were not explicitly informed about the differing teaching methods; they were simply told that new learning tools would be incorporated. Informed consent was obtained from all participants for the use of their learning data in this study. The results are summarized in Table 1.

Table 1.
Participant Demographics

Group	N	Age Range	Gender Ratio (M:F)	Baseline Programming Score (Pre-test)	Baseline English Proficiency Score
Control Group	30	18–20	15:15	70.5	68.2
Experimental Group	30	18–20	16:14	70.8	67.9

3.3. Instructional Tools and Methods

Both groups were taught by experienced bilingual instructors following the same syllabus. The control group relied on conventional scaffolding strategies. Instructors provided simplified examples, analogies, and step-by-step prompts during lectures. During practice sessions, teachers and teaching assistants circulated the classroom, offering guidance through probing questions to help students overcome difficulties. As students progressed, the level of scaffolding was gradually reduced—culminating in a final project that required students to work independently, with instructors only providing suggestions when necessary.

In contrast, the experimental group received additional support through GAI tools integrated into the scaffolding framework. Specifically, OpenAI's ChatGPT was deployed via a dedicated course interface to interact with students. Instructors occasionally introduced ChatGPT-generated materials during lectures, such as summarizing complex English technical documents or translating code comments to Chinese, thereby reducing the language burden. During practice sessions, students could consult ChatGPT for hints when encountering difficulties. Importantly, they were instructed to use ChatGPT for guidance rather than as a source of direct answers—for example, asking "How should I break down this problem?" or "Which functions might be useful?" ChatGPT responded with step-by-step advice, resembling an interactive tutor rather than simply providing complete code solutions. Instructors and teaching assistants monitored interactions to ensure the AI's responses were accurate and relevant. This human–machine collaboration aimed to merge the expertise of educators with the immediacy and resource richness of AI support.

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3.4. Data Collection

Data were collected on three fronts: academic performance, learning attitudes, and post-course behavior.

Academic Performance: Classroom assessments (unit tests, mid-term exams) and final project scores were compared between groups. The final project, which encompassed roughly 80% of the course content, was evaluated on code accuracy, structure, style, and creativity. Additionally, the frequency and types of assistance sought during project development (e.g., teacher/TA queries versus ChatGPT interactions) were recorded as an index of scaffold dependency.

Student Feedback Surveys and Interviews: At the end of the semester, students completed a survey addressing overall satisfaction, self-efficacy, classroom engagement, and opinions regarding the instructional methods. The survey included Likert-scale items (e.g., "The instructional approach enhanced my interest in programming") along with open-ended questions (e.g., "How did AI-assisted learning influence your learning experience?"). In addition, a subset of students was selected for semi-structured interviews to gain deeper insights into their perceptions of scaffolding and GAI support. The control group provided feedback on traditional supports (e.g., sufficiency of teacher prompts).

Continued Learning Behavior: To evaluate long-term impact, we examined (1) delayed post-tests administered one month after the course to assess retention of core concepts, (2) the rate of enrollment in advanced programming courses the following semester, and (3) self-reported autonomous learning behaviors (such as continued use of ChatGPT for other subjects). These data help determine whether the GAI-assisted scaffolding method fosters enduring learning motivation and habits.

Quantitative data were analyzed using appropriate statistical methods (e.g., t-tests for exam score comparisons and chi-square tests for course enrollment rates), while qualitative data underwent coding and content analysis to extract recurring themes.

4. Analysis and Comparison

4.1. Comparison of Learning Outcomes

After one semester of intervention, the experimental group demonstrated significant improvements in academic performance relative to the control group. For instance, during formative assessments (unit tests and mid-term exams), the experimental group consistently outperformed the control group. In the mid-term exam, the experimental group achieved an average score of 80.5 out of 100 compared to 74.3 for the control group—a difference that was statistically significant ($p < .05$). This result indicates that GAI-assisted scaffolding helped students better grasp incremental knowledge. In particular, for applied programming tasks requiring comprehension of English prompts and code writing, the experimental group made notably fewer errors. Although both groups completed the final project, the experimental group's projects averaged 86.7, approximately 8 points higher than those of the control group. Detailed reviews revealed that experimental projects were more polished and better structured, with higher-quality code annotations. Part of this success may be attributed to the use of ChatGPT; records showed that experimental students asked ChatGPT an average of 15.2 questions during development (ranging from debugging advice to language clarifications), thereby compensating for difficulties in English comprehension or debugging skills (Yang et al., 2025). In contrast, control group students had to rely on limited in-class support from teachers and assistants, often spending more time struggling through problems independently. Overall, these findings support the first hypothesis that integrating GAI tools with scaffolding enhances student learning outcomes—a conclusion consistent with prior research on AI-assisted learning (Ma et al., 2025). The results are summarized in Table 2.

