Regional Heterogeneity in College–Company Collaboration and Generative AI–Enabled Teaching in Vocational Undergraduate Education: Evidence from Multi-Group PLS-SEM

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Abstract

Generative Artificial Intelligence (GAI) is increasingly used in vocational undergraduate education. Empirical evidence remains limited regarding how college–company collaboration, GAI-supported teaching processes, learning outcomes, and ethical risk perception are connected within vocational undergraduate education. This study developed and evaluated a structural model incorporating College–Company Collaboration Intensity (CCI), the AI teaching process (AI_Process), Learning Outcomes, and Ethical Risk Perception (ERP). The model was analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) and Multi-Group Analysis (MGA).

CCI had a significant positive effect on AI_Process ($\beta = 0.742$, $p < 0.001$). AI_Process showed a strong positive association with Learning Outcomes ($\beta = 0.892$, $p < 0.001$), while Learning Outcomes was positively associated with ERP ($\beta = 0.635$, $p < 0.001$). The structural model achieved a high explanatory power for Learning Outcomes ($R^2 = 0.796$), with AI_Process serving as the direct predictor. The multi-group analysis found differences among the three participating institutions in the CCI→AI_Process and Learning_Outcomes→ERP paths. The AI_Process→Learning_Outcomes path differed significantly in one pairwise comparison but not in the other two.

The findings show that college–company collaboration was closely related to the integration of GAI into teaching, and that the AI teaching process was strongly associated with learning outcomes. Several structural paths differed across the three participating institutions.

Keywords: generative artificial intelligence, college–company collaboration, vocational undergraduate education, learning outcomes, ethical risk perception, PLS-SEM

1. Introduction

1.1 Research Background

Generative artificial intelligence (GAI) is becoming part of teaching practice in higher education. It is used not only to generate learning materials, but also to provide feedback, support classroom activities, and assist teachers in course design. In some courses, it is also used to support curriculum planning and competency-based tasks (Dai et al., 2026). One feature of GAI is that its responses can change based on the questions asked and the information provided by the learner. This makes it possible to offer different forms of support to students who are working at different levels or progressing at different speeds (Joshi, 2025). For this reason, recent research has paid increasing attention to its actual use in teaching and to its possible influence on students' professional learning (Yu & Guo, 2023).

Vocational undergraduate education aims to develop application-oriented professionals by combining industry-oriented curricula with workplace-based learning (Zhong, 2025). Despite ongoing reforms, challenges remain in aligning educational provision with changing industry requirements. Course content does not always reflect current industry needs, classroom teaching is often separated from actual work processes, and the standard of practical teaching differs from one institution to another (Hu, 2024).

Generative AI provides new possibilities for addressing these challenges in vocational undergraduate education. Through applications such as intelligent tutoring, workplace scenario simulation, and adaptive learning support, GAI can help students connect classroom knowledge with practical engineering tasks. These applications may also create more opportunities for students to apply professional knowledge in work-related contexts (Ye, 2023). However, previous studies have mainly focused on the use of GAI in specific courses or its association with student performance. Less is known about how GAI functions within the broader teaching system of vocational undergraduate education.

College–Company Collaboration Intensity (CCI) describes the degree to which enterprises participate in curriculum design, practical training, project-based learning, and student assessment. Greater enterprise involvement can help universities align teaching content and training activities with current industry requirements (Risdwiyanto et al., 2023). However, many existing collaboration models were established before generative AI became widely used in education. As a result, they offer little direction on how colleges and companies can jointly incorporate GAI into teaching and training. The way in which CCI contributes to the use of GAI in vocational undergraduate education therefore remains unclear (El Hayani & Benamar, 2025).

GAI-enabled teaching may not develop in the same way across regions. Differences in local economies, industrial conditions, digital infrastructure, educational resources, and enterprise participation can affect both CCI and the use of GAI in teaching (Liu et al., 2024). Its educational effects may therefore vary from one region to another. Regional differences should be taken into account when studying GAI in vocational undergraduate education.

1.2 Research Gaps

Research on digital technologies has provided evidence of their potential to improve teaching and learning in higher education. However, vocational undergraduate education has received comparatively limited attention, despite its distinct educational objectives, curriculum structure, and level of industry participation.

One limitation of the existing literature is its emphasis on general higher education. Previous research on digital technologies has mainly focused on their effects on general higher education outcomes, such as academic performance and student engagement. However, the specific characteristics of vocational undergraduate education have received less attention. Factors such as industry-oriented curricula, practical competency development, and College–Company Collaboration (CCI) may influence the integration of generative AI into this educational context. Therefore, existing research provides limited understanding of how GAI contributes to student development in vocational undergraduate education.

The mechanisms through which GAI influences learning outcomes have not yet been fully clarified. Existing studies have mainly examined the effects of AI applications on learning outcomes, while less attention has been paid to the teaching processes that connect technology use to these outcomes. In particular, dimensions such as student engagement, pedagogical adaptation, and competency development are often examined separately rather than within an integrated framework (Guo & Liu, 2023). Consequently, limited empirical evidence is available regarding how GAI-enabled teaching processes, including Generative AI Usage (GAU) and Teaching–Pedagogical Adaptation (TPA), contribute to learning outcomes.

Differences in institutional and regional contexts represent another area requiring further investigation. Although previous research has acknowledged variations in economic development and educational resources, limited attention has been paid to how contextual conditions and College–Company Collaboration (CCI) jointly influence GAI-enabled teaching in vocational undergraduate education (Wei et al., 2025). Existing comparative studies provide insufficient evidence regarding whether the structural relationships associated with GAI remain consistent across different contexts.

Therefore, a more integrated examination of CCI, GAI-enabled teaching processes, learning outcomes, ethical risk perception, and contextual differences is needed to understand better the application of generative AI in vocational undergraduate education.

