Teacher Role Reconfiguration in AI-Enabled TVET: Linking Institutional Digital Transformation and Teacher AI Application

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Abstract

This study develops a mediation framework explaining how institutional digital This article develops a conceptual framework explaining how institutional digital transformation may be translated into teacher role reconfiguration in technical and vocational education and training (TVET). Drawing on sociotechnical systems theory, role theory and human-AI collaboration research, the article argues that digital transformation does not alter teacher roles simply by providing platforms, data systems or smart training environments. Its professional significance depends on teacher AI application as an enacted pedagogical practice. The framework specifies a mediation pathway from perceived institutional digital transformation to teacher AI application and then to teacher role reconfiguration. Teacher role reconfiguration is conceptualised as five-dimensional professional expansion: learning designer, data-informed mentor, smart skills coach, industry-education broker and AI ethics steward. Using Liaoning, China, as an illustrative industrial-region context, the article outlines a three-wave empirical validation protocol involving second-order construct modelling and structural equation modelling. The contribution is twofold: it shifts TVET digitalisation research from technology provision to teacher enactment, and it offers a measurable role-centred framework for studying AI-enabled professional change in vocational education.

Keywords: artificial intelligence integration; teacher role reconfiguration; digital transformation; technical and vocational education and training; mediation framework; human-AI collaboration; Liaoning, China

1. Introduction

Digital transformation has become a strategic condition for renewing technical and vocational education and training (TVET). In vocational institutions, digitalisation reaches beyond the conversion of teaching materials into online resources. It affects learning platforms, smart training environments, simulation rooms, school-enterprise cooperation, assessment evidence, student support and institutional governance. For TVET, these changes are consequential because vocational programmes are expected to translate technological change in industry into teachable tasks, assessable competences and credible pathways to work (UNESCO, 2022; Ma et al., 2025; Xu et al., 2024).

The expansion of artificial intelligence (AI) has intensified this transformation. AI-supported lesson preparation, adaptive resources, automated feedback, learning analytics, generative content tools and intelligent simulation systems increasingly enter everyday teaching debates (Chen et al., 2020; Crompton & Burke, 2023; Bond et al., 2024; Almasri, 2024; Tan et al., 2025). Yet the educational significance of AI does not lie in tool availability alone. In TVET, AI becomes meaningful when teachers use it to design occupational tasks, diagnose learning progress, coach practical performance, connect curricula with industrial change and guide responsible technology use.

This article treats teacher AI application as a mediating practice. Digital transformation creates institutional conditions: infrastructure, platforms, data systems, digital resources and policy incentives. Teacher role change occurs when those conditions are incorporated into pedagogical routines, workshop activities, formative assessment and professional judgement. This logic follows a sociotechnical view of technology, in which digital systems do not determine organisational outcomes by themselves but become consequential through situated practice (Orlikowski, 2000; Vial, 2019; Verhoef et al., 2021).

Liaoning offers a meaningful reference context for developing the framework. As a traditional industrial base in Northeast China, the province is closely associated with equipment manufacturing, petrochemicals, industrial services and the upgrading of legacy manufacturing systems. Its TVET institutions are therefore positioned between industrial digitalisation and educational reform. In such a setting, digital transformation is tested not only through online platforms but also through workshops, simulation rooms, intelligent equipment maintenance tasks, enterprise-linked projects and skills assessment rubrics. Studies on data elements, digital capacity building and organisational resilience in Chinese industrial settings further suggest that digital transformation operates through capability-building mechanisms rather than through technology investment alone (Lin & Zhang, 2025; Zhang & Li, 2025a, 2025b).

China's education policy context reinforces the relevance of this problem. The national teacher digital literacy standard signals the importance of teachers' digital competence (Ministry of Education of the People's Republic of China, 2022). The 2025 white paper on smart education frames digital education as a system-level transformation rather than a narrow technology project (Ministry of Education of the People's Republic of China, 2025; Yang & Peters, 2026). The 2026 AI literacy plan further promotes AI integration into vocational programmes connected with traditional industries, linking AI literacy to high-skilled talent development for industrial transformation (State Council of the People's Republic of China, 2026).

The existing literature remains fragmented in three respects. First, educational digital transformation research explains institutional platforms and governance reforms more fully than the teacher-level enactment through which these reforms become pedagogically meaningful (Rauseo et al., 2022; Zhong & Juwaheer, 2024). Second, AI-in-education studies have examined intelligent tutoring, learning analytics and generative AI tools, yet educator roles have often remained less visible in the research conversation (Zawacki-Richter et al., 2019), and the professional reorganisation of vocational teachers remains particularly under-explained (Ouyang & Jiao, 2021; Miao & Holmes, 2023; Kasneci et al., 2023). Third, teacher role change in TVET is often described normatively rather than operationalised as a multidimensional construct that can be empirically validated. These gaps leave the mechanism between institutional digital transformation and teacher role reconfiguration undertheorised.

Recent work by Xianghan Zhang helps position this gap without becoming the primary theoretical foundation. Zhang (2026) shows in vocational and applied higher education that teaching-oriented reforms influence student value outcomes through motivational and commitment-related mechanisms, demonstrating the importance of analysing vocational education reform through intervening processes rather than direct input-output assumptions. Extending this mechanism-oriented reasoning, the present article shifts the intervening process from student motivation or organisational capability to teacher AI application, and shifts the outcome from student value or organisational resilience to professional role reconfiguration.

The guiding research question is: How can teacher AI application mediate the relationship between perceived institutional digital transformation and teacher role reconfiguration in TVET? Figure 1 presents the proposed mediation logic. The model intentionally uses the term perceived institutional digital transformation because the empirical validation design relies on teacher-level survey data. The construct therefore captures teachers' perceptions of institutional digital conditions rather than a purely objective school-level index.

