# Teacher's Perspective on Generative Artificial Intelligence-Driven Innovation of Vocational Undergraduate Teaching Models in Road and Bridge Engineering—An Empirical Study Based on Structural Equation Modeling

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**Abstract**

This study examines the role mechanism of generative artificial intelligence (GAI) in empowering the innovation of vocational undergraduate teaching modes in road and bridge engineering from the teachers' perspective. Integrating the Technology Acceptance Model (TAM), Constructivist Learning Theory (CLT), and Engineering Education Theory (EET), a multidimensional Structural Equation Model (SEM) is constructed, covering Teaching AI Literacy (TAL), Generative AI Use Behavior (GAU), Teaching Perception of Adaptation (TPA), Learning Engagement (LE), Learning Outcomes (LO), Engineering Problem Solving Skills (EPS), Teaching Satisfaction (TS), Ethical Risk Perception (ERP), and College-Company Collaboration Intensity (CCI) as a contextual moderating variable. Taking all 54 teachers of the road and bridge engineering program at Qinghai Vocational and Technical University as the empirical sample, the study showed that teachers' AI literacy significantly contributed to AI usage behavior and students' learning engagement; AI usage behavior further positively affected learning engagement by enhancing teachers' teaching perception of adaptation; and learning engagement significantly and positively impacted the students' learning outcomes, which in turn improved their engineering problem-solving ability and teaching satisfaction. The increase in learning engagement also considerably enhanced students' ability to perceive the ethical risks of AI. The intensity of school-enterprise collaboration (CCI) as a contextual variable was significantly and positively correlated with both teacher AI literacy TAL and generative AI usage behavior (GAU). This study has significant practical implications for the generative AI-driven reform of vocational undergraduate teaching modes and school-enterprise synergy in road and bridge engineering.

**Keywords:** generative artificial intelligence, vocational undergraduate education, road and bridge engineering program, teachers' perspectives, teaching model innovation, structural equation modeling

## 1. Introduction

### *1.1 Statement of the Problem*

Since the concept of "artificial intelligence" was first introduced at the Dartmouth Conference in 1956, AI has undergone several stages of development, progressing from initial logic and symbol processing to machine learning and now to deep learning and neural networks (Dubey et al., 2024). Unlike traditional AI, which relies primarily on rules and data-driven methods, generative AI is an AI based on algorithms, models, and rules for generating content such as text, images, sound, video, and code, and it utilizes a variety of methods to sift through the data to identify the characteristics of a given object and, in turn, generate new content (Jovanovic & Campbell, 2022). Generative AI has demonstrated potential for a wide range of applications in various aspects of education, including instructional design, resource development, classroom interaction, and personalized learning support (Wei et al., 2025). This technological advancement has injected new impetus into engineering vocational undergraduate education, providing possible paths for innovative teaching modes.

In the current development context of vocational undergraduate education, the potential of generative AI has not been fully leveraged, and this issue is particularly pronounced in the road and bridge engineering program (Harris, 2024). The road and bridge engineering program is tasked with cultivating technically skilled personnel who possess systematic theoretical knowledge and the ability to handle complex engineering situations and solve practical problems. The current teaching mode still has multiple deficiencies: firstly, there is an apparent disconnect between the course content and industry practice, which makes it difficult for students to develop comprehensive practical skills in real-world work scenarios (Kolmos et al., 2016). Secondly, there are significant differences in generative AI literacy and teaching behaviors among the teacher community. Some teachers lack sufficient trust or awareness of the capabilities of generative AI, which affects the in-depth advancement of the teaching reform and its actual impact (Al-Abdullatif, 2024). Finally, the introduction of generative AI in classroom teaching also raises concerns regarding academic integrity, the accuracy of information, and over-reliance on it. Vocational undergraduate education, specifically, is deficient in fostering student cognitive development and ethical instruction to mitigate these risks (Agarwal & Sivaraman, 2025). In vocational undergraduate education, it is still necessary to further explore and validate how to systematically integrate university-enterprise collaboration into the teaching and learning process by enhancing teachers' digital literacy, which will improve classroom teaching effectiveness and strengthen the connection between talent cultivation and enterprise practice (Wu & Shi, 2024).

This study focuses on the application of generative AI in the vocational undergraduate teaching mode of road and bridge engineering from the perspective of teachers. It examines the mechanism by which teachers' AI literacy influences their AI use behavior and their teaching perception of adaptation. It explores how the application of generative AI impacts the development of students' abilities and teaching satisfaction through learning engagement and learning outcomes and investigates the role of university-enterprise collaborative intensity in this context. This study not only deepens theoretical research on the educational application of generative AI but also provides empirical evidence and practical guidance for reforming the vocational undergraduate curriculum and developing industry-teaching collaboration.

### *1.2 Rationale of the Study*

With the rapid popularization of artificial intelligence technology, generative artificial intelligence has entered a new stage of development, reshaping the concepts and modes of many industries at a breakneck pace. In the field of education, the application of generative AI is not only essential for promoting the modernization of education but also a key driving force in reconstructing teaching concepts and modalities. (Liu et al., 2024) Educational practices around the world have gradually introduced generative AI into classroom teaching. The generation and application of multimodal resources, such as text, images, and videos, have significantly improved students' understanding of theoretical knowledge, ability development, and the depth and effectiveness of participation in practical aspects of the curriculum (Chakraborty, 2024).

The empowerment of technology also comes with significant ethical and governance challenges. In its Guidelines for the Application of Generative Artificial Intelligence in Education and Research (September 7, 2023), UNESCO explicitly states that educators must pay close attention to the ethical risks posed by the application of AI, including the protection of the privacy of learning data and personal information, the challenges of transparency and fairness arising from technological dependence, and the potential for inequalities to be aggravated by the uneven distribution of educational resources (Morandín-Ahuerma, 2024).

The central role of the teacher remains irreplaceable, and adapting to the shift in teaching responsibilities facilitated by AI has become an important topic that requires urgent attention. The introduction of generative AI presents opportunities to improve classroom efficiency, construct personalized learning paths, and enhance digital classrooms. However, educational institutions still face numerous challenges in implementing full-scale applications (Yao, 2024).

