Learning Satisfaction as a Key Mechanism in Higher Vocational Students' Continuance Intention to Use Generative AI for Computer Course Learning

Learning Satisfaction and GAI Continuance Intention

Jinhua Huang[a], Choat Inthawongse[b] *, Noppadol Amdee[c]

Muban Chom Bueng Rajabhat University, No.46, Moo 3, Chom Bueng Subdistrict, Chom Bueng District, Ratchaburi Province, 70150, Thailand

[a]hjhflower21@gmail.com, *[b]Choatint@mcru.ac.th, [c]noppadolamd@mcru.ac.th

Abstract. This study examines higher vocational students' continuance intention to use generative artificial intelligence (GAI) in computer course learning. Drawing on the Technology Acceptance Model and continuance-use research, it tests whether perceived usefulness, perceived ease of use, and learning engagement affect continuance intention through learning satisfaction. Data from 320 students in Heilongjiang Province, China, were analyzed using structural equation modeling and bootstrap mediation analysis. The results show that perceived usefulness, perceived ease of use, and learning engagement significantly enhance learning satisfaction, which has the strongest direct effect on continuance intention and mediates all three antecedent effects. Perceived usefulness does not directly affect continuance intention, whereas perceived ease of use retains a small but significant direct effect. The findings suggest that continued GAI use depends on whether students' perceptions and engagement are translated into satisfying, task-oriented learning experiences.

Keywords: generative artificial intelligence, learning satisfaction, continuance intention, computer course learning, higher vocational education, computing education

1 Introduction

Generative artificial intelligence (GAI) tools such as ChatGPT are increasingly used in higher education for writing, programming, explanation generation, and learning support[2]. Unlike earlier digital learning tools that mainly provide fixed resources or predefined feedback, GAI can generate adaptive responses through conversational interaction. This feature is especially relevant to higher vocational computer course learning, where students need to complete practical tasks such as code understanding, debugging, SQL query design, Linux command learning, and technical report revision.

Z. Ge et al. (eds.), *Proceedings of the 2026 6th International Conference on Education, Information Management and Service Science (EIMSS 2026)*, Atlantis Highlights in Computer Sciences 25,
https://doi.org/10.2991/978-94-6239-766-8_43

However, initial GAI use does not necessarily lead to continued use. Initial use may be driven by novelty, convenience, peer influence, or teacher recommendation, whereas continued use depends more strongly on post-use experiences. Prior research identifies perceived usefulness and perceived ease of use as key beliefs in technology acceptance [4, 7, 12], while continuance-use research emphasizes satisfaction as a central factor in repeated use [3]. More empirical evidence is still needed on how students' perceptions and engagement are transformed into continuance intention in vocational computing education.

To address this gap, this study examines higher vocational students' continuance intention to use GAI for computer course learning in Heilongjiang Province, China. Drawing on the Technology Acceptance Model and continuance-use research, it develops a mediation model in which perceived usefulness, perceived ease of use, and learning engagement influence continuance intention through learning satisfaction. The study contributes by extending GAI continuance research to vocational computer course learning and clarifying learning satisfaction as a key perception-to-experience mechanism.

2 Theoretical Background and Hypotheses

This study draws on the Technology Acceptance Model (TAM) and continuance-use research to explain higher vocational students' continued use of GAI in computer course learning. TAM identifies perceived usefulness (PU) and perceived ease of use (PEOU) as two central beliefs shaping technology acceptance [4]. In this study, PU refers to whether students believe that GAI helps them complete practical computing-related tasks, while PEOU refers to whether they find it easy to interact with GAI, understand AI-generated explanations, and apply AI-generated suggestions to computer course tasks.

Continuance intention differs from initial adoption because it depends more strongly on post-use evaluation. Continuance-use research emphasizes satisfaction as a key factor in repeated use after initial adoption [3]. Therefore, this study treats learning satisfaction (SAT) as an experiential mechanism through which students' technology-related perceptions and learning engagement are transformed into continuance intention.

PU is expected to improve SAT because students are more likely to be satisfied when GAI helps them solve concrete learning problems, such as understanding code logic, generating SQL examples, explaining Linux commands, or revising technical reports. However, PU may not directly lead to continuance intention unless such usefulness produces a satisfying learning experience. PEOU may affect both SAT and continuance intention because ease of use reduces the cognitive and operational burden of asking questions, refining prompts, testing outputs, and applying AI-generated suggestions.

Learning engagement (ENG) is included because GAI-supported computer course learning requires students to ask questions, refine prompts, evaluate AI-generated responses, test outputs, and revise their work. Engagement may improve satisfaction, but it may not automatically lead to continuance intention unless students perceive the engagement process as helpful and rewarding. Finally, SAT is expected to directly increase continuance intention because satisfied students are more likely to continue using GAI in future learning tasks.