Table 2.
Comparison of Academic Performance.

Assessment Type	Control Group Mean Score	Experimental Group Mean Score	Statistical Significance (p-value)
Unit Test	72.3	77.8	< .05
Mid-term Exam	74.3	80.5	< .05
Final Project	78.7	86.7	< .05

4.2. Student Satisfaction and Engagement

Survey results indicated that the experimental group reported significantly higher overall satisfaction with the course experience compared to the control group. For instance, 90% of experimental students agreed or strongly agreed with the statement "I am satisfied with my overall learning experience in this course," versus 70% in the control group. Open-ended responses further highlighted that experimental student felt that ChatGPT enhanced their learning confidence and participation. Comments such as, "When I am uncertain about an English prompt, I can immediately ask ChatGPT, which reassures me," and "The AI hints encouraged me to try different problem-solving approaches" were common. In contrast, many control group respondents mentioned hesitancy in asking questions in class for fear of posing "too elementary" queries, which may have hindered timely resolution of doubts.

Classroom observation and self-assessments further supported these findings: the experimental group exhibited more frequent participation, with an average of five voluntary contributions per session compared to two in the control group. The availability of ChatGPT-generated prompts often sparked new ideas that led to more dynamic discussions. For example, during a lesson on recursive algorithms, one student in the experimental group introduced a real-life analogy suggested by ChatGPT—"like an endless mirror reflection"—which ignited a lively classroom discussion. Importantly, while the experimental group used ChatGPT for hints, their direct requests for teacher or TA help were not higher—and in some cases even lower—than those in the control group. This suggests that the additional resource did not create an over-reliance but rather fostered independent inquiry. Overall, the data indicate that GAI-assisted scaffolding not only improves academic performance but also creates a more engaging and supportive learning environment. The results are summarized in Table 3.

Table 3.
Student Satisfaction and Engagement.

Measure	Control Group (%)	Experimental Group (%)	Notes
Overall Satisfaction (Agree/Strongly Agree)	70%	90%	Based on Likert-scale survey responses.
Active Class Participation (Avg. per class)	~2	~5	Based on teacher observation records.
Confidence in Self-Learning	65%	80%	Self-reported via survey item.

4.3. Impact on Continued Learning

A key focus of this study was whether the integration of GAI tools into instruction has a lasting effect on students' autonomous learning behaviors. Delayed post-test scores administered one month after course completion revealed that the experimental group maintained a higher retention of core concepts, with an average score of 78 compared to 72 in the control group ($p < .05$). This suggests that experimental students not only learned more effectively but also internalized the material to a greater extent—particularly for tasks requiring the application of learned algorithms in novel contexts.

Furthermore, data on subsequent course enrollment showed a slightly higher rate of advanced course registration among the experimental group (60% vs. 50% in the control group). Survey responses corroborated these findings; nearly half of the experimental students expressed increased confidence in self-learning new programming languages or technologies due to their positive experience with AI-assisted learning. One student commented, "After this course, I started using ChatGPT to help me learn C++ outside of class, so I decided to enroll in an advanced C++ course next semester." In contrast, some control group students expressed concerns about the difficulty of programming and their limited English proficiency, which may have dampened their motivation to pursue further studies in the field.

Another notable finding was that experimental students demonstrated a greater willingness to engage in self-directed learning. Approximately 80% of experimental students agreed that "this course boosted my confidence to solve programming problems on my own," compared to 65% of control group students. Follow-up interviews revealed that many experimental students continued to use ChatGPT for academic support after the course ended—using it as a learning assistant rather than a crutch for copying answers. These trends strongly indicate that the integration of GAI tools with scaffolding not only improves immediate academic outcomes but also fosters lifelong learning skills, particularly important in the rapidly evolving field of information technology. The results are summarized in Table 4.