Global technological and industrial changes are accelerating the industrial revolution, placing higher demands on vocational education and talent training. Students should not only master solid traditional engineering skills but also develop innovative literacy, interdisciplinary integration skills, and systematic problem-solving abilities to adapt to future technological changes. Existing traditional teaching modes are challenging to meet this demand for transformation, and reforming teaching modes in vocational education is imminent (Masrifah & Sudira, 2020).

Exploring the effective application path of generative AI in vocational undergraduate education, especially in engineering majors, is not only of great theoretical significance but also of outstanding practical value.

*1.3 Research Objectives*

This study systematically explores the innovative path and mechanism of action of the Generative Artificial Intelligence (GAI)-driven vocational undergraduate teaching model for road and bridge engineering from the perspective of teachers. The research objectives primarily align with the technology acceptance model (TAM), constructivist learning theory, and engineering education theory.

(1) Theoretical model construction: to reveal the relationships among teacher AI literacy (TAL), AI use behavior (GAU), teaching perception of adaptation (TPA), learning engagement (LE), learning outcomes (LO), engineering problem-solving skills (EPS), teaching satisfaction (TS), and ethical risk perception (ERP), and to build and validate a generative model applicable to vocational undergraduate education's structural equation model (SEM) of AI teaching mode.

(2) Mechanism and path analysis: To explore how teachers' AI literacy affects students' learning engagement through AI usage behavior and teaching perception of adaptation and further affects learning outcomes, engineering problem-solving ability, teaching satisfaction, and ethical risk perception, to reveal the mediating mechanism and key influence paths of generative AI-enabled teaching mode innovation.

(3) Contextual effect test: The university-enterprise collaborative intensity (CCI) is included in the model as a moderating variable to analyze its moderating role in the key paths of AI usage behavior and teaching perception of adaptation, to reveal the critical value of industry-teaching integration in the application of generative AI in teaching and learning.

*1.4 Research Hypothesis/Hypotheses*

To thoroughly investigate the role mechanism of generative artificial intelligence (GAI)-driven teaching mode innovation in vocational undergraduate road and bridge engineering programs, this study proposes the following research hypotheses, guided by the Technology Acceptance Model (TAM), constructivist learning theory, and theories of engineering education. It should be noted that all hypotheses with letter suffixes (e.g., H1a, H1b) belong to different refinement directions under the same central hypothesis, which are used to clearly differentiate the paths of action of the same variable on various outcomes.

(1) The role of teacher AI literacy

H1a: There is a significant positive effect of teacher AI literacy (TAL) on generative AI use behavior (GAU). H1b: There is a significant positive effect of teacher AI literacy (TAL) on learning engagement (LE).

(2) Relationship between AI use behavior and teaching perception of adaptation

H2: There is a significant positive effect of Generative AI use behavior (GAU) on Teaching Perception of Adaptation (TPA).

(3) The Role of Teaching Perception of Adaptation

H3: There is a significant positive effect of Teaching Perception of Adaptation (TPA) on Learning Engagement (LE).

(4) Role of Learning Engagement

H4a: There is a significant positive effect of Learning Engagement (LE) on Learning Outcomes (LO).

H4b: There is a significant positive effect of learning engagement (LE) on ethical risk perception (ERP).

(5) Follow-up effects of learning outcomes

H5a: There is a significant positive effect of learning outcomes (LO) on engineering problem-solving skills (EPS).

H5b: There is a significant positive effect of learning outcomes (LO) on teaching satisfaction (TS).

(6) Moderating Effect of School-Company Collaboration Intensity

H6: There is a significant moderating effect of School-Company Collaboration Intensity (CCI) in the relationship between Generative AI Usage Behavior (GAU) and Teaching Perception of Adaptation (TPA), i.e., the pathway relationship is more significant at high levels of collaboration.

*1.5 Research Variables and Conceptual Model*

Based on the Technology Acceptance Model (TAM), constructivist learning theory, and engineering education theory, this study constructs a conceptual model containing exogenous variables, mediating variables, outcome variables, and contextual variables around the role mechanism of Generative Artificial Intelligence (GAI) in the innovation of the vocational undergraduate teaching mode of road and bridge engineering.

**Table 1.** Categorization and Definition of Study Variables

| Variable Type | Variable Name | Abbreviation | Definition |
|---|---|---|---|
| Exogenous Variable | Teachers' AI Literacy | TAL | The level of teachers' knowledge, skills, and attitudes in understanding, operating, and evaluating generative AI tools is a fundamental factor influencing their AI usage behavior and teaching effectiveness. |
| Mediating Variables | Generative AI Use Behavior | GAU | The frequency, manner, and depth of teachers' use of GAI in teaching reflect the extent to which technology is integrated into instructional practice. |
| | Teaching Perception of Adaptation | TPA | Teachers' perception of how well GAI aligns with curriculum objectives, teaching content, and instructional methods. |
| | Learning Engagement | LE | The degree of students' attention, interaction, and initiative in the learning process is a key process variable in GAI-empowered instruction. |
| | Learning Outcomes | LO | The comprehensive results of students' knowledge and skill acquisition supported by GAI serve as a bridge linking the learning process (LE) and learning outcomes (EPS, TS). |
| Outcome Variables | engineering problem-solving skills | EPS | Students' ability to analyze, design, and solve complex engineering problems. |
| | Teaching Satisfaction | TS | Students' overall satisfaction with the classroom teaching process and learning experience. |
| | Ethical Risk Perception | ERP | Students' perceived risks of academic misconduct, over-reliance on technology, or misinformation when using GAI. |
| Contextual (Moderating) Variable | College-Company Collaboration Intensity | CCI | The depth and breadth of collaboration between universities and enterprises in curriculum design, teaching implementation, and practice moderate the relationship between GAU and TPA. |

(2) Conceptual Model

The conceptual model of this study is shown in the conceptual framework (SEM hypothetical model) in Fig. 1.