Accordingly, this study hypothesizes that PU, PEOU, and ENG positively affect SAT (H1–H3) and CI (H4–H6), SAT positively affects CI (H7), and SAT mediates the relationships between PU, PEOU, ENG and CI (H8a–H8c).

The proposed mediation model is shown in Figure 1.

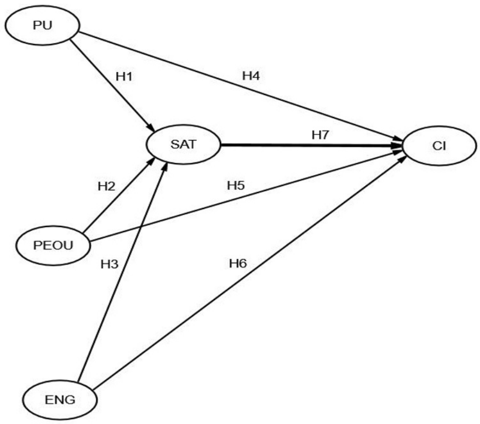

Fig. 1. Proposed research model.

3 Method

This study used a quantitative cross-sectional survey to examine higher vocational students' continuance intention to use GAI for computer course learning. Respondents were students from higher vocational colleges in Heilongjiang Province, China, who had used GAI tools in computer course learning contexts. GAI-supported computer course learning referred to the use of GAI in computing-related tasks such as programming explanation, code debugging, database query design, Linux command understanding, algorithmic problem solving, and technical report revision.

After data screening, 320 valid responses were retained. The sample included 140 male students (43.8%) and 180 female students (56.2%). By grade level, 69 were first-year students (21.6%), 81 were second-year students (25.3%), 96 were third-year students (30.0%), and 74 were from other grade levels (23.1%). Regarding major type, 117 students were from computer-related majors (36.6%), while 203 were from other related majors (63.4%).

The questionnaire measured perceived usefulness (PU), perceived ease of use (PEOU), learning engagement (ENG), learning satisfaction (SAT), and continuance intention (CI). PU, PEOU, ENG, and SAT were each measured with four items, while CI was measured with three items, using a five-point Likert scale from 1 = strongly disagree to 5 = strongly agree. To improve transparency and reproducibility, the full questionnaire items are reported in Table 1.

Table 1. Measurement items used in the questionnaire.

Construct	Code	Item
Perceived usefulness	PU1	Using GAI helps me better understand computer course content.
	PU2	Using GAI improves my efficiency in completing computer course learning
	PU3	Using GAI helps me solve problems related to programming, database, Linux,
	PU4	Overall, GAI is useful for my computer course learning.
Perceived ease of use	PEOU1	I find it easy to use GAI for computer course learning.
	PEOU2	It is easy for me to ask GAI questions related to computer course tasks.
	PEOU3	I can easily understand the explanations or suggestions generated by GAI.
	PEOU4	I can easily apply GAI-generated suggestions to my computer course learning
Learning engagement	ENG1	I actively use GAI to explore problems in computer course learning.
	ENG2	I refine my questions or prompts when using GAI for computer course
	ENG3	I compare and evaluate the answers or suggestions generated by GAI.
	ENG4	I use GAI feedback to revise my learning outputs.
Learning satisfaction	SAT1	I am satisfied with my experience of using GAI for computer course learning.
	SAT2	Using GAI makes my computer course learning experience more positive.
	SAT3	GAI-supported learning meets my expectations in computer course learning.
	SAT4	Overall, I am satisfied with GAI-supported computer course learning.
Continuance intention	CI1	I intend to continue using GAI for computer course learning in the future.
	CI2	I will frequently use GAI to support my future computer course learning.
	CI3	I would recommend using GAI for computer course learning to other students.

Data were analyzed using SPSS and AMOS. Following established multivariate data analysis procedures [6], reliability was assessed using Cronbach ' s alpha and composite reliability, convergent validity was evaluated using standardized factor loadings and average variance extracted, and discriminant validity was examined using the square roots of AVE and HTMT values. The structural model was then tested to examine the direct effects among PU, PEOU, ENG, SAT, and CI. Bootstrap mediation analysis with 5,000 resamples was conducted to test the indirect effects of PU, PEOU, and ENG on CI through SAT.

4 Results

Harman's single-factor test showed that the first factor explained 41.93% of the total variance, suggesting that common method bias was unlikely to dominate the data structure. The measurement model showed acceptable reliability and validity: Cronbach's alpha = 0.839–0.874, standardized loadings = 0.714–0.851, composite reliability = 0.840–0.876, and AVE = 0.568–0.657. Discriminant validity was supported by the square roots of AVE and HTMT values of 0.478–0.679.

