A Study on the Risks and Challenges of Teaching Vue in Vocational Schools in the Context of AI Applications

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Abstract. Generative AI is transforming the way programming is taught, yet its impact on vocational education remains uncertain. Taking a Vue course in secondary vocational education as a case study, this paper constructs a phased model of AI-assisted teaching, identifies five categories of risks—including increased dependency and diminished emphasis on the learning process—and proposes an analytical framework of 'technology-driven—behaviour-mediated—outcome-oriented' to reveal how these risks are amplified through changes in learning behaviour. Based on this, the paper proposes strategies such as tool standardisation, task restructuring and formative assessment, thereby providing guidance for optimising programming instruction in vocational education within an AI-driven environment.

Keywords: GenAI; Vue instruction; Vocational education; Risks and challenges; Learning behaviour.

1 Introduction

Generative artificial intelligence is reshaping the way programming is taught,[1] with related tools approaching the level of human tutors.[2] Taking the Vue course in vocational secondary education as an example, whilst it emphasises practical application, there are significant variations in students' prior knowledge. AI lowers the barrier to entry but alters the learning pathway, bringing with it risks such as over-reliance and a dilution of the learning process;[3] it is therefore necessary to analyse its performance and mechanisms to provide a basis for teaching.

2 Research Context and the Development of an AI-Assisted Vue Teaching Model

With the introduction of AI into the classroom, programming education has gradually shifted from being 'analysis-driven' to 'generation-driven', leading to a reconfiguration of the learning pathway. Building upon this, a phased model for AI-assisted Vue teaching has been developed, as shown in Figure 1.

C. V. Garcés et al. (eds.), *Proceedings of the 6th International Conference on Internet, Education and Information Technology (IEIT 2026)*, Atlantis Highlights in Social Sciences, Education and Humanities 53,
https://doi.org/10.2991/978-94-6239-733-0_21

This model comprises three phases: pre-class, in-class and post-class. AI performs different functions in each phase, with its use regulated by the teacher. The pre-class stage focuses on the construction of foundational knowledge, where students utilise AI to access syntax examples and conceptual explanations, though this does not involve the generation of complete tasks; the in-class stage centres on project-based practice, allowing AI to participate in error analysis and local optimisation, whilst requiring students to explain key code to ensure engagement throughout the learning process; the post-class stage emphasises reflection and integration, promoting the stable formation of knowledge structures through AI-assisted summarisation and error analysis. Compared with traditional teaching, this model is characterised by three key features: firstly, AI is embedded within the teaching process rather than existing as a standalone tool; secondly, its use is constrained through task design; and thirdly, regulation is centred on learning behaviour, ensuring that the role of technology remains within a controlled scope.

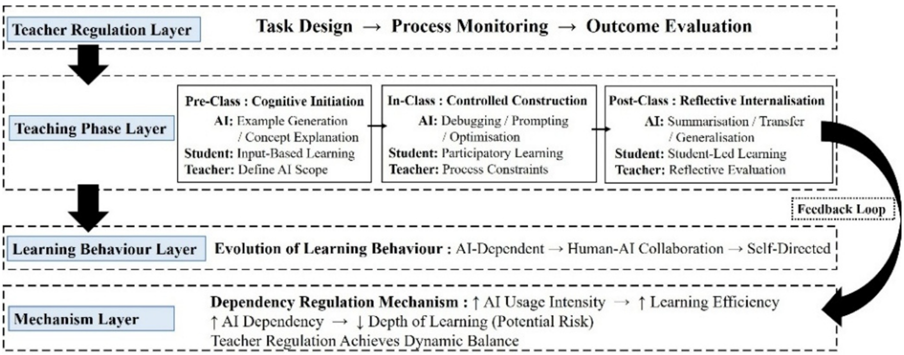

Fig. 1. Phased Teaching Model and Dependency Regulation Mechanism for AI-Empowered Vue Courses.

3 The Risk Structure of AI-Assisted Vue Teaching

AI has evolved from a peripheral tool to a core element, lowering the barrier to entry whilst altering the cognitive investment required; the risks involved are structural in nature, and students themselves have reported both perceived benefits and concerns regarding AI use in learning.[4] Drawing on Vue courses in secondary vocational education, this paper identifies five categories of risk:

(1) Dependency risk: Students bypass analysis and directly invoke AI to generate code, lacking deep understanding and the ability to identify AI-generated errors;[5] the learning pathway shifts from 'understanding—implementation' to 'invocation—adjustment', thereby weakening the foundation of their skills.

(2) Process-weakening risk: AI provides complete solutions, bypassing requirements analysis and component design, compressing intermediate stages and hindering the development of computational thinking and problem-solving skills.[6]

(3) Risk of superficial knowledge: AI's 'on-demand explanation' leads to fragmented knowledge that is difficult to integrate systematically, resulting in superficial understanding and reduced learning motivation.[7]

(4) Academic integrity risk: Increased code replicability makes it difficult for outcomes to reflect genuine effort, undermining the validity and fairness of assessment.