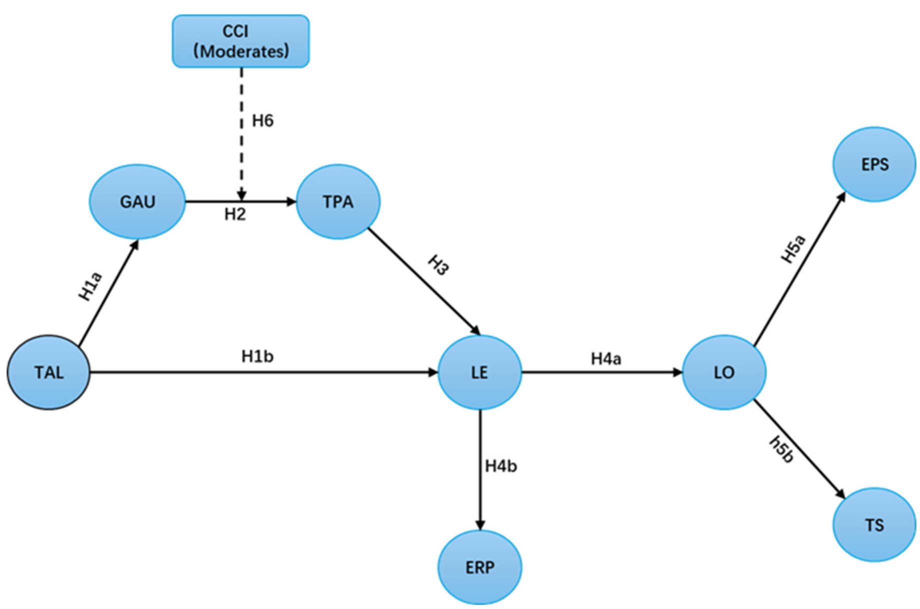


**Figure 1.** Conceptual Framework (SEM hypothetical model)

Teacher AI literacy (TAL), as an exogenous variable, not only directly and positively predicts his/her generative AI-use behavior (GAU), but also significantly and directly affects students' learning engagement (LE). Generative AI use behavior (GAU), on the other hand, indirectly enhances learning engagement (LE) by improving teachers' Teaching Perception of Adaptation (TPA). Learning engagement (LE) not only positively influences learning outcomes (LO) but also directly strengthens ethical risk perception (ERP). Additionally, it further influences engineering problem-solving skills (EPS) and teaching satisfaction (TS) through learning outcomes. College-Company Collaboration Intensity (CCI), as a contextual variable, plays a moderating role in the relationship between GAU and TPA.

## 2. Literature Review

### *2.1 Application of Generative AI in Vocational Education*

Generative AI is rapidly transforming various aspects of vocational education, including the development of teaching resources, personalized learning, intelligent tutoring, virtual training, and engineering simulation. The following summarizes the main application directions and typical benefits.

Generative AI provides a new approach to developing teaching resources. Teachers can use generative AI to create adaptive materials tailored to learners' diverse needs, such as case study tasks, test items, and supplementary learning resources (Ranuharja et al., 2025; Pugach & Startseva, 2024). This approach not only reduces the labor and time required for resource creation but also enhances diversity and adaptability. In road and bridge engineering, generative AI can generate construction scenarios or contract text templates, enabling contextualized learning experiences.

Generative AI also shows strong potential in personalized learning and intelligent tutoring. By dynamically generating personalized prompts, practice tasks, interactive content, and real-time on-demand feedback, generative AI significantly improves the level of individualized instruction (Wei et al., 2025). Such "learner-specific" support aligns well with the competence-oriented goals of vocational education.

In terms of virtual training and simulation, the integration of generative AI with VR, BIM, and digital simulation technologies enables students to access high-fidelity virtual construction and engineering environments (Wong et al., 2020). These environments enable repeated practice in a safe and cost-effective setting, thereby strengthening students' ability to solve real-world engineering problems.

In summary, generative AI has demonstrated clear advantages in vocational education, especially in resource development, personalization, intelligent tutoring, and immersive engineering simulation. It creates new opportunities for contextualized learning and competence-based training in engineering programs.

### *2.2 Research on the teaching mode of road and bridge engineering majors*

The teaching mode of road and bridge engineering centers on combining theory with practice. As a key branch of civil engineering, road and bridge courses require not only an understanding of theoretical knowledge but also the cultivation of practical engineering problem-solving abilities (Lyu et al., 2022). Therefore, teaching reforms in vocational undergraduate programs emphasize strengthening engineering practice and innovation capacity.

Traditional lecture-based instruction often fails to fully meet industry demands for application-oriented talent. Although it helps students build foundational theoretical frameworks, it provides limited opportunities for developing real-world engineering problem-solving skills, resulting in gaps between training and professional requirements (He & Cheng, 2008).

To address this issue, diversified teaching modes have emerged as important reform strategies. Project-based learning (PBL) and case-based learning (CBL) are widely applied in civil engineering to foster students' analytical and innovative thinking (Wang et al., 2018). U-Learning and CDIO approaches further integrate theory with practice, strengthening independent learning and hands-on capabilities.

The introduction of digital intelligence technologies—such as BIM, virtual simulation platforms, and intelligent construction site systems—has accelerated teaching transformation. These technologies reproduce real-world construction processes and visualize engineering conditions, making teaching more intuitive and realistic while improving learning effectiveness (Zhang & Mo, 2022).

Overall, teaching in road and bridge engineering is shifting from traditional theory-centered models toward competence-oriented, digitally supported, industry-aligned instructional modes.

*2.3 Teacher's Role in Generative AI-Driven Teaching*

In generative AI-enabled vocational education, teachers remain irreplaceable. While generative AI supports resource generation and personalized tutoring, teachers continue to provide emotional care and moral leadership beyond technological capabilities (Vashishth et al., 2025). They play key roles in shaping students' AI literacy and guiding the ethical use of AI (Sipahioglu, 2024).

Teachers act as "learning designers," using generative AI to support curriculum standards, instructional planning, and resource design. However, the accuracy and appropriateness of AI-generated content must be reviewed and refined by teachers, particularly in technical fields such as road and bridge engineering (Yang et al., 2024).

Teachers also serve as "learning facilitators" and "competence developers." They guide students in integrating generative AI tools into problem-solving and project-based learning, fostering creativity and engineering reasoning (Akhsan, 2023). As "ethical guardians," teachers provide essential guidance on academic integrity, data security, and the responsible use of AI (Rane et al., 2024).