The structural model showed good fit: $\chi^2/df = 1.286$, RMR = 0.009, GFI = 0.945, AGFI = 0.926, RMSEA = 0.030, NFI = 0.947, IFI = 0.988, TLI = 0.985, and CFI = 0.988. The model explained 48.0% of SAT and 52.0% of CI. As shown in Table 2, PU, PEOU, and ENG significantly predicted SAT; SAT had the strongest direct effect on CI; PU and ENG did not directly predict CI; and SAT significantly mediated all three antecedent effects.

Table 2. Structural path and mediation results.

Hypothesis	Path	Effect	p / 95% BC CI	Result
H1	PU → SAT	$\beta = 0.298$	$p < .001$	Supported
H2	PEOU → SAT	$\beta = 0.214$	$p = .003$	Supported
H3	ENG → SAT	$\beta = 0.326$	$p < .001$	Supported
H4	PU → CI	$\beta = 0.144$	$p = .055$	Not supported
H5	PEOU → CI	$\beta = 0.141$	$p = .046$	Supported
H6	ENG → CI	$\beta = 0.104$	$p = .125$	Not supported
H7	SAT → CI	$\beta = 0.459$	$p < .001$	Supported
H8a	PU → SAT → CI	Indirect = 0.137	[0.066, 0.229]	Supported
H8b	PEOU → SAT → CI	Indirect = 0.098	[0.034, 0.190]	Supported
H8c	ENG → SAT → CI	Indirect = 0.150	[0.084, 0.255]	Supported

4.1 Supplementary Multi-Group Analysis by Major Type

To examine whether the structural relationships differed by major type, a supplementary multi-group analysis was conducted between computer-related majors ($n = 117$) and other related majors ($n = 203$). An unconstrained model was compared with a structural weights constrained model in which the seven structural paths were constrained to be equal across the two groups. The unconstrained model showed acceptable fit: $\chi^2 = 363.896$, $df = 284$, $\chi^2/df = 1.281$, CFI = .976, TLI = .971, and RMSEA = .030. The constrained model also showed acceptable fit: $\chi^2 = 371.225$, $df = 291$, $\chi^2/df = 1.276$, CFI = .976, TLI = .972, and RMSEA = .029. The model comparison indicated that constraining the seven structural paths did not substantially reduce model fit, with $\Delta\chi^2 = 7.329$, $\Delta df = 7$, and $\Delta CFI = .000$. Since ΔCFI was below .01, the perception-to-experience mechanism was generally stable across the two major-type groups. Therefore, the structural relationships among PU, PEOU, ENG, SAT, and CI can be interpreted as a relatively consistent pattern among higher vocational students using GAI for computer course learning.

5 Discussion

The findings highlight the central role of learning satisfaction in students' continued use of GAI for computer course learning. PU, PEOU, and ENG all significantly predicted SAT, and SAT had the strongest direct effect on CI. This suggests that students are more likely to continue using GAI when prior use produces a satisfying experience in practical computing-related tasks, such as code understanding, debugging, SQL query design, Linux command learning, and technical report revision [1, 8, 10].

The different direct effects of PU and PEOU on CI provide a theoretically meaningful finding. PU did not directly affect CI, whereas PEOU retained a small but significant direct effect. This pattern suggests that perceived usefulness may influence continuance intention mainly through satisfaction: students may recognize that GAI is useful, but they may continue using it only when such usefulness leads to a positive learning experience. By contrast, ease of use can directly reduce the effort required to refine prompts, understand explanations, test generated code or commands, and apply AI-generated suggestions. Therefore, PEOU may directly support continued use by lowering the operational burden of GAI-supported learning.

The non-significant direct effect of ENG on CI further supports the perception-to-experience pathway. Although engagement had the strongest effect on SAT, active engagement may lead to continued use mainly when it results in satisfaction. The supplementary multi-group analysis also showed that the structural relationships were generally stable across computer-related and other related majors, as indicated by Δ CFI = .000. This suggests that the proposed mechanism may reflect a relatively general pattern among higher vocational students using GAI for computer course learning.

Overall, the findings show that learning satisfaction is not only an outcome of GAI use but also a key mechanism through which students' perceptions and engagement shape future intention to use GAI in vocational computing education [5, 9, 11].

6 Implications and Conclusion

This study provides implications for research and practice. Theoretically, it extends GAI continuance research to higher vocational computer course learning and shows that learning satisfaction serves as a key mechanism linking perceived usefulness, perceived ease of use, learning engagement, and continuance intention [3, 5, 11]. Practically, institutions and teachers should not evaluate GAI-supported learning only by usage frequency, but should focus on whether GAI helps students understand technical concepts, complete computing tasks, verify AI-generated outputs, and revise their work.