1.3 Research Objectives and Research Questions

The study tests three sequential relationships: CCI→AI_Process, AI_Process→Learning_Outcomes, and Learning_Outcomes→ERP. It also compares the path estimates among the three participating institutions. Because one institution was sampled from each region, the comparison provides preliminary evidence of regional heterogeneity rather than fully representative findings for all vocational undergraduate institutions across the three regions.

AI_Process and Learning_Outcomes are modeled as reflective–reflective higher-order constructs. AI_Process has two lower-order components: Generative AI Usage (GAU) and Teaching–Pedagogical Adaptation (TPA). These components represent students' use of GAI and their perceptions of how teaching is adapted in GAI-supported learning environments. Learning_Outcomes has three lower-order components: Learning Engagement (LE), Engineering Problem-Solving Ability (EPS), and Teaching Satisfaction (TS). These components represent students' participation in learning, professional problem-solving competence, and evaluation of instruction.

Multi-group comparisons are used to assess whether these structural relationships differ among the three sampled institutions located in eastern, central, and western China.

The study addresses the following research questions:

RQ1: Does CCI significantly influence AI_Process?

RQ2: Does AI_Process significantly influence Learning_Outcomes?

RQ3: Does the higher-order Learning_Outcomes construct significantly influence ERP?

RQ4: Do these structural relationships differ significantly among the participating institutions located in eastern, central, and western China?

The research questions provide the basis for examining the proposed structural relationships and comparing their differences across the three sampled institutional contexts. The results are expected to contribute to a better understanding of how CCI and generative AI are integrated into vocational undergraduate education.

2. Literature Review and Research Hypotheses

2.1 College–Company Collaboration Intensity, CCI, and the Artificial Intelligence Teaching Process

College–Company Collaboration Intensity (CCI) reflects the degree of enterprise involvement in vocational education, including participation in curriculum development, teaching activities, practical training, project cooperation, and student assessment. In vocational undergraduate education, enterprises can contribute industry knowledge, technical resources, workplace tasks, and occupational standards that may not be readily available within educational institutions. Resource Dependence Theory helps explain why vocational institutions depend on enterprise participation to keep teaching content aligned with current industry requirements (Pfeffer & Salancik, 2015; Zhuang et al., 2024).

The use of generative artificial intelligence in education also requires suitable professional tasks and realistic workplace situations. Through their participation, enterprises can provide engineering cases, technical data, project requirements, and practical problems. These materials can then be used in GAI-supported simulation, feedback, and task-based learning. CCI may therefore help connect the use of GAI in vocational teaching with actual professional practice.

Collaborative Governance Theory also emphasizes the value of joint participation by educational institutions and enterprises in curriculum design, practical teaching, and assessment (Ansell & Gash, 2008). Enterprise involvement in these areas may help ensure that AI-supported teaching reflects the competencies required in professional work.

CCI may also affect Teaching–Pedagogical Adaptation by providing teachers with access to information on workplace requirements and current professional practices. Teachers can use this information to revise teaching content and learning tasks. At the same time, students can apply GAI tools in project-based and practice-oriented activities. These conditions may make the use of GAI more relevant to the teaching process (Davis, 1989; Zary & Zary, 2025).

Based on this analysis, the following hypothesis is proposed:

H1: College–Company Collaboration Intensity (CCI) has a significant positive effect on the AI teaching process (AI_Process).

2.2 Hierarchical Modeling of the AI Teaching Process

The role of generative AI in teaching is not limited to the use of technological tools; it also depends on how these tools are integrated into instructional practices. It also requires changes in how teaching content and learning activities are organized. For this reason, AI_Process was specified as a hierarchical component model rather than as a single first-order construct.

The Technology Acceptance Model (TAM) emphasizes that technology adoption involves both the actual use of technology and users' perceptions of its usefulness and suitability (Davis, 1989). Based on this perspective, AI_Process was conceptualized as a higher-order construct consisting of two lower-order dimensions: Generative AI Usage (GAU) and Teaching–Pedagogical Adaptation (TPA). GAU reflects students' engagement with generative AI tools in learning activities, including the frequency, depth, and application contexts of AI use. TPA refers to students' perceptions of how well generative AI is integrated with course objectives, instructional content, and learning tasks (Hou et al., 2025). Previous research has suggested that effective technology integration depends not only on technology use itself but also on the alignment between technology and teaching practices (Mittal et al., 2025).

AI_Process was specified as a reflective–reflective higher-order construct composed of GAU and TPA. The two lower-order constructs were treated as manifestations of the broader AI teaching process. A two-stage approach was used to estimate the higher-order construct in the subsequent analysis.

2.3 The AI Teaching Process and Learning Outcomes

The contribution of technology to learning depends on how it is used in relation to course content, teaching methods, and learning tasks. Technology integration theory argues that technology is more likely to support learning when its use is consistent with pedagogical goals and subject content (Koehler et al., 2014). In this study, AI_Process is represented by Generative AI Usage (GAU) and Teaching–Pedagogical Adaptation (TPA). Together, these two dimensions describe both students' use of generative AI and the extent to which that use fits the teaching process.

GAI may influence learning in several ways. Timely feedback and interactive activities can encourage students to participate more actively in learning (Asrifan et al., 2026). In engineering education, case analysis, task generation, and scenario simulation can give students more opportunities to work through practical problems (Mosly, 2024). Personalized support may also improve students' evaluations of the teaching they receive (Muslim et al., 2025).