Thus, even in AI-enhanced environments, teachers remain central as designers, facilitators, competence trainers, and ethical advisors.

*2.4 Theoretical Foundation: Technology Acceptance Model (TAM), Constructivism, and Industry-Education Integration Theory*

This study draws on the Technology Acceptance Model (TAM), constructivist learning theory, and industry-education integration theory as its core theoretical foundations. These three types of theories provide a theoretical basis for the innovation of generative AI-driven teaching modes in the vocational undergraduate road and bridge engineering program, focusing on the dimensions of technology adoption, learning construction, and educational synergy.

(1) Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM) was proposed by Davis (1989), who argued that two factors, "perceived usefulness" (PU) and "perceived ease of use" (PEOU), significantly affect an individual's willingness to use a new technology (Calle-Díaz et al., 2024). The model has been widely used and validated in educational technology research. It has been further developed through iterative models, such as TAM2 and UTAUT, which enhance the predictive power and applicability of the original TAM (Keller, 2011).

In vocational education scenarios, teachers' willingness to use generative AI tools in their teaching depends on whether they believe that these tools can significantly enhance teaching and learning (usefulness) and whether they are convenient to operate and can be integrated into the existing teaching system (ease of use). It has been shown that teachers' Artificial Intelligence Literacy (TAL) significantly influences their acceptance and use behavior (GAU) of AI tools (Ma & Lei, 2024), and generative AI use behavior (GAU) further influences their perception and judgment of Teaching Perception of Adaptation (TPA) (Karataş et al., 2025). Thus TAM provides a solid theoretical foundation for this study to reveal the path of action of TAL → GAU → TPA.

(2) Constructivist Learning Theory (CLT)

Constructivist learning theory emphasizes that learning is not a passive input of knowledge but a process in which the learner continuously reorganizes and constructs knowledge through experience in appropriate, authentic environments, practical work tasks, and social interactions (Mattar, 2018). This theory advocates "student-centered," authentic, task-driven learning in authentic or near-authentic contexts and the promotion of deep understanding and knowledge transfer through inquiry, collaboration, and reflection (Mishra, 2023).

The constructivist theory has outstanding applicability in teaching and learning in the road and bridge engineering program. The road and bridge engineering program enables students to "learn by doing" in real or simulated engineering situations through engineering case studies, virtual simulation training, and hands-on project practice, thereby developing the ability to solve complex engineering problems. The application of generative artificial intelligence provides new support for constructivist teaching. Generative AI can generate construction organization designs, design plans, or contract texts to help students learn in an environment that closely resembles a real-world situation. Generative AI enables students to enhance learning engagement (LE) and learning outcomes (LO) in contextualized learning environments. The instant feedback and personalized support provided by generative AI promote knowledge reflection and transfer, thereby enhancing students' engineering problem-solving (EPS) and teaching satisfaction (TS) through collaborative learning. Additionally, in conjunction with experiential learning theory, students are more likely to identify potential limitations and risks and enhance their perception of ethical risks

(ERP) through continuous experience and reflection during high-level engagement in the learning process (Morris, 2020). Constructivism, therefore, provides an essential theoretical basis for this study, explaining how generative AI affects EPS, TS, and ERP by influencing LE and LO.

(3) Theory of Industry-Education Integration (IEI)

The theory of industry-education integration emphasizes a deep connection between industry and education, fostering an organic link between the education, talent, industry, and innovation chains through collaboration between schools and enterprises. The theory of integrating industry and education originated from the German “dual system” model and has been widely adopted in China's vocational education system reform. The core of the theory of industry-teaching integration is to promote the in-depth participation of enterprises in curriculum development, teaching implementation, and practical applications, enabling students to enhance their engineering problem-solving and innovation abilities in real or near-real work situations (Wang et al., 2019).

The theory of industry-teaching integration is of great significance in innovating the teaching mode for the vocational undergraduate program in road and bridge engineering. Generative artificial intelligence-related technical means can simulate construction scenes and processes, reducing the cost of practical training and expanding the learning experience. The depth and breadth of school-enterprise collaboration (CCI) have a significant impact on the effectiveness of teaching resources and the suitability of the curriculum. Within the depth of school-enterprise cooperation, enterprise mentors can not only provide practical guidance to students but also identify the differences between learning resources and industry norms, thereby improving the fit and applicability of course content (Lyu et al., 2022). The theory of industry-education integration provides solid theoretical support for introducing “college-enterprise collaborative intensity (CCI)” as a moderating variable in this study.

The theoretical foundation of this study integrates three main lines: the technology acceptance model (TAM), constructivism (including experiential learning), and industry-teaching integration, to form the theory of “teacher-technology-context-learning process-learning outcome.” TAM explains the relationship between teachers' AI literacy, AI usage behavior, and teaching perception of adaptation from the perspective of “technology adoption.” Constructivist learning theory emphasizes the role of generative AI in promoting student learning engagement (LE) and learning outcomes (LO). Combined with experiential learning theory to explain its effect on ethical risk perception (ERP), which further acts on engineering problem-solving skills (EPS) and teaching satisfaction (TS). The theory of industry-teaching integration, on the other hand, reveals the moderating effect of school-enterprise collaboration in promoting the integration of generative AI into vocational education. To enhance conceptual clarity, Table 2 offers an integrated summary of the three theoretical foundations—TAM, CLT, and IEI—and their respective contributions to the proposed research framework.

**Table 2.** Theoretical Integration Framework (TAM + CLT + IEI)

| Theory | Key Constructs | Contribution to This Study |
|---|---|---|
| Technology Acceptance Model (TAM) | PU, PEOU, AI use behavior | Explains how teachers’ AI literacy influences AI use and perceived adaptation. |
| Constructivist Learning Theory (CLT) | Authentic learning, engagement, and knowledge construction | Explains how AI-enhanced engagement improves learning outcomes and skills. |
| Industry–Education Integration (IEI) | School–enterprise collaboration, practical training alignment, and curriculum relevance | Supports the use of CCI as a moderating variable and explains how industry involvement enhances the effectiveness of AI-enabled teaching. |

## 3. Research Methodology

### *3.1 Overall and Sample*

The overall population of this study comprises all faculty members of the School of Water Resources and Civil Engineering at Qinghai Vocational and Technical University. As a typical vocational undergraduate college in the western region, the school's road and bridge engineering program is characterized by its application-oriented and regional focus, reflecting the actual situation of generative AI application in vocational undergraduate education in western high-altitude areas.