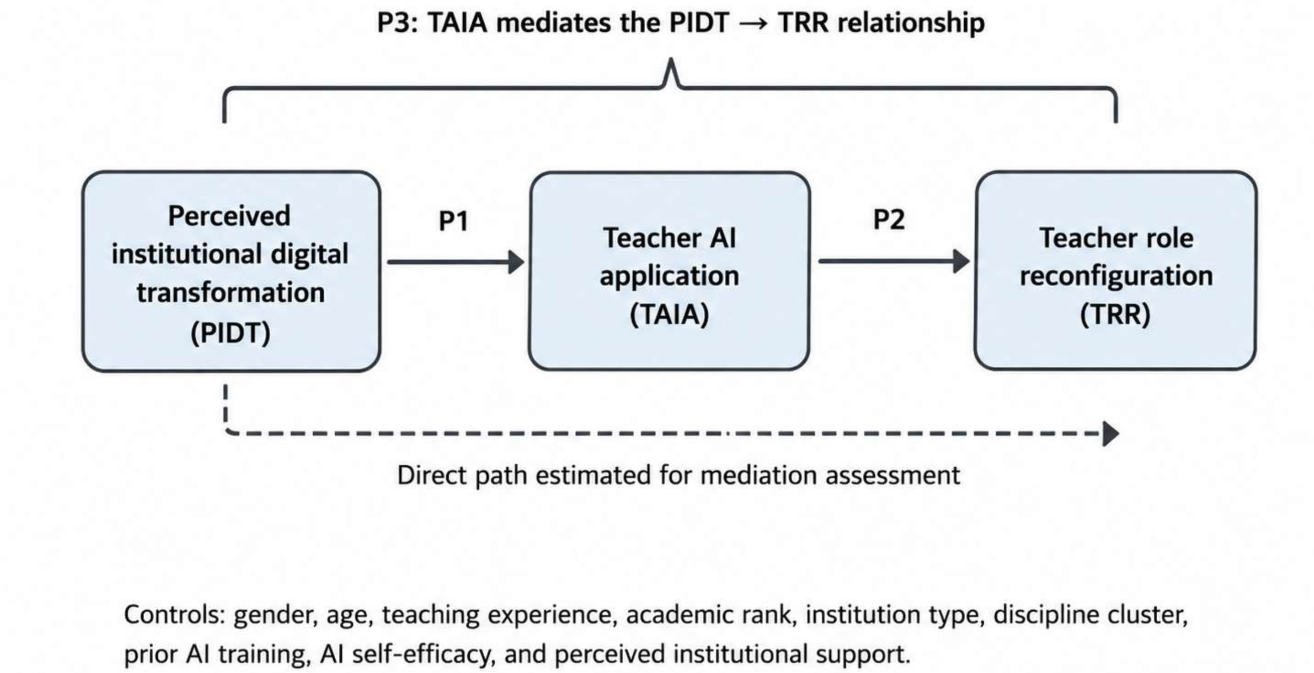

Figure 1. Conceptual mediation model linking perceived institutional digital transformation, teacher AI application and teacher role reconfiguration.

Note. PIDT = perceived institutional digital transformation; TAIA = teacher AI application; TRR = teacher role reconfiguration. The dashed direct path is estimated for mediation assessment; the core theoretical mechanism remains the indirect PIDT -> TAIA -> TRR pathway.

Table 1 positions the article within recent literature. The table clarifies that the contribution is not another general account of AI in education, but a role-centred framework explaining how institutional digitalisation may become teacher-level professional change in TVET.

Table 1. Positioning of the study in relation to recent literature

Literature stream	Typical emphasis	Remaining limitation	Contribution of this article
Educational digital transformation	Institutional strategy, platforms, governance and digital infrastructure.	Teacher-level professional enactment is often treated as secondary.	Explains how institutional digital conditions become meaningful through teacher AI application.
AI in education	AI-supported instruction, feedback, learning analytics, generative AI and ethics.	AI adoption is frequently discussed as tool use rather than professional role change.	Conceptualises AI application as an enacted pedagogical practice.
TVET digitalisation	Smart training environments, vocational digital competence and school-enterprise cooperation.	Teacher role implications of AI-enabled TVET remain under-modelled.	Builds a five-dimensional model of TVET teacher role reconfiguration.
Vocational education mechanism studies	Mediating processes linking reform inputs to student, institutional or capability outcomes.	Teacher AI application has rarely been theorised as the intervening mechanism.	Uses mediation logic to connect digital transformation with role expansion.

Note. The table uses selected literature to define the gap addressed by the conceptual framework.

The article makes three contributions. First, it advances a sociotechnical explanation of TVET digitalisation by treating AI application as teacher enactment rather than a technology-input variable. Second, it operationalises teacher role reconfiguration as a five-dimensional professional expansion. Third, it offers a validation protocol that can be used in Liaoning and similar industrial regions to test whether digital transformation changes teacher work through AI-supported pedagogical practice.

2. Literature Review and Theoretical Foundation

2.1 Digital transformation in TVET

Digital transformation refers to changes in organisational processes, value creation and actor relationships enabled by digital technologies and data infrastructures (Vial, 2019; Verhoef et al., 2021). In education, this concept is broader than digitisation. It involves institutional redesign: how teaching is organised, how resources are distributed, how learning evidence is collected, how quality is monitored and how institutions relate to external stakeholders. For TVET, the stakes are distinctive because vocational programmes are embedded in occupational standards, equipment use, workplace routines and regional industry needs.