Learning outcomes in vocational undergraduate civil engineering education are not limited to knowledge acquisition. In this study, Learning_Outcomes includes Learning Engagement (LE), Engineering Problem-Solving Ability (EPS), and Teaching Satisfaction (TS) (Kim et al., 2024; Mohd Noor et al., 2019). It was therefore modeled as a higher-order reflective construct, with these three lower-order dimensions reflecting it.

Based on this analysis, the following hypothesis is proposed:

H2: The AI teaching process (AI_Process) has a significant positive effect on learning outcomes (Learning_Outcomes).

2.4 Learning Outcomes and Perception of Ethical Risks

The growing use of generative AI in education has drawn greater attention to issues such as data privacy, algorithmic bias, misinformation, academic integrity, and overreliance on AI-generated content (da Conceição Silva, 2025). Most previous studies have treated ethical risk perception as a factor that may affect students' willingness to use AI. Its relationship with students' learning outcomes has received much less attention (Agrawal, 2026).

Cognitive development theory suggests that the development of knowledge and problem-solving ability is associated with stronger critical evaluation and reflective judgment (King & Kitchener, 1994). Students who participate more actively in learning and develop stronger problem-solving skills may be better able to assess the limitations and risks of generative AI.

Students who are more engaged in AI-supported learning activities are likely to encounter both the strengths and the limitations of AI tools, which may increase their awareness of related risks (Choi et al., 2024). Students with stronger engineering problem-solving ability may also be better at identifying problems such as algorithmic bias, excessive reliance on generated results, and a lack of transparency in AI-assisted decisions (Mosly, 2024). Teaching satisfaction may indicate that students have a clearer understanding of how AI is incorporated into teaching, which may help them evaluate its educational use more carefully (Al Amrani, 2025).

Based on this analysis, the following hypothesis is proposed:

H3: Learning outcomes (Learning_Outcomes) have a significant positive effect on ethical risk perception (ERP).

2.5 Regional Differences in the Structural Model

Regional differences in industrial structure, digital infrastructure, educational resources, and college–company collaboration may influence the implementation of AI-supported vocational education. These institutional and regional conditions may shape the implementation of AI-supported teaching by influencing digital resources, access to workplace-based learning materials, and the degree of enterprise participation in educational activities.

Regional development gradient theory emphasizes that technological, industrial, and institutional resources are not equally distributed across regions (Williamson, 1965). In vocational undergraduate education, differences in economic conditions, industrial structures, and educational resources may influence the availability of enterprise cooperation resources and the capacity to integrate generative AI into teaching practices.

From the perspective of digital divide theory, unequal access to digital technologies and differences in users' ability to apply these technologies may lead to variations in educational outcomes (van Dijk, 2006). Institutions with better digital infrastructure and stronger industry connections may have more favorable conditions for incorporating generative AI into teaching activities. Meanwhile, students' experiences with AI-supported learning environments may influence their learning outcomes and understanding of potential ethical risks (Wei et al., 2011).

Taken together, these perspectives indicate that the relationships among CCI, AI_Process, Learning_Outcomes, and ERP may not be identical across different institutional contexts. Since this study included one institution from each region, the comparison is intended to explore possible variations among the sampled institutions rather than represent all vocational undergraduate institutions in eastern, central, and western China.

Based on the above discussion, the following hypothesis was proposed:

H4: The structural relationships among CCI, AI_Process, Learning_Outcomes, and ERP differ across the three participating institutions representing eastern, central, and western China.

3. Methodology

3.1 Sample and Data Collection

Data were collected through a questionnaire survey of first- and second-year students in the Road and Bridge Engineering programs at vocational undergraduate institutions in China. This program was selected because it emphasizes practical training and close connections with industry practice. In this context, generative AI has been applied in activities such as engineering design support, information retrieval, and learning assistance.

Three vocational undergraduate institutions were selected, one from each of the eastern, central, and western regions of China, according to the national regional classification. Purposive sampling was adopted to recruit students from the Road and Bridge Engineering programs. Since only one institution was selected from each region, the comparisons in this study should be understood as differences among the sampled institutions rather than evidence representing all vocational undergraduate institutions in these regions. The regional analysis was therefore exploratory. Before the formal survey, a pilot study was conducted, and several questionnaire items were adjusted based on the feedback obtained. The revised questionnaire was distributed online, and participation was voluntary and anonymous.

A total of 300 questionnaires were distributed, of which 268 were valid, yielding a response rate of 89.33%. The final sample consisted of 81 students from the eastern institution, 92 from the central institution, and 95 from the western institution. The sample sizes across the three groups were relatively balanced, with a largest-to-smallest ratio of approximately 1.17, which meets the requirements for subsequent multi-group analysis (Hair et al., 2021).

All items were measured using a five-point Likert scale ranging from 1 ("strongly disagree") to 5 ("strongly agree"). The dataset was examined for missing values and potential outliers before analysis. Partial Least Squares Structural Equation Modeling (PLS-SEM) was used to estimate the higher-order constructs and conduct multi-group comparisons. The sample size was considered appropriate for the analysis procedure (Sarstedt et al., 2019).

3.2 Measurement Tools

The measurement items were adapted from existing scales reported in previous studies. Considering the characteristics of Road and Bridge Engineering students and the specific contexts in which generative AI is applied, several items were modified to better align with the research setting. The questionnaire was reviewed by experts and refined through a pilot survey before the formal data collection. All items were measured on a five-point Likert scale, ranging from 1 ("strongly disagree") to 5 ("strongly agree").

3.2.1 College–Company Collaboration Intensity, CCI

College–Company Collaboration Intensity (CCI) measures the degree of collaboration between vocational undergraduate institutions and enterprises across curriculum development, practical instruction, project cooperation, resource sharing, and talent cultivation, reflecting the depth and breadth of enterprise participation in vocational education. As a first-order reflective construct, CCI characterizes the overall level of college–company collaboration.