In this study, a questionnaire survey was conducted through a complete census of all faculty members engaged in teaching courses related to the road and bridge engineering program at this college. A total of 54 questionnaires were distributed, and 54 were validly returned. Although the sample size is relatively small, it includes teachers with diverse titles, ages, and levels of teaching experience in the college, lending it certain representativeness and credibility. It has been shown that a sample size of 50-100 can meet the basic analytical requirements of SEM when the model structure is more parsimonious, the number of latent variables is limited, and the factor loadings are high (McQuitty & Wolf, 2013). The model in this study comprises only eight latent variables with relatively simple path relationships, thereby reducing the need for a large sample size. Bootstrap resampling with robust fitting metrics was employed in the data analysis of this study to enhance the reliability of parameter estimation and significance testing under conditions of small sample sizes. The sample size of this study is methodologically acceptable and can support the empirical analysis of SEM.

*3.2 Research Instrument (Questionnaire Scale)*

This study employs a structured questionnaire as the primary research instrument, with all questions based on a five-point Likert scale (1 = “Completely Disagree,” 5 = "Completely Agree"). The questionnaire was revised in reference to mature scales from home and abroad and combined with the actual teaching situation of road and bridge engineering majors to ensure content validity and reliability. The structure of the questionnaire, the composition of the variables, and the basis of the design are presented in this section of the study to maintain methodological transparency. To ensure brevity, not all topics were itemized in the main text.

The formal questionnaire contains eight dimensions: Teacher AI Literacy (TAL), Generative AI Use Behavior (GAU), Teaching Perception of Adaptation (TPA), Learning Engagement (LE), Engineering Problem Solving Skills (EPS), Teaching Satisfaction (TS), Ethical Risk Perception (ERP), and College-Company Collaboration Intensity (CCI). The first six dimensions mainly reflect the cognitive, behavioral, and affective responses of teachers and students in the teaching and learning process. At the same time, ethical risk perception is used to reveal the possible hidden concerns in the application of generative AI. College-enterprise collaborative intensity, as a contextual variable, measures the degree of corporate involvement in curriculum construction, practical training, and resource sharing. Learning Outcomes (LO) is a latent variable introduced during the subsequent Structural Equation Modeling (SEM) modeling and revision process to better explain the relationship between Learning Engagement (LE), Engineering Problem Solving (EPS), and Teaching Satisfaction (TS). Three educational technologists reviewed the first draft of the questionnaire to ensure content validity; pre-testing was then conducted in a small sample size (N = 20). The results of the reliability analysis showed that the Cronbach's alpha coefficients for each dimension were above 0.7, indicating that the scale had good internal consistency. The final questionnaire contains a total of 29 items, which are used in the formal survey and support the empirical analysis of SEM.

*3.3 Research Process*

The implementation process of this study is divided into three steps. The first step involves designing the questionnaire based on the literature review and theoretical analysis and inviting educational technology experts to review it. This is followed by pre-testing and revision to form the final scale. The second step is to conduct a formal survey among all teachers teaching the relevant courses in road and bridge engineering at the College of Water Resources and Civil Engineering of Qinghai Vocational and Technical University. Fifty-four questionnaires were distributed, and 54 were recovered, resulting in a 100% recovery rate and validity rate. In the third step, the data were organized and cleaned, and descriptive statistics, reliability and validity tests, validated factor analysis (CFA), and structural equation modeling (SEM) analysis were conducted in sequence. The Bootstrap method was also employed to further test the mediation and moderating effects.

## 4. Results of the Study

*4.1 Descriptive Statistics Results*

To gain a comprehensive understanding of the basic characteristics of the research sample, this study statistically analyzed the mean (M), standard deviation (SD), skewness, and kurtosis of the variables using the 54 valid questionnaires. The results are presented in Table 3. As can be seen from the table, the mean values of the variables ranged from 3.90 to 4.13, which is significantly higher than the theoretical median (M = 3). This indicates that the teacher community generally has a positive attitude towards the application of generative AI in teaching road and bridge engineering. The high mean values of Teachers' Artificial Intelligence Literacy (TAL), Generative AI Use Behavior (GAU), and Teaching Perception of Adaptation (TPA) suggest that teachers already have a solid understanding and application of generative AI tools. They generally believe that there is a high degree of fit between generative AI technology and the objectives of the professional curriculum. In terms of learning effectiveness, the scores for Learning Engagement (LE), Engineering Problem Solving (EPS), and Teaching Satisfaction (TS) are at a high level, indicating that generative AI positively impacts students' classroom engagement and learning effectiveness. The mean value of Ethical Risk Perception (ERP) is also high, suggesting that while teachers affirm the value of AI, they are somewhat alert to its potential risks. The skewness and kurtosis coefficients of the variables are mostly close to zero, indicating that the data distribution generally conforms to the assumption of normality, which provides a solid data basis for subsequent reliability and validity tests, as well as structural equation modeling (SEM) analysis.

**Table 3.** Descriptive Statistics of Study Variables (N=54)

| Variable | Mean (M) | Standard Deviation (SD) | Skewness | Kurtosis |
|---|---|---|---|---|
| Teachers' AI Literacy | 3.97 | 0.72 | 0.24 | -1.15 |
| Generative AI Use Behavior | 4.01 | 0.74 | 0.02 | -1.36 |
| Teaching Perception of Adaptation | 4.13 | 0.75 | -0.36 | -1.13 |
| Learning Engagement | 4.04 | 0.73 | -0.28 | -0.82 |
| engineering problem-solving skills | 4.03 | 0.75 | -0.12 | -1.16 |
| Teaching Satisfaction | 4.09 | 0.74 | -0.25 | -0.95 |
| Ethical Risk Perception | 4.03 | 0.65 | -0.59 | 0.79 |
| College-Company Collaboration Intensity | 3.90 | 0.69 | 0.24 | -1.13 |

*4.2 Reliability and Validity Analysis*

(1) Reliability analysis (Reliability)

Cronbach's α coefficient and Composite Reliability (CR) were used to test the reliability of each latent variable, and the results are shown in Table 4. The results show that the Cronbach's α coefficient for each latent variable and the CR value are both greater than 0.70, indicating that the internal consistency of the scale is good and the reliability reaches an acceptable level.