TVET digital transformation can be understood as a multi-layered process. At the infrastructure level, it includes campus networks, learning platforms, smart classrooms, simulation facilities and data systems. At the pedagogical level, it involves digital resources, hybrid learning design, formative assessment and practical training scenarios. At the organisational level, it includes governance, teacher professional development, school-enterprise collaboration and curriculum updating. Recent studies of Chinese vocational colleges and polytechnic institutions show that digital transformation is increasingly linked to smart training environments, platform-based governance and institutional capacity building (Ma et al., 2025; Xu et al., 2024).

International TVET research also points to the teacher-facing side of digitalisation. Subrahmanyam (2022) identifies TVET teacher digital skills as a necessary condition for meaningful digital transformation, while Zhong and Juwaheer (2024) argue that TVET digital competence development requires a whole-institution approach rather than isolated training events. OECD (2025) similarly treats innovative technologies as opportunities to transform vocational learning only when curriculum, teacher capacity and workplace relevance are aligned. These arguments suggest that digital transformation is not complete until teachers can enact it in vocational learning tasks.

Table 2 defines the three core constructs used in the framework. The distinctions are important because the model does not treat digital transformation, AI application and role reconfiguration as interchangeable expressions of the same phenomenon.

Table 2. Construct definitions and operational dimensions

Construct	Definition in this article	Operational dimensions	Primary source basis
Perceived institutional digital transformation	Teachers' perception of the extent to which their institution has developed digital infrastructure, digital resources, data-informed governance and smart training environments.	Digital infrastructure; digital teaching resources; data-informed governance; smart training environments; school-enterprise digital connectivity.	Vial (2019); Verhoef et al. (2021); Ma et al. (2025); Xu et al. (2024).
Teacher AI application	Teachers' enacted use of AI-supported tools and systems for instructional design, feedback, analytics, practical training and responsible AI guidance.	AI-assisted design; AI-supported feedback; learning analytics; simulation/practical training; responsible AI guidance.	Ouyang & Jiao (2021); Miao & Holmes (2023); Bond et al. (2024); Tan et al. (2025).

Construct	Definition in this article	Operational dimensions	Primary source basis
Teacher role reconfiguration	The professional expansion through which TVET teachers move beyond conventional delivery roles towards AI-enabled design, mentoring, coaching, industry brokerage and ethical stewardship.	Learning designer; data-informed mentor; smart skills coach; industry-education broker; AI ethics steward.	Biddle (1986); Orlikowski (2000); Miao & Cukurova (2024); Ng et al. (2023).

Note. The first construct is treated as a teacher-level perception of institutional conditions; it is not an objective school-level index.

2.2 Teacher AI application as pedagogical enactment

AI in education has moved from specialised intelligent tutoring systems toward a wider ecosystem of generative AI, learning analytics, automated assessment, recommendation tools, simulation support and adaptive learning resources (Chen et al., 2020; Crompton & Burke, 2023; Bond et al., 2024; Tan et al., 2025). Systematic reviews indicate that AI can support lesson preparation, feedback, personalised learning and professional development, but they also caution against weak ethical governance, superficial tool adoption and insufficient teacher preparation (Almasri, 2024; Kasneci et al., 2023; U.S. Department of Education, Office of Educational Technology, 2023).

Teacher AI application is therefore defined here as pedagogical enactment, not simple technology adoption. It includes using AI to prepare learning materials, design vocational scenarios, provide formative feedback, interpret learning analytics, simulate practical tasks and guide students' responsible use of AI. Ouyang and Jiao's (2021) distinction among AI-in-education paradigms is useful because it moves the discussion away from a passive learner-as-recipient model and towards more collaborative configurations. In TVET, these configurations require the teacher to preserve contextual judgement about equipment, safety, quality standards, workplace norms and professional ethics.

UNESCO's AI competency framework for teachers is directly relevant because it identifies five competence domains: a human-centred mindset, ethics of AI, AI foundations and applications, AI pedagogy, and AI for professional learning (Miao & Cukurova, 2024). These domains support the present argument that AI application is inseparable from professional judgement. AI tools may assist teachers, but they do not remove the need for human interpretation, student care or ethical responsibility (Miao & Holmes, 2023).

The human-AI collaboration perspective adds a further insight. Teacher-AI collaboration can enhance engagement and instructional support when teachers understand how to coordinate AI outputs with their own pedagogical responsibilities (Ding et al., 2025). Hybrid intelligence research similarly stresses the quality of coordination between human actors and AI systems rather than the automation of professional work (Kong et al., 2025). This matters for TVET because teachers must connect AI-generated suggestions with embodied skills, equipment-based learning and occupational standards.

2.3 Teacher role reconfiguration in AI-enabled TVET

Role theory explains roles as bundles of expectations, responsibilities and enacted behaviours situated within social systems (Biddle, 1986). In technology-rich organisations, roles are also shaped by what systems make visible, calculable, delegable or automatable (Orlikowski, 2000). For teachers, AI changes not only the tools used for instruction but also the distribution of professional attention: lesson preparation, feedback, mentoring, assessment, curriculum updating and ethical guidance can all be reorganised.

In AI-enabled TVET, role reconfiguration is especially visible because vocational teachers already occupy hybrid roles. They are subject teachers, skills coaches, assessors, workshop supervisors, student mentors and sometimes industry-facing coordinators. AI-supported platforms and data systems add new expectations:

teachers may be required to design AI-supported learning activities, read learning analytics, coach students in smart training environments, collaborate with enterprise partners on digital curricula and protect academic integrity in AI-supported tasks.

The learning-designer dimension resonates with digital educator competence frameworks, particularly the expectation that teachers design, implement and evaluate digitally mediated learning environments (Redecker, 2017; Ng et al., 2023). The data-informed mentor role reflects the growing use of learning analytics and diagnostic feedback. The smart skills coach role addresses the TVET-specific need to connect digital or AI-supported simulation with hands-on competence. The industry-education broker role connects curriculum with workplace digitalisation. The AI ethics steward role is necessary because students increasingly need guidance on attribution, privacy, bias, hallucinated outputs and professional accountability.