3.2.2 Artificial Intelligence Teaching Process (AI_Process)

AI_Process is a second-order reflective construct (Reflective–Reflective HCM) composed of two first-order constructs:

(1) Generative AI Usage (GAU): Measures the frequency, depth, and breadth of students' use of generative AI tools.

(2) Teaching–Pedagogical Adaptation (TPA): Measures students' perceptions of how well AI aligns with course objectives, instructional content, and learning tasks, including evaluations of learning support, instructional assistance, and course adaptability.

3.2.3 Learning Outcomes (Learning_Outcomes)

Learning Outcomes (Learning_Outcomes) is a second-order reflective construct composed of three first-order constructs:

(1) Engineering Problem-Solving Ability (EPS): Measures students' ability to analyze, evaluate, and solve engineering problems in practice.

(2) Learning Engagement (LE): Measures the level of behavioral, cognitive, and emotional engagement of students in learning activities.

(3) Teaching Satisfaction (TS): Measures students' satisfaction with course content, the teaching process, and the overall learning experience.

3.2.4 Ethical Risk Perception (ERP)

Measures students' awareness of potential ethical risks associated with generative AI applications, including data privacy, algorithmic bias, information authenticity, and academic integrity. ERP is a first-order reflective construct.

3.2.5 Regional Variable (Region)

The Region variable is categorized into three groups—Eastern, Central, and Western—based on the geographic location of the students' institutions. This variable is used as a grouping variable for multi-group analysis (MGA) and does not directly participate in the structural model's path analysis.

3.2.6 Higher-Order Construct Modeling

AI_Process and Learning_Outcomes were modeled as reflective–reflective higher-order constructs. AI_Process was represented by Generative AI Usage (GAU) and Teaching–Pedagogical Adaptation (TPA), whereas Learning_Outcomes was represented by Learning Engagement (LE), Engineering Problem-Solving Ability (EPS), and Teaching Satisfaction (TS). These lower-order constructs were treated as manifestations of their respective higher-order constructs because they were expected to reflect a common underlying concept and to vary in the same general direction.

A formative–reflective specification was not adopted because it would treat the lower-order constructs as distinct components that jointly determine the higher-order construct. That interpretation did not match the conceptualization used in this study.

The higher-order constructs were estimated using a two-stage approach. In the first stage, the lower-order measurement models were assessed, and latent variable scores were obtained. In the second stage, these scores were used as indicators of AI_Process and Learning_Outcomes in the structural model. This procedure reduced model complexity and avoided the repeated use of all lower-order indicators in the higher-order model.

3.3 Data Analysis Methods

Data analysis relied on Partial Least Squares Structural Equation Modeling (PLS-SEM), run through SmartPLS 4 (Ringle et al., 2024). PLS-SEM was selected because the study emphasizes prediction, includes higher-order constructs, and uses multi-group analysis. The method is also suitable for models estimated under less restrictive distributional assumptions (Hair et al., 2022). Given that this study examines second-order hierarchical constructs and requires multi-group comparisons across regions, PLS-SEM was the more practical choice.

The analysis steps are as follows:

(1) Measurement model evaluation. Internal consistency reliability was assessed using outer loadings, Cronbach's α, and composite reliability (CR), while convergent validity was evaluated using average variance extracted (AVE). Discriminant validity was assessed using both the Fornell–Larcker criterion and the heterotrait–monotrait ratio (HTMT).

(2) Estimation of higher-order constructs. Both the AI teaching process (AI_Process) and learning outcomes

(Learning_Outcomes) are reflective-reflective hierarchical constructs (HCM). A two-stage approach was adopted: in the first stage, scores for first-order latent variables were estimated; in the second stage, these were used as indicators of the second-order constructs to estimate the higher-order model and its path relationships.

(3) Structural model evaluation. Bootstrapping with 5,000 subsamples was used to assess the significance of the structural path coefficients. Collinearity among the predictor constructs was examined using the inner variance inflation factor (VIF). The explanatory and predictive performance of the model was evaluated using path coefficients (β), t-values, p-values, the coefficient of determination (R^2), effect size (f^2), and predictive relevance (Q^2predict).

(4) Multi-group analysis (MGA). To examine regional differences, the MICOM procedure was first used to assess measurement invariance through three steps: configural invariance, compositional invariance, and the equality of composite mean values and variances. With partial measurement invariance established, bootstrapping-based multi-group analysis (MGA) was subsequently used to assess differences in structural path coefficients across the three participating institutions.

4. Research Results

4.1 Evaluation of Higher-Order Constructs

Both AI_Process and Learning_Outcomes were specified as reflective–reflective hierarchical constructs (HCM). Following the Two-Stage approach recommended by Sarstedt et al. (2019), the second-order constructs were assessed using the latent variable scores obtained from the first-stage analysis. The outer loadings of the higher-order construct indicators are reported in Table 1.

The outer loadings ranged from 0.968 to 0.975, exceeding the recommended value of 0.70 (Hair et al., 2019). Specifically, GAU and TPA loaded on AI_Process at 0.972 and 0.975, respectively. For Learning_Outcomes, the loadings of EPS, LE, and TS were 0.972, 0.969, and 0.968, respectively. All loadings were statistically significant ($p < 0.001$), supporting the reliability of the higher-order construct indicators.

For CCI and ERP, the first-order latent variable scores were used as single indicators in the second-stage analysis. Therefore, the outer loadings were fixed at 1.000, and significance tests were not applicable. This result is consistent with the Two-Stage approach's estimation procedure for modeling higher-order constructs.