(5) Teaching and management risks: Classrooms adopt a tripartite structure, making it difficult for teachers to monitor AI usage; student performance gaps widen; teachers must shift towards process regulation.

The aforementioned risks are mediated by changes in learning behaviour: increased reliance leads to process compression, triggering superficial knowledge acquisition and bringing evaluation and management issues to the fore. The interplay of technology, behaviour and environment shapes the risk structure.

4 Risk Generation Mechanisms in AI-Assisted Vue Teaching

The introduction of AI has shifted cognitive engagement partly towards the utilisation of technology and may influence programming learning outcomes.[8] Risks are driven by the dynamic interplay between technology, behaviour and the environment. This paper constructs a three-tiered progressive structure: the technology-driven layer, the behavioural intermediary layer and the outcome manifestation layer, as shown in Figure 2.

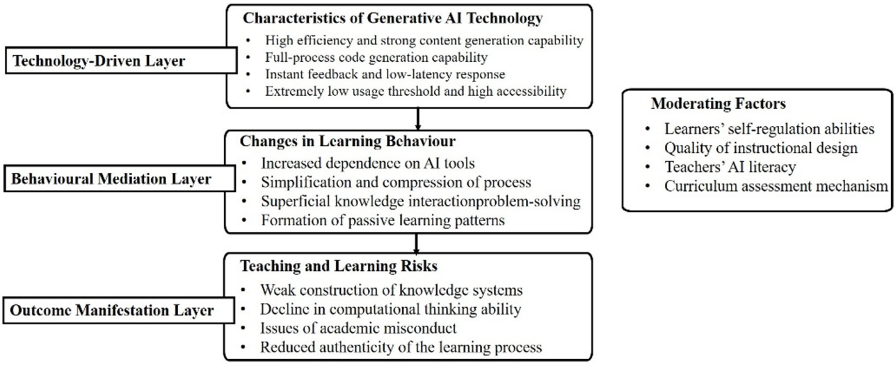

Fig. 2. Model of the Risk Generation Mechanism in AI-Assisted Vue Teaching.

Technology-driven layer: High generative capacity, instant feedback and low barriers to entry reshape learning decisions, compress problem-solving time and create the potential for 'process substitution'. Behavioural Mediation Layer: Technological characteristics trigger structural shifts in behaviour; students tend to rely on AI to obtain answers, weakening independent analysis. This leads to altered problem-solving pathways, compressed processes and reduced depth of knowledge interaction, thereby amplifying risks. Outcome Manifestation Layer: Risks such as increased dependency and weakened processes become manifest and accumulate synergistically; increased challenges regarding academic integrity and management are reflected in institutional frameworks. Environmental factors such as instructional design, self-regulation skills and teachers' AI literacy play a moderating role in these risk pathways. The core lies in the 'amplification effect': technology influences outcomes by altering learning behaviour; when behaviour deviates from the path of deep learning, risks gradually emerge and compound. AI is not the source of risk, but rather an amplifier. The key to instructional optimisation lies in regulating behaviour and the environment to intervene in the pathways through which risks arise.

5 Strategies for Optimising Teaching in an AI Environment

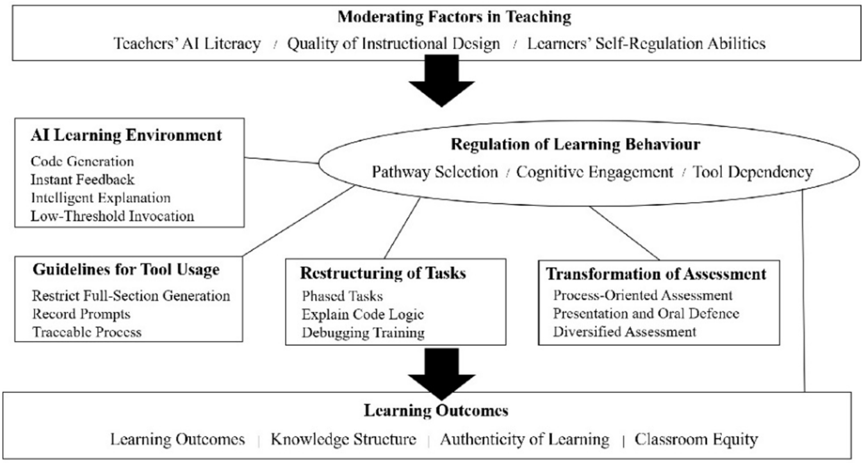

Fig. 3. Model of AI-assisted teaching optimisation strategies and behavioural regulation mechanisms.

As can be seen from the aforementioned analysis of the mechanism, AI plays a role in the learning process; therefore, teaching optimisation requires reshaping the relationship between students and tasks, tools, and knowledge, by redefining the role of tools, restructuring processes, and refining evaluation and feedback through structural adjustments to strengthen learning regulation [9] (Figure 3). There are four strategies:

(1) Tool usage guidelines: Establish a mechanism for recording and tracing usage. Adopt an 'AI Usage Record Form' to document problem descriptions, prompts, generated results, and modification notes, which will serve as the basis for formative assessment. Tiered access permissions: At the foundational stage, only conceptual explanations and error analysis are permitted; the generation of complete code is prohibited. At the project stage, partial code generation is permitted, but students must integrate the structure themselves; the submission of a complete project in a single go is prohibited. Teachers conduct process supervision by cross-checking the "code results" against the "log sheet".