It should be noted that the five-step framework is proposed as a practical instructional implication derived from the findings, rather than as an empirically tested process model in this study. Based on the findings, a practical GAI-supported learning process may include task clarification, technical explanation, output generation, verification and debugging, and reflection-based revision. Students may use GAI to clarify technical tasks, generate initial solutions, verify outputs, and revise their work through iterative feedback.

This study has several limitations. The cross-sectional design limits causal inference, and the self-reported data may not fully capture actual GAI use or learning performance. Future studies could use longitudinal designs and combine surveys with learning diaries, prompt records, system logs, code debugging records, SQL query accuracy, Linux command execution records, or teacher-rated technical reports. In addition, the proposed five-step framework should be tested through experimental or quasi-experimental designs comparing structured GAI-supported learning with unstructured GAI use. Because the sample was drawn from higher vocational students in Heilongjiang Province, future studies should further examine different majors, course types, technical skill levels, regions, and institutional contexts.

Overall, students' continued use of GAI depends on whether technology-related perceptions and learning engagement are translated into satisfying learning experiences. Learning satisfaction therefore serves as the key mechanism linking technology perceptions to continuance intention.

Acknowledgment

This paper is a phased research outcome of the Heilongjiang Vocational Education and Continuing Education Teaching Reform Research Project "Research and Practice on the Classroom Teaching Application Model of Artificial Intelligence-Empowered Higher Vocational Computer Courses" (Project No. SJGZY2025028).

References

1. Clare Baek, Tamara Tate, and Mark Warschauer. 2024. "ChatGPT seems too good to be true": College students' use and perceptions of generative AI. Computers and Education: Artificial Intelligence 7 (2024), Article 100294. https://doi.org/10.1016/j.caeai.2024.100294
2. Maria Ijaz Baig and Elaheh Yadegaridehkordi. 2024. ChatGPT in the higher education: A systematic literature review and research challenges. International Journal of Educational Research 127 (2024), Article 102411. https://doi.org/10.1016/j.ijer.2024.102411
3. Anol Bhattacherjee. 2001. Understanding information systems continuance: An expectation-confirmation model. MIS Quarterly 25, 3 (2001), 351–370. https://doi.org/10.2307/3250921
4. Fred D. Davis. 1989. Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly 13, 3 (1989), 319–340. https://doi.org/10.2307/249008
5. Cuong D. Duong, Thi H. Nguyen, Thi V. N. Ngo, Van T. Dao, Dang N. Do, and Thanh V. Pham. 2024. Exploring higher education students' continuance usage intention of ChatGPT: Amalgamation of the information system success model and the stimulus-organism-response paradigm. International Journal of Information and Learning Technology 41, 5 (2024), 556-584. https://doi.org/10.1108/IJILT-01-2024-0006
6. Joseph F. Hair, William C. Black, Barry J. Babin, and Rolph E. Anderson. 2019. Multivariate Data Analysis (8th ed.). Cengage Learning.
7. Mehmet Haldun Kaya and Tufan Adıgüzel. 2025. Exploring the acceptance of ChatGPT in higher education: A comprehensive quantitative study of university students and faculty. Frontiers in Education 10 (2025), Article 1652292. https://doi.org/10.3389/feduc.2025.1652292
8. Mahboobeh Mehrvarz, Ghasem Salimi, Samaneh Abdoli, and Bruce M. McLaren. 2025. How does students' perception of ChatGPT shape online learning engagement and performance? Computers and Education: Artificial Intelligence 9 (2025), Article 100459. https://doi.org/10.1016/j.caeai.2025.100459

9. Muhammad Farrukh Shahzad, Shuo Xu, and Iqra Javed. 2024. ChatGPT awareness, acceptance, and adoption in higher education: The role of trust as a cornerstone. International Journal of Educational Technology in Higher Education 21 (2024), Article 46. https://doi.org/10.1186/s41239-024-00478-x
10. Ahmed Shuhaiber, Mohammad Amin Kuhail, and Sinan Salman. 2025. ChatGPT in higher education: A student’s perspective. Computers in Human Behavior Reports 17 (2025), Article 100565. https://doi.org/10.1016/j.chbr.2024.100565
11. Pei-Chen Sun, Ray J. Tsai, Glenn Finger, Yueh-Yang Chen, and Dowming Yeh. 2008. What drives a successful e-Learning? An empirical investigation of the critical factors influencing learner satisfaction. Computers & Education 50, 4 (2008), 1183–1202. https://doi.org/10.1016/j.compedu.2006.11.007
12. Viswanath Venkatesh and Fred D. Davis. 2000. A theoretical extension of the Technology Acceptance Model: Four longitudinal field studies. Management Science 46, 2 (2000), 186–204. https://doi.org/10.1287/mnsc.46.2.186.11926