Table 1. Outer Loadings of the Higher-Order Constructs

Construct	Indicator	Loading (O)	STDEV	T-Value	P-Value
AI_Process	GAU	0.972	0.005	196.462	<0.001
	TPA	0.975	0.004	240.920	<0.001
Learning_Outcomes	EPS	0.972	0.006	154.608	<0.001
	LE	0.969	0.005	182.979	<0.001
	TS	0.968	0.006	164.045	<0.001
CCI	CCI	1.000*	0.000	—	—
ERP	ERP	1.000*	0.000	—	—

* Single-indicator construct.

4.2 Reliability and Validity Tests

Table 2 presents the results of the reliability and convergent validity assessment. Cronbach's α values ranged from 0.945 to 0.968, while composite reliability (CR) values ranged from 0.973 to 0.979, both exceeding the recommended threshold of 0.70 (Hair et al., 2019). The average variance extracted (AVE) ranged from 0.941 to 0.948, exceeding the recommended value of 0.50 (Fornell & Larcker, 1981). These results indicate satisfactory reliability and convergent validity.

Table 2. Reliability and Convergent Validity Results

Construct	Cronbach's α	Composite Reliability (CR)	AVE
AI_Process	0.945	0.973	0.948
Learning_Outcomes	0.968	0.979	0.941
CCI	1.000	1.000	1.000
ERP	1.000	1.000	1.000

Discriminant validity was examined using the Fornell–Larcker criterion and the HTMT ratio. Table 3 presents the Fornell–Larcker results. The diagonal values are the square roots of the AVE, and the off-diagonal values are the correlations between constructs. Each diagonal value was higher than the corresponding inter-construct correlations. The Fornell–Larcker criterion was therefore met.

Table 3. Discriminant Validity Assessment Using the Fornell–Larcker Criterion

Construct	AI_Process	CCI	ERP	Learning_Outcomes
AI_Process	0.973			
CCI	0.742	1.000		
ERP	0.524	0.730	1.000	
Learning_Outcomes	0.892	0.811	0.635	0.970

Table 4 reports the HTMT results, which ranged from 0.539 to 0.932. All construct pairs were below the 0.90 threshold, except for AI_Process and Learning_Outcomes, with an HTMT value of 0.932 (Henseler et al., 2015). The 95% bootstrap confidence interval for this pair ranged from 0.889 to 0.965 and did not include 1.00, supporting discriminant validity under HTMT inference. AI_Process and Learning_Outcomes were therefore retained as separate constructs. Nevertheless, the relatively high HTMT value indicates a close empirical association between them.

Table 4. Discriminant Validity Assessment (HTMT Criterion)

Construct	AI_Process	CCI	ERP	Learning_Outcomes
AI_Process	—	0.764	0.539	0.932
CCI	0.764	—	0.730	0.824
ERP	0.539	0.730	—	0.645
Learning_Outcomes	0.932	0.824	0.645	—

Note. The 95% bootstrap confidence interval for the HTMT value between AI_Process and Learning_Outcomes was [0.889, 0.965].

4.3 Structural Model Testing

Prior to evaluating the structural relationships, collinearity among predictor constructs was assessed using inner VIF values. Since each endogenous construct was predicted by only one construct, all inner VIF values were 1.000, indicating that multicollinearity was not a concern.

The structural model was estimated using bootstrapping with 5,000 subsamples. The standardized path coefficients and R^2 values are presented in Figure 1, while the detailed path estimates and significance results are provided in Table 5. The results showed that College–Company Collaboration Intensity (CCI) had a significant positive relationship with the AI teaching process (AI_Process) ($\beta = 0.742$, $t = 14.230$, $p < 0.001$), providing support for H1. AI_Process had a significant positive effect on Learning Outcomes ($\beta = 0.892$, $t = 44.397$, $p < 0.001$), supporting H2. Learning Outcomes also had a significant positive effect on Ethical Risk Perception (ERP) ($\beta = 0.635$, $t = 9.137$, $p < 0.001$), supporting H3.

All three hypothesized direct relationships were statistically significant. Therefore, H1, H2, and H3 were supported.

Table 5. Structural Path Estimates

Path	β (O)	Mean (M)	STDEV	T Value	P Value	Inner VIF
CCI → AI_Process	0.742	0.742	0.052	14.230	< 0.001	1.000
AI_Process → Learning_Outcomes	0.892	0.891	0.020	44.397	< 0.001	1.000
Learning_Outcomes → ERP	0.635	0.635	0.069	9.137	< 0.001	1.000

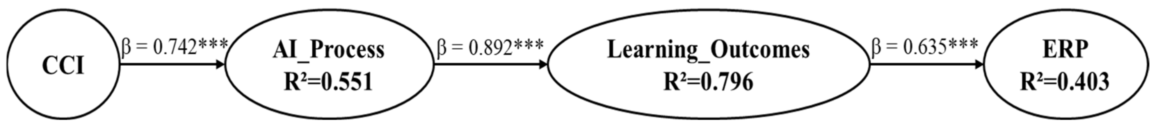

Figure 1. Structural Model Results

4.4 Explanatory Power, Effect Size, and Predictive Relevance

The structural model was further evaluated through explanatory power, effect size, and predictive relevance. Specifically, R^2 values were used to examine the variance explained in endogenous constructs, f^2 values were used to assess the contribution of predictor constructs, and Q^2predict values were used to evaluate predictive relevance. The interpretation of R^2 and f^2 followed the criteria suggested by Hair et al. (2019), where R^2 values of 0.25, 0.50, and 0.75 represent weak, moderate, and substantial explanatory power, and f^2 values of 0.02, 0.15, and 0.35 indicate small, medium, and large effects, respectively.

