Generative AI and Multimodal Profiling in Programming Education: A Systematic Review of Tools, Pedagogical Impacts, and Future Competencies

Aboul Hassane CISSE[a*] & Shoya ISHIMARU[b]
[a,b]*Graduate School of Informatics, Osaka Metropolitan University, Japan*
*sn22869p@st.omu.ac.jp

Abstract: This systematic review investigates the integration of generative artificial intelligence (GenAI) and multimodal learning analytics (MMLA) in programming education, with a focus on empirical implementations and their pedagogical implications. Drawing from 59 peer-reviewed studies published between 2015 and 2025, this review categorizes how GenAI tools such as ChatGPT, GitHub Copilot, and domain-specific tutors are being used to support real-time feedback, code generation, and learner scaffolding. While these tools enhance productivity and interaction, they also raise new challenges around critical thinking, overreliance, and the redefinition of assessment practices. The findings highlight a lack of longitudinal and cross-cultural studies and limited integration with multimodal sensing, such as eye tracking and emotion detection. We propose future directions for designing adaptive, ethically grounded learning environments that leverage GenAI alongside real-time multimodal feedback. This includes fostering AI literacy, ensuring learner agency, and equipping educators with tools for reflective and inclusive AI pedagogy.

Keywords: Generative Artificial Intelligence (GenAI), Programming Education, Multimodal Learning Analytics, Large Language Models (LLMs), AI-Assisted Learning

1. Introduction

Generative Artificial Intelligence (GenAI) is reshaping programming education by enabling real-time code generation, personalized feedback, and natural language explanations through tools such as ChatGPT and GitHub Copilot (Prather et al., 2025; Liu et al., 2024). These technologies promote a shift toward student-centered learning that emphasizes interaction and scaffolding (Zapata et al., 2025; Chan & Li, 2025).

Despite these benefits, concerns have emerged about overreliance, reduced critical thinking, and cognitive offloading (Bauer et al., 2025; Gerlich, 2025). At the same time, research on combining GenAI with multimodal learning analytics (MMLA) remains fragmented. MMLA leverages signals such as eye movements, keystrokes, and physiological responses to provide insights into learners' cognitive and emotional states (Bhatt et al., 2024; Morita et al., 2025). Yet few studies explore how GenAI and MMLA can be jointly used to enhance programming instruction.

This review addresses this gap through three objectives: (a) investigate GenAI-supported instructional practices; (b) categorize multimodal signals used; and (c) analyze their impact on engagement, self-efficacy, and skill acquisition. By consolidating recent findings, the study aims to inform the design of next-generation programming environments that are intelligent, adaptive, and pedagogically grounded.

2. Methodology

This study employed a systematic literature review (SLR) guided by PRISMA 2020 and software engineering guidelines, analyzing 59 empirical studies published between 2015–2025. Five databases (ACM, IEEE Xplore, Scopus, ResearchGate, arXiv) were searched using Boolean queries (e.g., "generative AI" AND "programming education"; "eye-tracking" AND "AI tutoring"). Inclusion criteria required empirical studies in English that used GenAI tools (e.g., ChatGPT, GitHub Copilot) within programming education and provided full-text access, excluding purely conceptual or technical papers. From 127 records, 59 met all criteria after PRISMA-documented screening (see repository: https://github.com/pachaboul/autoreviewx/tree/e774edc57c0e8d108455443292e7a300357eb819/data). Data were extracted with AutoReviewX, coding for GenAI tools, educational level, pedagogical design, modality, outcomes, and methods. Quality assessment (CASP, PICO, TAPUPAS) showed strengths in research clarity and transparency, with weaker reporting on limitations and accessibility.

3. Results

RQ1: How is GenAI integrated in programming education?
GenAI tools are mainly applied in code completion, prompt refinement, and AI tutoring, functioning as cognitive and instructional partners.

- ChatGPT supports explanations and debugging.
- GitHub Copilot generates context-aware multi-line suggestions.
- CodeHelp and CS50 Chatbot provide structured feedback and course-specific guidance (Prather et al., 2025; Chan & Li, 2025).

RQ2: What pedagogical changes does GenAI introduce?
Adoption shifts emphasis from coding to AI collaboration and critical evaluation. Emerging practices include:

- Prompt literacy: teaching students to design effective queries.
- Analytical reasoning: evaluating AI-generated outputs.
- Reflective practice: using GenAI as a tool for metacognitive growth (Chan & Li, 2025; Bauer et al., 2025).

RQ3: How does MMLA enhance GenAI use?
Though still limited, MMLA extends adaptivity by incorporating learner signals:

- Attention/engagement via eye-tracking and keystrokes (Bhatt et al., 2024).
- Affective states via facial, posture, or heart-rate cues (Melo et al., 2025).
- Personalization through fusion of text prompts and multimodal signals (Santhosh et al., 2024).

Challenges remain around privacy, cost, and ethics, but early prototypes suggest promise for hybrid, learner-centered ecosystems.

4. Discussion

This review shows that GenAI tools are becoming central in programming education, primarily supporting code generation, debugging, and tutoring. Their use shifts pedagogy from coding as a manual task toward collaborative engagement with AI, requiring students to evaluate, adapt, and reflect on outputs. Limited but promising studies demonstrate that multimodal extensions (e.g., gaze or emotion signals) can create more adaptive and inclusive learning environments.

Compared with traditional rule-based tutors, GenAI systems enable flexible, conversational learning, but also pose risks of overreliance, logic errors, and reduced critical thinking. This demands stronger metacognitive skills and AI literacy from learners.

Emerging trends highlight:

- Prompt literacy as a new programming skill.
- Multimodal integration to personalize support.
- Hybrid ecosystems combining GenAI with flipped or project-based learning.
- Innovative assessments (e.g., reflective tasks, oral defenses) to evaluate reasoning.

Theoretically, GenAI aligns with socio-constructivist and cognitive apprenticeship models, acting as a cognitive partner within the learner's zone of proximal development. Practically, educators should focus on AI literacy, reflective assessments, and explainability, while developers should prioritize personalization, ethics, and multimodal integration.

5. Conclusion

This review is limited by potential database and publication bias, as only five databases were searched and positive findings may be overrepresented. Most included studies were short-term pilots in well-resourced contexts, limiting generalizability to underrepresented or global settings.

Despite these limitations, the analysis of 59 studies shows that GenAI tools are increasingly integrated into programming education, supporting coding, debugging, and feedback. However, multimodal extensions (e.g., gaze, emotion, physiological signals) remain rare, leaving much of GenAI's adaptive potential unrealized.

Future research should:

- Examine long-term learning impacts beyond task performance.
- Combine GenAI with multimodal signals (eye-tracking, EEG, motion).
- Develop ethical, inclusive, and scalable practices.
- Provide educator training for effective and responsible adoption.

In sum, GenAI holds promise not as a replacement for human effort, but as a partner that supports deeper learning, reflection, and empowerment when combined with multimodal insights and sound pedagogy.

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