The model also draws on mechanism-oriented vocational education research. Zhang (2026) demonstrates that teaching-oriented reforms in vocational and applied higher education influence student social value outcomes through motivational and commitment-related mechanisms. Although Zhang's study focuses on students rather than teachers, it supports the broader argument that vocational education reform is best understood through intervening mechanisms rather than direct input-output assumptions.

Figure 2 depicts this five-dimensional role expansion model. The model treats AI-enabled teacher role reconfiguration as professional expansion rather than teacher replacement.

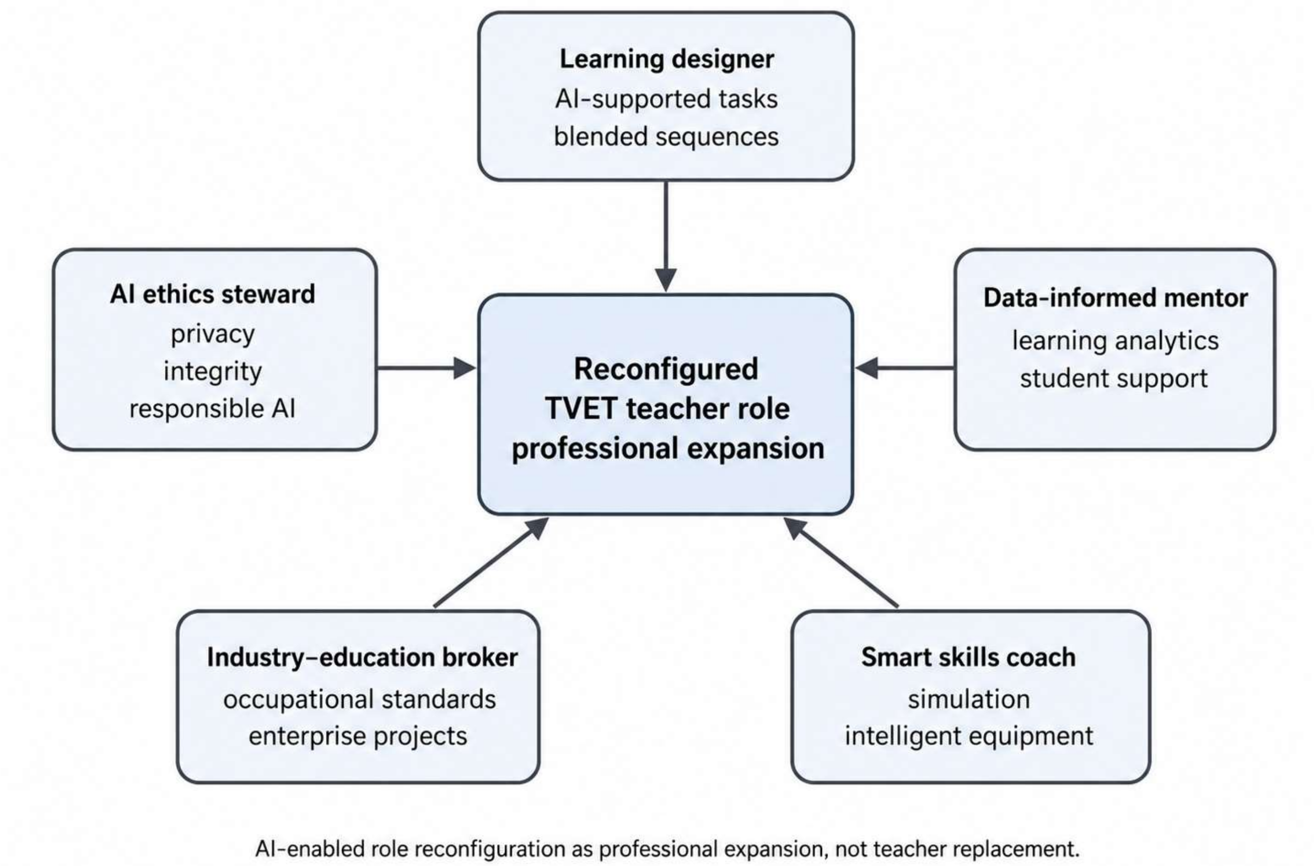

Figure 2. Five-dimensional model of TVET teacher role reconfiguration as professional expansion in AI-enabled teaching.

Note. The figure conceptualises AI-enabled role reconfiguration as professional expansion rather than teacher replacement.

2.4 Sociotechnical integration and regional relevance

The framework integrates sociotechnical systems theory, role theory and human-AI collaboration. Sociotechnical theory explains why digital infrastructure and platforms do not produce professional change by themselves. Role theory explains how professional expectations and enacted responsibilities shift when new tasks, tools and accountability structures enter work. Human-AI collaboration explains why AI is best conceptualised as a partner in pedagogical practice rather than as an autonomous substitute for the teacher.

The Liaoning setting strengthens the relevance of this integration. In an industrial province, TVET digitalisation is not only a question of online learning access. It is connected with intelligent manufacturing, equipment maintenance, industrial internet, digital business and service upgrading. Research on data-driven industrial upgrading and digital capacity building in Chinese settings suggests that digital change depends on the conversion of resources into organisational and professional capabilities (Lin & Zhang, 2025; Zhang & Li, 2025a, 2025b). This article applies that capability logic to TVET teacher work.

This regional emphasis does not make the model purely local. Liaoning functions as a theoretically useful reference context for industrial regions where TVET institutions must align digital education policy, industrial upgrading and teacher professional development. The model can therefore be adapted to other regional TVET systems facing similar pressures, provided that future empirical validation accounts for local institutional conditions and sectoral composition.