CCI explained 55.1% of the variance in AI_Process ($R^2 = 0.551$). AI_Process explained 79.6% of the variance in Learning_Outcomes ($R^2 = 0.796$), and Learning_Outcomes explained 40.3% of the variance in ERP ($R^2 = 0.403$). These values indicate moderate explanatory power for AI_Process, substantial explanatory power for Learning_Outcomes, and weak-to-moderate explanatory power for ERP.

The f^2 values were 1.229 for CCI → AI_Process, 3.891 for AI_Process → Learning_Outcomes, and 0.676 for Learning_Outcomes → ERP. All three f^2 values exceeded the threshold for a large effect size. The relatively high value of $f^2 = 3.891$ for the AI_Process→Learning_Outcomes relationship should be interpreted in light of the model's structure. In the current specification, AI_Process was the only construct directly predicting Learning_Outcomes, which resulted in a large change in explained variance when this predictor was removed. Therefore, the large f^2 value primarily reflects the contribution of AI_Process in this specific model rather than indicating an unusually strong effect that would necessarily persist in a model with additional predictors. Future studies may include additional relevant factors to examine the determinants of Learning_Outcomes further.

The Q^2predict values were 0.542 for AI_Process, 0.628 for Learning_Outcomes, and 0.435 for ERP. All values were above zero, indicating predictive relevance for the three endogenous constructs.

Table 6. Coefficient of Determination, Effect Size, and Predictive Relevance

Endogenous Construct	R^2	Q^2predict	Exogenous Construct	f^2
AI_Process	0.551	0.542	CCI	1.229
Learning_Outcomes	0.796	0.628	AI_Process	3.891
ERP	0.403	0.435	Learning_Outcomes	0.676

4.5 Measurement Invariance Tests

The MICOM procedure was conducted to examine whether the measurement models were comparable across the three participating institutions (Henseler et al., 2016). As shown in Table 7, configural invariance was achieved because all groups used identical indicators, measurement specifications, data processing procedures, and algorithm settings. The correlation coefficients for compositional invariance were 1.000 for all constructs, confirming that the composite scores had the same underlying structure across groups.

The permutation test indicated that the equality of composite means and variances was established for most constructs ($p > 0.05$). However, the mean value of AI_Process differed significantly among the three participating institutions ($p = 0.008$). Since compositional invariance was confirmed for all constructs, partial measurement invariance was established, allowing subsequent multi-group analysis.

Table 7. Measurement Invariance Assessment (MICOM Results)

Construct	Configural Invariance	Compositional Invariance (c)	Equal Means (p)	Equal Variances (p)
AI_Process	Established	1.000	0.008	0.360
CCI	Established	1.000	0.704	0.255
ERP	Established	1.000	0.573	0.596
Learning_Outcomes	Established	1.000	0.160	0.986

4.6 Results of Multi-Group Analysis

Whether structural paths differed among the three participating institutions was assessed using PLS multi-group analysis (PLS-MGA) with bootstrap resampling. According to Henseler et al. (2009), path differences were considered significant when the p-value was below 0.05 or above 0.95.

Table 8 shows that the AI_Process→Learning_Outcomes path differed significantly between the eastern and central institutions ($p = 0.029$). In contrast, the comparisons between the eastern and western institutions ($p = 0.284$) and between the central and western institutions ($p = 0.433$) did not reach statistical significance. Overall, the relationship between AI_Process and Learning_Outcomes appeared relatively stable across the three groups, although a significant difference was observed in the eastern–central comparison.

For the CCI→AI_Process path, significant differences were found in all three pairwise comparisons (eastern vs. central: $p = 0.001$; eastern vs. western: $p = 0.009$; central vs. western: $p = 0.996$). This indicates that the relationship between College–Company Collaboration Intensity and the AI teaching process differed among the three participating institutions.

For the Learning_Outcomes→ERP path, significant differences were found between the eastern and central institutions ($p < 0.001$) and between the eastern and western institutions ($p = 0.003$). The difference between the central and western institutions was not significant ($p = 0.260$). These results indicate that differences in this structural relationship were mainly observed between the eastern institution and the other two institutions.

Overall, the multi-group analysis identified differences in several structural paths among the three participating institutions. The observed differences suggest variation among the sampled institutions across the sampled institutional and regional contexts. Given that only one institution was included from each region, the results should not be generalized to all vocational undergraduate institutions in eastern, central, and western China. Within the scope of the present sample, H4 was supported.

Table 8. Multi-Group Analysis of Structural Path Differences (Bootstrapping MGA, Two-Tailed Test)

Path	East vs Central	East vs West	Central vs West
AI_Process → Learning_Outcomes	0.029*	0.284	0.433
CCI → AI_Process	0.001*	0.009*	0.996*
Learning_Outcomes → ERP	0.000*	0.003*	0.260

5. Discussion

5.1 Higher-Order Constructs

This study conceptualized the AI teaching process (AI_Process) and learning outcomes (Learning_Outcomes) as reflective–reflective higher-order constructs. The outer loadings of the lower-order constructs were high and statistically significant, supporting the higher-order construct specifications (Sarstedt et al., 2019). AI_Process comprised two dimensions: Generative AI Usage (GAU) and Teaching–Pedagogical Adaptation (TPA). These dimensions represent students' use of generative AI tools and their perceptions of the alignment between AI-supported activities and instructional objectives. Learning_Outcomes comprised Learning Engagement, Engineering Problem-Solving Ability, and Teaching Satisfaction. The findings are consistent with technology integration theory, which emphasizes the alignment of technology use with instructional content and pedagogical practices (Koehler et al., 2014). The higher-order specifications also reflect the emphasis of vocational undergraduate education on student participation, professional problem-solving ability, and learning experience.