**Table 4.** Reliability Test Results of Each Variable

| Variable | Number of Items | Cronbach's α | CR |
|---|---|---|---|
| Teachers' AI Literacy | 3 | 0.936 | 0.959 |
| Generative AI Use Behavior | 4 | 0.843 | 0.895 |
| Teaching Perception of Adaptation | 4 | 0.923 | 0.946 |
| Learning Engagement | 4 | 0.906 | 0.935 |
| engineering problem-solving skills | 3 | 0.897 | 0.936 |
| Teaching Satisfaction | 3 | 0.911 | 0.940 |
| Ethical Risk Perception | 4 | 0.821 | 0.874 |
| College-Company Collaboration Intensity | 4 | 0.858 | 0.901 |

(2) Validity analysis (reliability)

The validity analysis includes both convergent validity and discriminant validity. Convergent validity was assessed using validated factor analysis (CFA) to calculate standardized factor loadings and Average Variance Extracted (AVE), with the results presented in Table 5. The results indicate that the standardized factor loadings of each latent variable are all greater than 0.60, and most of the AVE values exceed 0.70. Only the AVE of ethical risk perception (ERP) is 0.581, which is still higher than the minimum threshold of 0.50. This indicates that the variables have good convergent validity. In summary, the scales of this study meet the standard requirements for social science research in terms of reliability, convergent validity, and discriminant validity, indicating that the research instrument is suitable for subsequent structural equation modeling (SEM) analysis.

**Table 5.** Results of validity analysis (N=54)

| Variable | Number of Items | AVE | Factor Loading Range |
|---|---|---|---|
| Teachers' AI Literacy | 3 | 0.887 | 0.931–0.956 |
| Generative AI Use Behavior | 4 | 0.681 | 0.781–0.893 |
| Teaching Perception of Adaptation | 4 | 0.812 | 0.852–0.921 |
| Learning Engagement | 4 | 0.782 | 0.843–0.918 |
| engineering problem-solving skills | 3 | 0.830 | 0.873–0.929 |
| Teaching Satisfaction | 3 | 0.848 | 0.883–0.952 |
| Ethical Risk Perception | 4 | 0.581 | 0.632–0.875 |
| College-Company Collaboration Intensity | 4 | 0.708 | 0.810–0.864 |

### *4.3 Structural Model Fitting Results*

To verify the overall goodness of fit of the structural model in this study, structural equation modeling was performed on the sample data (N = 54) using Maximum Likelihood Estimation (MLE) in AMOS 29.0. The main fitting metrics are presented in Table 6.

**Table 6.** Structural model fit metrics (N = 54)

| Fit Index | Recommended Standard | Actual Value | Evaluation |
|---|---|---|---|
| $\chi^2/df$ | < 3.00 | 1.230 | Good |
| p-value | > 0.05 | 0.240 | The model fits the data significantly. |
| GFI | > 0.90 | 0.920 | Good |
| AGFI | > 0.80 | 0.808 | Good |
| NFI | > 0.90 | 0.957 | Good |
| IFI | > 0.90 | 0.992 | Excellent |
| TLI | > 0.90 | 0.984 | Excellent |
| CFI | > 0.90 | 0.991 | Excellent |
| RMR | < 0.05 | 0.020 | Excellent |
| RMSEA | < 0.08 | 0.066 | Good |
| PCLOSE | > 0.05 | 0.363 | Acceptable |

The actual values of the fitted indicators in Table 5 show that the overall fit of the model in this study is good. $\chi^2/df$ = 1.230, p = 0.240, indicating that the difference between the model and the sample data is not significant; GFI, CFI, TLI, and IFI are higher than 0.90, which suggests that the model has a high degree of goodness of fit; and the RMSEA = 0.066 and RMR = 0.020 are both below the recommended thresholds (0.08 and 0.05), showing that the level of residuals is low and the model residuals are well fitted. The Bollen-Stine Bootstrap test result is p = 0.494 (> 0.05), further indicating that the model remains robust and statistically sound under small sample conditions.

### *4.4 Results of Significance Test of Structural Paths*

To test the establishment of the research hypotheses and the statistical significance of the path relationships, this study relies on the standardized regression coefficients (standardized regression weights), standard errors (S.E.), critical ratios (C.R.), and significance levels (p-values) output from the AMOS software to carry out the model's paths. Test. The results are shown in Table 7.

**Table 7.** Results of Significance Test for Structural Paths (N = 54)

| Hypothesis | Path Relationship | Standardized Estimate | S.E. | C.R. | p-value | Significance | Result |
|---|---|---|---|---|---|---|---|
| H1a | TAL→GAU | 0.775 | 0.094 | 8.270 | *** | p<0.001 | Supported |
| H2 | GAU→TPA | 0.801 | 0.084 | 9.542 | *** | p<0.001 | Supported |
| H3 | TPA→LE | 0.711 | 0.065 | 10.915 | *** | p<0.001 | Supported |
| H1b | TAL→LE | 0.241 | 0.064 | 3.798 | *** | p<0.001 | Supported |
| H4a | LE→LO | 0.947 | 0.093 | 10.225 | *** | p<0.001 | Supported |
| H4b | LE→ERP | 0.496 | 0.113 | 4.384 | *** | p<0.001 | Supported |
| H5a | LO→EPS | 1,000 | — | — | — | Fixed path | Supported |
| H5b | LO→TS | 1.005 | 0.103 | 9.729 | *** | p<0.001 | Supported |

Note: *** denotes $p < 0.001$, and path coefficients are standardized estimates.

According to the test results in Table 6, all hypothesized paths in the model of this study reach the significance level ($p < 0.001$), reflecting the strong statistical significance and theoretical explanatory power of the model. The specific path relationships are as follows:

(1) The critical role of teacher AI literacy

Teacher AI literacy (TAL) has a significant positive effect on generative AI use behavior (GAU) ($\beta = 0.775$, $p < 0.001$). It directly promotes students' learning engagement (LE) ($\beta = 0.241$, $p < 0.001$), and Hypotheses H1a and H1b therefore hold.