3. Theoretical Propositions and Conceptual Model

3.1 From perceived institutional digital transformation to teacher AI application

Perceived institutional digital transformation is expected to support teacher AI application because AI-supported teaching requires infrastructure, data access, technical support, policy legitimacy and usable digital resources. Teachers are unlikely to incorporate AI into teaching routines when institutional systems are fragmented, unreliable or disconnected from curriculum work. Conversely, when digital platforms, smart classrooms and training environments are embedded in institutional practice, AI application becomes more feasible and professionally legitimate.

P1: Perceived institutional digital transformation is positively associated with teacher AI application in TVET.

3.2 From teacher AI application to teacher role reconfiguration

Teacher AI application can reorganise teacher roles because it changes the nature of design, feedback, assessment, mentoring and practical coaching. When teachers use AI to generate scenarios, interpret analytics, provide adaptive support or guide responsible technology use, their professional work extends beyond conventional content delivery. They become learning designers, data-informed mentors, smart skills coaches, industry-education brokers and AI ethics stewards.

P2: Teacher AI application is positively associated with teacher role reconfiguration in TVET.

3.3 Teacher AI application as mediating practice

The central proposition is that teacher AI application mediates the relationship between perceived institutional digital transformation and teacher role reconfiguration. Institutional digital transformation supplies the conditions for change, but role reconfiguration becomes visible only when teachers enact those conditions in AI-supported pedagogical practice. In this sense, AI application is not merely an outcome of digital transformation; it is the practical mechanism through which digital transformation enters teacher work.

P3: Teacher AI application mediates the relationship between perceived institutional digital transformation and teacher role reconfiguration in TVET.

Future empirical testing also needs to estimate the direct PIDT -> TRR path. This direct path is not the main theoretical contribution; it is included because the distinction between partial and full mediation depends on whether the direct effect remains credible after teacher AI application is included in the model.

Table 3 summarises the propositions and indicates how future empirical work can test them. The table uses propositions rather than hypotheses because the present article develops a conceptual and empirical validation framework rather than reporting completed field results.

Table 3. Theoretical propositions and future empirical tests

Proposition / path	Relationship	Theoretical rationale	Future empirical test

Proposition / path	Relationship	Theoretical rationale	Future empirical test
P1	PIDT -> TAIA	Institutional digital transformation supplies the conditions that make teacher AI application feasible and legitimate.	Positive structural path from PIDT to TAIA.
P2	TAIA -> TRR	AI-supported pedagogical practice reorganises design, feedback, mentoring, coaching and ethical responsibilities.	Positive structural path from TAIA to TRR.
P3	PIDT -> TAIA -> TRR	Teacher AI application translates institutional digital conditions into professional role expansion.	Bootstrapped indirect effect; confidence interval excluding zero.
Control path	PIDT -> TRR	A direct path is needed to distinguish partial from full mediation.	Estimate direct effect after TAIA is included.

Note. PIDT = perceived institutional digital transformation; TAIA = teacher AI application; TRR = teacher role reconfiguration.

4. Empirical Validation Protocol

4.1 Design and sampling

The proposed validation protocol uses a three-wave teacher survey. Time 1 measures perceived institutional digital transformation and control variables; Time 2 measures teacher AI application; Time 3 measures teacher role reconfiguration. This sequence does not by itself establish causality, but it provides stronger temporal separation than a single cross-sectional questionnaire and helps reduce same-source inflation (Podsakoff et al., 2024).

The target population comprises full-time teachers in higher vocational colleges, secondary vocational schools and technician colleges in Liaoning Province. A stratified sampling approach can cover institution type, city and discipline cluster. Relevant discipline clusters include intelligent manufacturing, equipment maintenance, information technology, transportation, business services, health services, cultural-creative programmes and modern agriculture-related training. A final matched sample of at least 300-500 teachers would be appropriate for the proposed structural equation modelling design, subject to model complexity and data quality (Hair et al., 2022; Kline & Little, 2023).

Table 4 reports the sampling, ethics and data collection protocol. The protocol is designed to improve transparency, reduce single-institution bias and ensure that any future empirical study is reported as a completed study rather than as a template.

Table 4. Sampling, ethics and data collection protocol

Design element	Proposed specification	Purpose
Target population	Full-time teachers in higher vocational colleges, secondary vocational schools and technician colleges in Liaoning.	Aligns the sample with the TVET focus of the framework.
Sampling strategy	Stratified sampling by institution type, city and discipline cluster.	Reduces overrepresentation of a single institution or field.
Three-wave design	T1: PIDT and controls; T2: TAIA; T3: TRR.	Separates predictor, mediator and outcome measures.

Design element	Proposed specification	Purpose
Instrument development	Translation and back-translation; expert review by TVET, AI education and methodology specialists.	Improves semantic and contextual validity.
Pilot testing	Pilot study with 30-50 TVET teachers.	Checks item clarity, survey duration and preliminary reliability.
Ethics protocol	Institutional ethics approval before empirical fieldwork; informed consent and anonymity protection.	Protects participants and improves reporting credibility.
Reporting discipline	Report invitations, responses, matched cases, exclusions and attrition across waves.	Prevents opaque sample reporting.
Additional evidence	Where possible, triangulate with training records, platform logs or supervisor/student evaluations.	Reduces reliance on self-reported perceptions alone.

Note. The present article is conceptual and does not involve participant recruitment; the protocol applies to future empirical validation.

Figure 3 presents the three-wave workflow for future empirical validation. The sequence separates the predictor, mediator and outcome measures before the measurement and structural assessments are conducted.