5.2 Measurement Model

The measurement model satisfied the requirements for reliability and convergent validity (Hair et al., 2019). The HTMT value between AI_Process and Learning_Outcomes was 0.932, exceeding the commonly used threshold of 0.90. However, its 95% bootstrap confidence interval was 0.889–0.965 and did not include 1.00, supporting the empirical distinction between the two constructs.

AI_Process and Learning_Outcomes were maintained as two distinct higher-order constructs because they reflect different stages of AI-supported teaching and learning. AI_Process captures the implementation process of generative AI in education through Generative AI Usage and Teaching–Pedagogical Adaptation, whereas Learning_Outcomes reflects students' responses to this process through Learning Engagement, Engineering Problem-Solving Ability, and Teaching Satisfaction. Although the HTMT value between the two constructs was relatively high, the bootstrap confidence interval did not include 1.00, indicating that they remained empirically distinguishable (Henseler et al., 2015). Nevertheless, the close relationship between these constructs suggests that future studies should continue to improve measurement items and further examine their conceptual boundaries.

5.3 Structural Relationships

A positive relationship was found between College–Company Collaboration Intensity and the AI teaching process, supporting H1. Enterprise involvement appears to provide institutions with access to resources useful when generative AI is introduced into teaching. These resources may include current industry knowledge, engineering cases, and information about workplace requirements. Their availability can help teachers connect AI-supported activities with professional practice. This finding can be understood through Resource Dependence Theory, since vocational institutions often rely on enterprises for resources that are not readily available within the institution (Pfeffer & Salancik, 2015). It also reflects the collaborative role of colleges and enterprises described in Collaborative Governance Theory (Ansell & Gash, 2008).

The AI_Process→Learning_Outcomes relationship had the largest path coefficient in the model, supporting H2. This finding indicates that the educational influence of generative AI is closely tied to how it is incorporated into curriculum design, teaching activities, and learning tasks. In this study, higher levels of AI_Process were associated with greater learning engagement, stronger engineering problem-solving ability, and greater teaching satisfaction. This result further emphasizes the importance of combining technological applications with appropriate pedagogical arrangements (Koehler et al., 2014).

The positive association between Learning_Outcomes and Ethical Risk Perception supported H3. Students with higher levels of learning engagement and problem-solving ability may have more opportunities to recognize both the benefits and limitations of generative AI. Therefore, improved learning experiences may contribute to students' awareness of issues such as reliability, academic integrity, and responsible AI use. This explanation is consistent with cognitive development theory and reflective judgment theory (King & Kitchener, 1994).

5.4 Explanatory Power

AI_Process accounted for 79.6% of the variance in Learning_Outcomes. Students who reported greater integration of generative AI into teaching activities also tended to report higher learning engagement, stronger engineering problem-solving ability, and greater teaching satisfaction. The unusually large f^2 value for the AI_Process→Learning_Outcomes path also reflects the model's structure. AI_Process was the only direct predictor of Learning_Outcomes, so removing it caused a substantial reduction in the variance explained.

CCI explained 55.1% of the variance in AI_Process, indicating that college–company collaboration was an important factor in students' use of generative AI and in the adaptation of teaching practices. In addition, Learning_Outcomes explained 40.3% of the variance in ERP, suggesting that students with better learning outcomes tended to have a higher awareness of ethical issues related to generative AI.

The model explained a substantial proportion of the variance in AI_Process, Learning_Outcomes, and ERP. The result for Learning_Outcomes, however, requires careful interpretation because AI_Process was the only direct predictor of Learning_Outcomes in the model. Other influences were not examined. Adding factors such as teacher support, digital competence, previous experience with AI, and organizational support would help show whether the relationship remains as strong in a broader model.

5.5 Measurement Invariance

The MICOM procedure confirmed that the three groups used comparable measurement models and that compositional invariance was achieved. With partial measurement invariance established, the structural path differences among groups were further examined using multi-group analysis (Henseler et al., 2016).

The permutation test showed that most constructs satisfied the criteria for equality of composite means and variances. However, the mean value of AI_Process differed significantly among the three participating institutions ($p = 0.008$). The difference in AI_Process mean values suggests that students' perceptions of AI-supported teaching varied across the sampled institutions. Since only one institution was selected from each region, this variation may reflect a combination of institutional characteristics and regional contexts. These findings also motivated the subsequent analysis of whether the structural relationships among the constructs differed across the three groups.

5.6 Discussion of Regional Multi-Group Analysis Results

The multi-group analysis identified differences in several structural relationships among the three participating institutions. However, these differences should be interpreted with caution, as the comparison was based on a single institution from each region. The findings reflect variations among the sampled institutions rather than representing all vocational undergraduate institutions in eastern, central, and western China.

For the CCI→AI_Process relationship, significant differences were observed in all three pairwise comparisons. This indicates that the extent to which college–company collaboration was associated with AI-supported teaching differed across the sampled institutions. Such differences may be related to the local conditions of collaboration, including enterprise participation, available digital resources, teaching capacity, and institutional practices. These observations are consistent with the view that unequal access to resources and technological conditions may influence the implementation of digital education (van Dijk, 2006).

For the AI_Process→Learning_Outcomes path, a significant difference was found only between the eastern and central institutions. The other two comparisons were not significant. The relationship was therefore relatively consistent across the three institutions, though not identical. This suggests that the association between AI-supported teaching and learning outcomes may be less sensitive to institutional context than the relationship between college–company collaboration and the AI teaching process.

For the Learning_Outcomes→ERP path, significant differences were observed between the eastern and central institutions and between the eastern and western institutions. In contrast, the difference between the central and western institutions was not significant. This result may be associated with differences in students' exposure to generative AI, the range of situations in which AI was used, and the extent to which ethical issues were addressed in teaching. Differences between the institutions themselves may also have affected the results.