(2) Mediating Effect of AI Use Behavior

Generative AI Use Behavior (GAU) significantly and positively affects Teaching Perception of Adaptation (TPA) ($\beta = 0.801$, $p < 0.001$), suggesting that the more teachers use AI tools in high frequency and in depth in their teaching, the more they perceive their level of fit with the content, and Hypothesis H2 is supported.

(3) Driving Effect of Teaching Perception of Adaptation

Teaching Perception of Adaptation (TPA) has a significant positive impact on Learning Engagement (LE) ($\beta = 0.711$, $p < 0.001$), suggesting that teachers perceive that AI is more effective in boosting students' motivation to participate in the classroom when it is a high match to the course content, and Hypothesis H3 is supported.

(4) Dual-path effects of learning engagement

Learning engagement (LE) not only significantly and positively predicted learning outcomes (LO) ($\beta = 0.947$, $p < 0.001$), but also significantly enhanced ethical risk perception (ERP) ($\beta = 0.496$, $p < 0.001$). This suggests that high engagement not only promotes learning outcomes but also enhances students' perceived awareness of the potential risks associated with AI, supporting hypotheses H4a and H4b.

(5) Extended Effect of Learning Outcomes

Learning outcomes (LOs) have a significant positive effect on both engineering problem solving (EPS) ($\beta = 1.000$) and teaching satisfaction (TS) ($\beta = 1.005$, $p < 0.001$), which supports both Hypotheses H5a and H5b, suggesting that increased learning effectiveness directly contributes to students' enhanced engineering practice ability and teaching satisfaction.

The p-values of all hypothesized paths in the model are less than 0.001, indicating that the data strongly support all hypothesized relationships proposed in the theoretical model and are statistically highly significant.

*4.5 Analysis of Mediating and Moderating Effects*

(1) Mediating effects

This study employed the bootstrap method (resampling 5,000 times) to test the mediating effects, using a 95% confidence interval. The results show that teacher AI literacy (TAL) has a significant indirect effect on learning engagement (LE) through generative AI usage behavior (GAU) and teaching perception of adaptation (TPA).

The indirect effect of the path TAL → GAU → TPA → LE was significant ($\beta = 0.441$, $p < 0.001$), while the direct effect ($\beta = 0.241$, $p < 0.001$) remained significant, suggesting a partially mediated effect. Learning engagement (LE) significantly enhanced learning outcomes (LO) ($\beta = 0.947$, $p < 0.001$) and further influenced engineering problem-solving skills (EPS, $\beta = 1.000$) and teaching satisfaction (TS, $\beta = 1.005$) through learning outcomes, showing a fully mediated effect. The direct effect of LE on ethical risk perception (ERP) was significant ($\beta = 0.496$, $p < 0.001$), indicating that high-engagement learning enhances students' perception of and reflection on the potential risks associated with AI.

(2) Moderating effect

The school-enterprise collaborative intensity (CCI) showed a significant moderating effect in the model. The data showed a significant interaction effect between CCI and generative AI usage behavior (GAU) (covariance = 0.078, $p = 0.012$). The impact of AI usage behaviors on the teaching perception of adaptation is more substantial in a highly collaborative environment. This validates the role of business engagement in facilitating the implementation of AI instructional solutions.

## 5. Discussion

The results of this study offer a clearer picture of how generative AI can reshape vocational undergraduate teaching, especially in the highly applied field of road and bridge engineering. Rather than looking at AI as a standalone tool, the findings highlight a more holistic process—one that begins with teachers' literacy, travels through their perceptions and behaviors, and eventually reaches student learning and ethical awareness. This section discusses how these results connect with and extend existing research.

(1) Teacher AI Literacy: More Than Just a Technical Skill

The strong predictive effect of Teacher AI Literacy (TAL) on AI use behavior (GAU) is consistent with earlier studies showing that teachers are more willing to adopt AI when they feel confident and knowledgeable about it (Ma & Lei, 2024; Al-Abdullatif, 2024). What emerges here, however, is the important role of literacy not only in using AI but in shaping the learning environment itself.

Teachers with higher AI literacy tended to create more engaging learning spaces for students. This direct link between TAL and Learning Engagement (LE) has rarely been emphasized in previous studies. The finding suggests that AI literacy is not just about operating tools—it influences how teachers design activities, communicate expectations, and interact with students. In other words, AI literacy becomes a pedagogical asset.

(2) When Teachers Feel That AI "Fits": Adaptation as a Turning Point

The path from AI use behavior (GAU) to Teaching Perception of Adaptation (TPA) supports the argument made by Karataş et al. (2025) that teachers' sense of alignment between AI tools and curriculum goals matters greatly.

What this study adds is a clearer view of why this alignment matters:
Teachers who feel that AI fits well with their subject matter tend to see a noticeable boost in student engagement. This indicates that TPA acts as a bridge—it turns frequent or competent AI use into something that genuinely benefits students.

This finding underscores that institutional pushes for technology adoption may fall short unless teachers also feel that AI makes pedagogical sense in their context.

**(3) Learning Engagement: The Energy That Drives Two Outcomes**

The results reaffirm the central role of learning engagement, echoing constructivist views that active, meaningful participation leads to deeper learning (Morris, 2020; Wei et al., 2025). Students who were more engaged achieved better learning outcomes, which is unsurprising. What is more interesting is the second pathway: higher engagement also increased students' ethical risk perception (ERP).

This suggests that in AI-driven classrooms, ethical awareness doesn't arise only from lectures or rules. Instead, when students genuinely participate in AI-supported tasks—experimenting, reflecting, and troubleshooting—they seem to develop a more mature understanding of AI's limitations, risks, and boundaries.

This dual-pathway result enriches existing literature by emphasizing that meaningful engagement encourages not just better learning, but also better judgment.

**(4) Learning Outcomes: A Full Mediator Toward Real Competence**

The finding that learning outcomes (LO) fully mediate the link between engagement and engineering problem-solving skills (EPS) or teaching satisfaction (TS) provides valuable clarity. It confirms that enthusiasm alone is not enough—students need to consolidate that engagement into genuine mastery before it translates into practical competence.