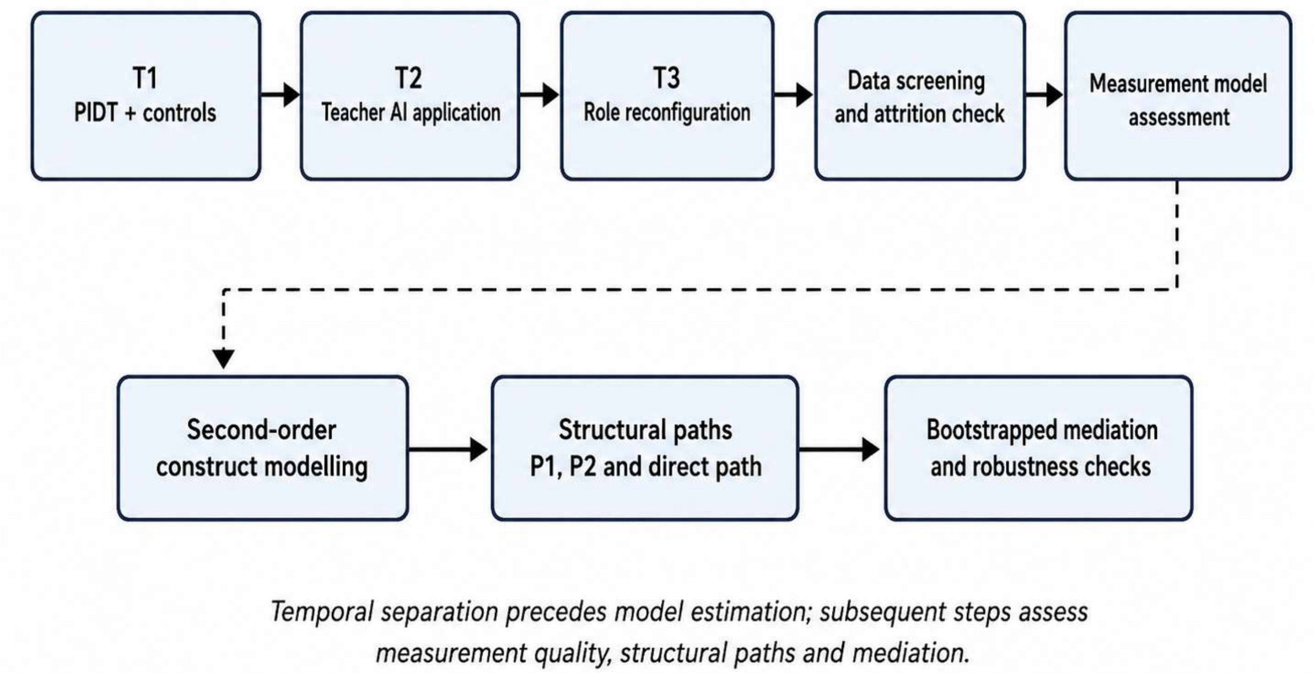

Figure 3. Three-wave empirical validation workflow and analysis sequence.

Note. The workflow is a validation protocol. It does not imply that causal effects have already been established.

4.2 Measurement architecture and hierarchical component modelling

The proposed instrument uses a seven-point Likert scale ranging from 1 = strongly disagree to 7 = strongly agree. The three higher-order constructs can be specified as reflective-formative hierarchical component models. Individual items reflect their first-order dimensions, whereas the first-order dimensions jointly form the broader construct. This specification is appropriate because the dimensions are not fully interchangeable: for example, digital infrastructure, smart training environments and school-enterprise digital connectivity represent distinct but complementary aspects of perceived institutional digital transformation.

Table 5 presents the second-order architecture for perceived institutional digital transformation. The construct is defined as teachers' perception of institutional digital conditions because the proposed empirical design collects teacher-level survey data rather than objective school-level indicators.

Table 5. Second-order measurement architecture for perceived institutional digital transformation

First-order dimension	Indicative item focus	Rationale	Source basis
Digital infrastructure	Stable platforms, smart classrooms, network access and equipment support.	Infrastructure provides the material condition for digitally mediated teaching.	Vial (2019); Verhoef et al. (2021).
Digital teaching resources	Updated digital repositories, simulation materials and vocational task resources.	Teachers need usable resources to redesign learning activities.	Ma et al. (2025); Xu et al. (2024).
Data-informed governance	Teaching quality monitoring, learning evidence and platform data use.	Digital transformation changes how institutions observe and support teaching.	Yang & Peters (2026); Ministry of Education of the People's Republic of China (2025).
Smart training environments	Simulation rooms, intelligent equipment, digital twins or smart workshops.	TVET digitalisation must enter practical learning spaces, not only online platforms.	Subrahmanyam (2022); OECD (2025).
School-enterprise digital connectivity	Digital collaboration with enterprises, curriculum updating and project-based platforms.	Vocational relevance depends on links between teaching and industrial digitalisation.	UNESCO (2022); Zhong & Juwaheer (2024).

Note. The item wording is indicative and requires expert review, pilot testing and psychometric refinement before empirical use.

Table 6 focuses on teacher AI application as enacted pedagogical practice. It separates AI use for instructional design, feedback, analytics, practical training and responsible guidance.

Table 6. Measurement architecture for teacher AI application

Dimension	Indicative item focus	Rationale	Source basis
AI-assisted instructional design	Using AI to prepare lessons, generate vocational scenarios and adapt materials.	AI use becomes pedagogically meaningful when it shapes learning design.	Miao & Holmes (2023); Tan et al. (2025).
AI-supported feedback and assessment	Using AI to support formative feedback, rubrics and diagnostic assessment.	Feedback and assessment are central to teacher work and student development.	Chen et al. (2020); Bond et al. (2024).
Learning analytics use	Using AI-generated evidence to understand progress, risk and learning needs.	Analytics can support mentoring only when interpreted by teachers.	Ouyang & Jiao (2021); Kong et al. (2025).
AI-supported simulation/practical training	Using AI or intelligent systems in simulation, equipment diagnosis or practical tasks.	TVET AI application needs to connect with skills and workplace competence.	OECD (2025); Subrahmanyam (2022).