The results do not show a consistent east-to-west pattern. The three institutions differed in several structural paths, but these differences cannot be attributed to regional context alone. Conditions within the individual institutions may also have played a role. Studies involving several institutions in each region are needed before broader regional conclusions can be drawn.

6. Conclusions and Implications

6.1 Conclusions

This study examined how college–company collaboration, the AI teaching process, learning outcomes, and ethical risk perception were related in vocational undergraduate education. Stronger collaboration was associated with a more developed AI teaching process. In turn, students who reported stronger AI-supported teaching processes also reported better learning outcomes. Higher learning outcomes were accompanied by greater awareness of the ethical risks associated with generative AI.

AI_Process was represented by Generative AI Usage and Teaching–Pedagogical Adaptation. Learning_Outcomes covered learning engagement, engineering problem-solving ability, and teaching satisfaction. The strongest relationship in the model was found between AI_Process and Learning_Outcomes. This result suggests that the use of generative AI matters most when it is incorporated into course content, teaching activities, and learning tasks. Merely providing access to AI tools may not produce the same result.

The pattern of group differences did not remain the same across all three structural paths. The CCI→AI_Process path differed in all three pairwise comparisons. For the Learning_Outcomes→ERP path, the eastern institution differed from both the central and western institutions. By comparison, the relationship between AI_Process and Learning_Outcomes changed less across the groups, although the eastern and central institutions still differed significantly. These results may be related to differences in enterprise participation, teaching arrangements, or digital resources among the three institutions. They should not be treated as evidence of general regional patterns because only one institution was included from each region. Studies using several institutions in each region are needed before broader conclusions can be drawn.

6.2 Theoretical Implications

The findings of this study extend existing research on AI-supported undergraduate vocational education in three respects.

The first contribution is the development of a Resources–Process–Outcomes framework that connects College–Company Collaboration Intensity (CCI), the AI teaching process (AI_Process), learning outcomes, and ethical risk perception. Previous studies have often examined technology use or learning outcomes separately. By integrating Resource Dependence Theory and Technology Integration Theory, this study highlights the role of collaboration resources in shaping the implementation of generative AI in teaching practices.

A second contribution is the treatment of AI_Process and Learning_Outcomes as higher-order constructs. AI_Process brings together Generative AI Usage and Teaching–Pedagogical Adaptation, whereas Learning_Outcomes covers Learning Engagement, Engineering Problem-Solving Ability, and Teaching Satisfaction. Keeping these dimensions within two separate higher-order constructs makes it possible to distinguish what occurs during AI-supported teaching from the outcomes reported by students.

The third contribution is the consideration of institutional and regional differences in the analysis of AI-supported teaching. The multi-group analysis showed that several structural relationships differed among the three participating institutions. Although the findings are based on a limited number of institutions, they indicate that the effects of college–company collaboration, AI integration, and learning outcomes may depend partly on contextual conditions. This provides a basis for further investigation into regional differences in digital transformation and the development of vocational education.

6.3 Practical Implications

The findings have practical implications for the way generative AI is used in vocational undergraduate courses. College–company collaboration should extend beyond internships and practical training. Enterprises can take part in revising course content, selecting engineering cases, and developing tasks drawn from workplace practice. Their involvement would help connect AI-supported teaching with the kinds of problems students are likely to encounter in professional work.

Enterprises may also support teaching by making selected projects, technical materials, and workplace situations available for instructional use. Such resources would give students opportunities to work with problems that resemble those encountered in professional practice. This is particularly relevant in vocational undergraduate programs, where the value of AI depends in part on whether it is used for tasks related to occupational requirements.

Third, the differences identified among the three participating institutions indicate that AI integration is influenced by institutional conditions, including digital resources and the existing level of college–company collaboration. Education authorities and institutional administrators should therefore consider differences in development conditions when promoting AI-supported education; however, because this study included only one institution per region, policy recommendations regarding regional differences should be informed by evidence from broader samples. In addition, ethical issues related to generative AI should be addressed in teaching practice to improve students' awareness of responsible AI use.

6.4 Limitations and Future Research

The study used data collected at one point in time. It therefore cannot determine whether the relationships identified in the model change as students become more familiar with generative AI. Following the same students over a longer period would provide evidence on whether these relationships remain consistent. Interviews and classroom observations may also clarify how generative AI is actually incorporated into teaching practice.

The institutional coverage was also limited. One vocational undergraduate institution was included from each of the eastern, central, and western regions. The differences found in the multi-group analysis may therefore be connected not only to regional context but also to conditions within individual institutions. These may include available teaching resources, staff experience, student composition, and the existing form of college–company collaboration. The results describe the three sampled settings and should not be treated as representative of all institutions in the three regions. Broader studies would need several institutions from each region, together with sampling and analytical methods that account for differences between institutions.

Third, this study focused on students in Road and Bridge Engineering programs. Since disciplinary contexts may influence the way AI is integrated into teaching and learning, the findings may not be directly transferable to other fields. Future research could test the proposed model in disciplines such as intelligent manufacturing, information technology, and service-related programs.

The model did not include several factors that may also shape AI-supported learning. Teachers' digital competence, institutional support, students' trust in AI, and their previous experience with AI tools were outside the scope of the analysis. Examining these factors in later studies would help determine whether the relationships identified here remain stable after a broader set of influences is taken into account.

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Authors contributions

Prof. Dr. Tiejun Hou was responsible for conceptualization, research design, methodology, data analysis, and preparation of the original manuscript. Shuxuan Bai, Chenchen Zhang, Yuan Yuan, and Leqing Liu contributed to data collection, data organization, and manuscript revision. Saifon Songsiengchai contributed to methodological review, interpretation of the results, and critical revision of the manuscript. All authors read and approved the final manuscript.

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Data sharing statement

No additional data are available.