Previous studies highlight the importance of practice-oriented teaching in engineering (Wang et al., 2018; Lyu et al., 2022), but few have captured how AI-supported engagement turns into measurable engineering skills. This study offers that missing link: strong engagement → deeper learning outcomes → better engineering capabilities and satisfaction.

This reinforces the idea that AI shouldn't replace hands-on learning but should enrich it in ways that deepen understanding.

**(5) Industry Collaboration: The Context That Makes AI Work Better**

One of the most distinctive findings of this study is the moderating role of College–Company Collaboration Intensity (CCI). While previous literature has long advocated for stronger school–industry partnerships in vocational education (Wang et al., 2019), empirical evidence on how collaboration interacts with AI usage has been limited.

This study shows that when school–enterprise collaboration is strong, teachers perceive AI as more suitable for teaching. This may be because collaboration brings real-world cases, expert validation, and more authentic learning scenarios, which help teachers see the true relevance of AI tools.

In short, AI works better when teachers operate in a context where industry expectations and practical applications are already visible.

**(6) Contributions to the Broader Literature**

This study adds to the growing field of AI-in-education research in three key ways:

**6.1** It connects three major theories—TAM, Constructivism, and Industry–Education Integration—

into one coherent model**,** offering a more comprehensive framework for understanding AI-enabled teaching.

**6.2** It identifies the unique role of Teaching Perception of Adaptation (TPA) as the cognitive turning point that turns AI use into real student engagement.

**6.3** It highlights the importance of industry collaboration in amplifying the benefits of AI, and aspect that has been underexplored in previous research.

Overall, the findings show that successful AI integration does not rely solely on technology—it depends on teachers' confidence, their perception of pedagogical alignment, student engagement, and the broader ecosystem of school–industry cooperation.

## 6. Conclusions

This study takes Generative Artificial Intelligence (GAI)-enabled vocational undergraduate teaching model as the research direction, and constructs a model that covers Teacher AI Literacy (TAL), AI Usage Behavior (GAU), Teaching Perception of Adaptation (TPA), Learning Engagement (LE), Learning Outcomes (LO), Engineering Problem Solving Skills (EPS), Teaching Satisfaction (TS), Ethical Risks Perception (ERP) and University-Enterprise Collaboration Intensity (CCI) variables of structural equation modeling. Through the empirical analysis of 54 teachers' samples from Qinghai Vocational and Technical University (based on AMOS software), the main research conclusions are as follows:

(1) The overall fitting effect of the model is good. The key indices have reached the ideal level ($\chi^2/df = 1.23$, GFI = 0.920, CFI = 0.991, RMSEA = 0.066), indicating that the hypothesized model effectively explains the relationship between the latent variables and provides a strong theoretical basis with robust data support.

(2) Teacher AI literacy (TAL) has a significant positive effect on both AI use behavior (GAU) and learning engagement (LE). The standardized path coefficient of TAL on GAU is 0.775 ($p < 0.001$), and the direct effect on LE is 0.241 ($p < 0.001$). This suggests that improving teachers' AI literacy is a foundational factor in promoting the effective integration of AI technology into classroom teaching. At the same time, it directly facilitates the creation of a positive learning atmosphere and encourages student engagement.

(3) Teaching Perception of Adaptation (TPA) plays a key mediating role between AI usage behavior (GAU) and learning engagement (LE). The path analysis revealed that the coefficient of GAU on TPA was 0.801, and the coefficient of TPA on LE was 0.711, with an indirect effect value of 0.441, which was statistically significant. The

results suggest that the Teaching Perception of Adaptation developed by teachers when using AI tools is an essential cognitive mechanism for transforming technological behaviors into actual teaching effects.

(4) Learning outcomes (LO) play a fully mediating role between learning engagement (LE) and outcome variables. The path coefficient of LE on LO is 0.947, while LO further significantly affects engineering problem-solving skills (EPS, $\beta = 1.000$) and teaching satisfaction (TS, $\beta = 1.005$). This suggests that generative AI-driven high-engagement learning can comprehensively improve engineering competence and teaching satisfaction through outcome outputs.

(5) There is a significant positive effect of learning engagement (LE) on ethical risk perception (ERP) ($\beta = 0.496$, $p < 0.001$). This finding suggests that the higher the level of faculty and student engagement in an AI-assisted teaching environment, the greater the ability to perceive and reflect on the potential ethical risks of technology. This reflects the critical dimension of technology-enabled education.

(6) The intensity of school-enterprise collaboration (CCI) has a significant moderating effect on the AI teaching path. The covariance between CCI and GAU is substantial ($p = 0.012$), suggesting that in contexts with better conditions for school-enterprise collaboration, teachers' use of AI tools is more likely to lead to a positive perception of pedagogical fitness, thereby strengthening overall teaching efficacy.

In summary, the generative AI-enabled vocational undergraduate teaching model is a multi-level, dynamic system based on the main line of “literacy-driven-behavioral transformation-cognitive adaptation-participation-promotion-results generation”. It is a multilevel and dynamic system that embodies the organic integration of intelligent technology and the educational process. It provides a theoretical basis and practical path for the high-quality development of vocational undergraduate education.

## 7. Research Limitations and Prospects

(1) Limitations of Sample Source and Size

The sample of this study was selected from a single institution (College of Water Resources and Civil Engineering, Qinghai Vocational and Technical University), with a limited sample size (N=54), a fact that limits the external validity and generalizability of the study's conclusions to some extent. In view of this, future research can further expand the sample coverage to include faculty groups from different regions and types of institutions, thereby enabling the model constructed in this study to be more comprehensively validated and expanded through a multi-regional and multi-institutional comparative study, which will enhance the generalizability of the study's conclusions.

(2) Room for expansion of variable structure and perspective

The model constructed in this study is primarily based on teaching behavior variables from the teachers' perspective and has not yet adequately included multidimensional indicators such as students' learning effectiveness, affective commitment, and evaluation by business mentors. Subsequent research can introduce more diversified data sources and analysis perspectives, and further deepen the systematic understanding of the generative AI technology-enabled vocational undergraduate teaching mode through cross-validation and multi-level modeling.

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**Data sharing statement**

No additional data are available.