Dimension	Indicative item focus	Rationale	Source basis
Responsible AI guidance	Guiding students on attribution, privacy, bias, hallucination and professional accountability.	Responsible use is part of teacher stewardship in AI-enabled education.	Miao & Cukurova (2024); U.S. Department of Education, Office of Educational Technology (2023).

Note. The table treats AI application as teacher enactment, not as simple tool availability.

Table 7 specifies teacher role reconfiguration as a five-dimensional outcome. The dimensions are analytically separable but collectively represent professional role expansion in AI-enabled TVET.

Table 7. Measurement architecture for teacher role reconfiguration

Dimension	Indicative item focus	Rationale	Source basis
Learning designer	Designing blended, AI-supported and vocationally authentic learning sequences.	Digital educator competence frameworks emphasise design and evaluation of mediated learning.	Redecker (2017); Ng et al. (2023).
Data-informed mentor	Using learning data to provide targeted support and diagnostic guidance.	AI-supported analytics expand mentoring responsibilities.	Chen et al. (2020); Miao & Cukurova (2024).
Smart skills coach	Coaching students through smart equipment, simulation and digital evidence of performance.	TVET teachers need to connect digital tools with embodied skills.	Subrahmanyam (2022); Xu et al. (2024).
Industry-education broker	Translating industry digitalisation needs into curriculum tasks and project-based learning.	TVET role expansion includes boundary-spanning work with industry.	Ma et al. (2025); OECD (2025).
AI ethics steward	Guiding responsible AI use, academic integrity, data privacy and human judgement.	AI-enabled learning requires ethical and professional stewardship.	Miao & Holmes (2023); U.S. Department of Education, Office of Educational Technology (2023).

Note. The item wording is indicative and is not presented as a validated scale.

4.3 Analytical strategy

The proposed validation protocol is compatible with either PLS-SEM or CB-SEM, depending on the final research objective and data properties. PLS-SEM is suitable when the emphasis is prediction, exploratory hierarchical component modelling and formative higher-order constructs; CB-SEM is suitable when theory confirmation and global model fit are prioritised (Hair et al., 2022; Kline & Little, 2023).

The core mediation equations can be specified as follows:

$$TAIA_i = \alpha_0 + \alpha_1 PIDT_i + \gamma Controls_i + \varepsilon_i$$

$$TRR_i = \beta_0 + \beta_1 PIDT_i + \beta_2 TAIA_i + \gamma Controls_i + \varepsilon_i$$

$$Indirect\ effect = \alpha_1 \times \beta_2$$

The measurement model needs to report factor loadings, reliability, convergent validity and discriminant validity. Discriminant validity can be examined using HTMT, which is often more stringent than the traditional Fornell-Larcker criterion in SEM applications (Henseler et al., 2015). Full-collinearity VIF can provide an additional diagnostic for common method bias in PLS-SEM settings (Kock, 2015). Mediation analysis should use bootstrapping, with at least 5,000 resamples, and report confidence intervals for the indirect effect (Hayes, 2022).

Table 8 specifies the analytical quality checks. These checks are included to prevent the common weakness of under-reported survey-based mediation studies.

Table 8. Analytical quality checks and reporting criteria

Assessment area	Recommended check	Reporting criterion
Data screening	Missing values, careless responses, normality, outliers and wave attrition.	Report removal rules, final matched sample and attrition comparison.
Reliability	Cronbach's alpha and composite reliability.	Prefer values above 0.70 while avoiding inflated redundancy.
Convergent validity	Standardised loadings and AVE.	Loadings preferably above 0.70; AVE above 0.50.
Discriminant validity	HTMT and, where appropriate, Fornell-Larcker results.	HTMT below conventional thresholds and theoretically interpretable correlations.
Hierarchical component modelling	Assess first-order dimensions before estimating higher-order constructs.	Justify reflective-formative specification and check collinearity among dimensions.
Common method bias	Temporal separation, anonymity, marker variable, common latent factor or full-collinearity VIF.	Report procedural and statistical safeguards rather than relying only on Harman's test.
Structural model	Path coefficients, confidence intervals, R^2, f^2 and predictive relevance where applicable.	Interpret effect size and uncertainty, not only significance.
Robustness	Alternative model, control-variable model, subgroup checks and possible multilevel extension.	Show whether the mediation logic remains stable under plausible alternatives.

Note. HTMT = heterotrait-monotrait ratio; AVE = average variance extracted; VIF = variance inflation factor.

4.4 Ethics, common method bias and reporting discipline

Because this article is conceptual, no ethics approval is required for the present manuscript. Empirical validation, however, requires institutional ethics approval before fieldwork, informed consent, voluntary participation, anonymity and secure data management. The survey instrument should avoid collecting unnecessary identifiable information.

Common method bias is a particular concern because the proposed model relies on teacher perceptions. The three-wave design creates temporal separation among predictor, mediator and outcome measures. The validation protocol also includes procedural separation of constructs, neutral wording, anonymity assurance and statistical diagnostics. Podsakoff et al. (2024) caution that common method bias is complex and cannot be solved by a single test; hence, the proposed design combines procedural and statistical safeguards.

If future data include sufficient school-level observations, multilevel SEM can distinguish school-level digital transformation from teacher-level AI application and role reconfiguration. Intraclass correlations and aggregation statistics would then be needed before treating institutional digital transformation as a school-level variable.