(2) Restructuring of task design: Restore the learning process through phased design. For example, component communication instruction is divided into four stages: Problem Analysis (independent analysis and sketching, with AI disabled); Solution Design (AI limited to checking ideas, with generation of complete code prohibited); Coding Implementation (partial AI access, with a focus on copying behaviour); and Explanation and Review (mandatory output of key logic). Retaining the analysis–design–implementation–explanation sequence alleviates the compression of the learning process. Error-driven tasks are introduced to shift the role of AI from direct generation to auxiliary reasoning.

(3) Adjustment of the Assessment Mechanism: A shift from outcome-oriented to process-oriented assessment. Process-based assessment accounts for 60%, focusing on the appropriate use of AI, code traceability, and the understanding and expression of key logic; outcome-based assessment accounts for 40%, measuring functional implementation and code standardisation. Through version comparisons, classroom questioning and random explanations, a model of 'visible process and verifiable results' is established to encourage deep engagement.

(4) Reconstruction of Teacher Competencies: Transitioning from knowledge disseminators to process regulators. This requires behavioural identification (assessing AI usage through the discrepancy between 'code performance and explanatory ability'), classroom intervention (follow-up questioning and task restructuring), differentiated guidance (addressing variations in AI usage proficiency), and an understanding of AI tools (generative logic and common errors).

The aforementioned strategies operate through the synergistic interaction of "tool standards—task design—assessment feedback—teacher regulation", transforming AI from a substitute into a cognitive support tool, thereby mitigating risks and enhancing teaching quality.[10]

6 Conclusion

Taking a Vue course in secondary vocational education as an example, this paper identifies five types of risks arising from the integration of AI, including increased dependency and the weakening of the learning process; the core mechanism lies in the 'amplification effect' generated by technology through the alteration of learning behaviour. The proposed 'technology-driven—behaviour-mediated—outcome-manifested' framework provides an analytical tool for understanding the pathways through which these risks arise. Teaching optimisation should focus on behavioural regulation; through tool standardisation, task restructuring and assessment adjustments, AI should be transformed from a substitute into a cognitive support tool. The role of AI depends on how the teaching structure is regulated; in future, the effectiveness of these strategies must be empirically tested, whilst paying attention to differences in learner behaviour.

References

1. Nathaniel, J., Oyelere, S. S., Suhonen, J., & Tedre, M. (2025). Literature Review on the Integration of Generative AI in Programming Education. International Journal of Artificial Intelligence in Education, 1-32.
2. Phung, T., Pădurean, V. A., Cambronero, J., Gulwani, S., Kohn, T., Majumdar, R., ... & Soares, G. (2023, August). Generative AI for programming education: Benchmarking ChatGPT, GPT-4, and human tutors. In Proceedings of the 2023 ACM Conference on International Computing Education Research-Volume 2 (pp. 41-42).
3. Özer, M. (2024). Potential Benefits and Risks of Artificial Intelligence in Education. Bartin University Journal of Faculty of Education, 13(2).
4. Pitts, G., Marcus, V., & Motamedi, S. (2025). Student perspectives on the benefits and risks of AI in education. arXiv preprint arXiv:2505.02198.
5. Kohen-Vacs, D., Usher, M., & Jansen, M. (2025). Integrating generative AI into programming education: Student perceptions and the challenge of correcting AI errors. International Journal of Artificial Intelligence in Education, 1-19.
6. Matobobo, C., Ncube, P. D. N., Ngesimani, N. L., Dzvapatsva, G. P., & Chinhamo, E. (2025, April). Enhancing computational thinking and problemsolving in programming education through generative AI: A scoped review. In 2025 IEEE global engineering education conference (EDUCON) (pp. 1-9). IEEE.
7. Boguslawski, S., Deer, R., & Dawson, M. G. (2025). Programming education and learner motivation in the age of generative AI: student and educator perspectives. Information and Learning Sciences, 126(1-2), 91-109.
8. Alanazi, M., Soh, B., Samra, H., & Li, A. (2025). The Influence of artificial intelligence tools on learning outcomes in computer programming: A systematic review and meta-analysis. Computers, 14(5), 185.
9. Ouyang, F., Wu, M., Zhang, L., Xu, W., Zheng, L., & Cukurova, M. (2023). Making strides towards AI-supported regulation of learning in collaborative knowledge construction. Computers in Human Behavior, 142, 107650.
10. Habiyambere, J. D., & Niyibizi, O. (2025). Assessing the Influence of AI-Supported Learning Methods on Instructional Quality in Higher Education. Educational Journal of Technology and Innovation, 2(1).