Table 4.
Continued Learning Outcomes.

Outcome Measure	Control Group	Experimental Group
Delayed Post-Test Mean Score (1 month later)	72	78
Enrollment in Advanced Programming Course (%)	50%	60%

5. Conclusion

5.1. Key Findings and Academic Contributions

This study examined the effects of integrating generative AI tools with scaffolding-based learning in an English-medium programming course. Our quasi-experimental design yielded several key findings: (1) Enhanced Academic Performance: Compared to traditional scaffolding, students in the experimental group demonstrated significantly better performance in both interim assessments and final project scores, especially on tasks requiring advanced comprehension and application (Ma et al., 2025). (2) Improved Learning Experience: Students receiving AI-assisted scaffolding reported higher satisfaction and engagement levels, were more active in classroom discussions, and expressed increased confidence in their abilities (Mowreader, 2025). (3) Fostering Autonomous Learning: The experimental group not only retained knowledge more effectively—as evidenced by delayed post-test scores—but also showed a greater propensity to enroll in advanced courses and engage in self-directed learning after the course ended. Collectively, these results confirm that the complementary benefits of GAI tools and scaffolding-based learning effectively mitigate language-related learning barriers in EMI programming courses, facilitating both immediate and long-term educational gains.

Academically, this research fills a gap in the literature by extending the application of GAI in education to the challenging context of bilingual programming instruction. While prior studies have primarily focused on general learning contexts or language education, our work demonstrates that integrating AI within a scaffolding framework can yield measurable improvements in technical subjects taught in English. Furthermore, by combining educational psychology with state-of-the-art AI technology, this study provides empirical support for a novel teaching model that can serve as a blueprint for future research and practice.

5.2. Future Research Recommendations

Although the findings are promising, several limitations warrant further investigation. First, the sample was limited to a single institution, and future studies should incorporate larger and more diverse populations to enhance the generalizability of the results. Second, the study's timeframe was confined to one semester; longer-term investigations are needed to assess sustained impacts on academic performance and career readiness. Future research could track students' progress over one year or more, examining outcomes such as subsequent course performance or capstone project quality, and evaluating the long-term effects on skills like autonomous learning and problem-solving. Third, while we took measures to prevent direct answer copying from ChatGPT, academic integrity issues remain a concern. Subsequent studies should explore mechanisms to detect over-dependence on AI and assess the effectiveness of academic integrity training in mitigating such risks. Finally, further analysis is warranted to examine how different types of scaffolding (e.g., conceptual versus procedural support) interact with AI assistance and whether individual differences (such as varying levels of English proficiency or self-directed learning ability) moderate the effectiveness of the intervention.

5.3. Practical Implications for Bilingual Education

The outcomes of this study carry significant implications for educational practice. In classroom settings, our findings suggest that integrating AI tools such as ChatGPT into scaffolding frameworks is not only feasible but can also serve as a valuable supplement to traditional instruction. For educators teaching EMI courses, incorporating AI assistance—beginning with simple tasks like summarizing bilingual materials and translating technical terms—can enhance students' understanding without compromising the rigorous use of English in professional contexts. By designing AI prompts to foster inquiry rather than provide direct answers (for instance, employing a Socratic method approach), teachers can preserve the focus on critical thinking and independent problem solving.

From a policy perspective, these results underscore the potential for institutional investment in AI-assisted learning systems tailored to EMI environments. University teaching centers might develop guidelines and training programs for faculty to effectively integrate AI tools, ultimately improving course pass rates and overall teaching quality. Given that language barriers are a prominent challenge in EMI courses, AI-driven language support can relieve the dual burden on instructors, enabling them to focus on higher-level conceptual instruction. In terms of promoting educational equity, GAI-assisted scaffolding offers a pathway to personalized instruction that accommodates students with varying English proficiency levels, thereby supporting differentiated instruction in diverse classrooms.

In summary, the successful integration of GAI tools and scaffolding-based learning demonstrated in this study suggests that, when well-designed, such an approach can significantly enhance both the immediate and long-term learning outcomes in bilingual programming courses. As AI technology continues to evolve, its thoughtful application in educational settings promises to open new avenues for teaching and learning, equipping students with the skills required to excel in an increasingly globalized and technologically driven world.

Transparency:

The author confirms that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

Copyright:

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