Table 9 explains the interpretation logic for the proposed mediation model. It also makes explicit that causal language remains inappropriate unless future validation uses stronger longitudinal, experimental or quasi-experimental designs.

Table 9. Proposed tests and interpretation logic for the mediation model

Test	Expected evidence	Interpretation
P1: PIDT -> TAIA	Positive and statistically credible path coefficient.	Institutional digital conditions are associated with stronger teacher AI application.
P2: TAIA -> TRR	Positive and statistically credible path coefficient.	AI-supported pedagogical practice is associated with role expansion.

Test	Expected evidence	Interpretation
P3: PIDT -> TAIA -> TRR	Bootstrapped indirect effect with confidence interval excluding zero.	Teacher AI application transmits the relationship between digital transformation and role reconfiguration.
Direct path: PIDT -> TRR	Direct effect estimated after TAIA is included.	Significant direct and indirect effects suggest partial mediation; a non-significant direct effect with significant indirect effect suggests stronger mediation.
Alternative model	Compare with TAIA -> PIDT -> TRR or TRR -> TAIA alternatives where theoretically plausible.	Reduces the risk of accepting the proposed sequence without comparison.
Subgroup checks	Compare discipline clusters, prior AI training or institution types.	Identifies whether the framework works similarly across TVET contexts.

Note. The interpretation remains inferential. Statistical mediation alone does not prove causality.

5. Discussion

5.1 Conceptual contribution

The article contributes to TVET digitalisation research by specifying a mechanism between institutional transformation and teacher role change. Instead of assuming that digital platforms, data systems or AI tools automatically alter teaching, the framework identifies teacher AI application as the mediating practice through which institutional conditions become professionally consequential. This shifts attention from technology provision to teacher enactment.

The article also contributes to teacher role theory by conceptualising role reconfiguration as professional expansion. The five-dimensional model clarifies that AI-enabled TVET teachers do not simply become more efficient content deliverers. They become designers of AI-supported learning, mentors who interpret data, coaches who connect smart systems with practical skills, brokers who translate industrial digitalisation into curriculum and stewards who protect ethical judgement. This role-centred vocabulary is more precise than broad claims that AI will transform teaching.

5.2 Implications for AI-enabled TVET reform in industrial regions

For TVET leaders in Liaoning and comparable industrial regions, the framework shifts evaluation away from infrastructure indicators alone and towards evidence of teacher role expansion. A school may possess platforms, simulation rooms and AI tools, yet still fail to transform teacher work if teachers are not supported to redesign tasks, interpret learning data, guide responsible AI use and connect curricula with industry needs.

The framework also suggests a different approach to teacher development. AI training that focuses only on prompt techniques or tool operation is insufficient. TVET teachers need professional learning that integrates AI pedagogy, occupational task design, learning analytics, formative assessment, smart practical training and ethical guidance. This aligns with broader teacher AI competency work while retaining the distinctive practical and industry-facing character of TVET (Miao & Cukurova, 2024; Subrahmanyam, 2022).

Table 10 translates the conceptual model into practical implications. The table is framed for Liaoning but can be adapted to other TVET systems facing similar industrial and educational transitions.

Table 10. Practical implications derived from the mediation model

Reform area	Common risk	Recommended action	Expected teacher role expansion

Reform area	**Common risk**	**Recommended action**	**Expected teacher role expansion**
Digital infrastructure	Platforms exist but remain weakly connected with classroom and workshop practice.	Integrate platforms, simulation systems, assessment evidence and enterprise resources.	Learning designer.
Teacher AI training	Training focuses on tool operation and ignores pedagogy.	Build modules on AI pedagogy, prompt design, feedback, learning analytics and ethics.	Human-AI collaborator.
Practical training	Digital resources are separated from skills coaching.	Use simulation, intelligent equipment data and digital evidence in practical modules.	Smart skills coach.
Assessment	Assessment remains examination-centred and weakly diagnostic.	Combine AI-supported formative assessment with teacher judgement.	Data-informed mentor.
School-enterprise cooperation	Industry input is occasional and document-based.	Use digital collaboration platforms for curriculum updating and enterprise projects.	Industry-education broker.
AI ethics	Students use AI without clear norms or professional accountability.	Develop course-level rules for attribution, privacy, bias, verification and responsible use.	AI ethics steward.

Note. The actions are implications derived from the conceptual framework rather than evaluated policy effects.

5.3 Future empirical validation

The framework is designed for empirical testing. Future studies can collect three-wave teacher survey data across multiple TVET institutions and use structural equation modelling to test the proposed pathway. Validation studies need to report not only whether the indirect effect is statistically credible but also whether the measurement model supports the proposed second-order constructs.

Future validation can also extend the model. AI self-efficacy, prior AI training, perceived institutional AI support, discipline digital intensity and school-enterprise collaboration intensity can be tested as controls or moderators. Comparative designs across provinces can examine whether industrial structure shapes the strength of the PIDT -> TAIA -> TRR pathway. Mixed-method studies can use interviews, platform logs and teaching artefacts to explain how teachers experience role tension, workload change and professional identity reconstruction during AI-enabled reform.

6. Limitations and Future Research

The article has three limitations. First, it is conceptual and therefore does not claim that the proposed mediation pathway has already been empirically confirmed. Its contribution lies in specifying the mechanism, constructs and validation logic required for future testing. Second, the framework uses Liaoning as an illustrative industrial-region context. This improves contextual relevance but requires empirical adaptation before generalisation to other provinces or countries. Third, the proposed constructs depend partly on teacher perceptions. Future research can strengthen validity by combining surveys with student evaluations, supervisor assessments, training records, platform logs and teaching artefacts.

Future studies can proceed in several directions. Longitudinal research can examine whether teacher AI application leads to durable role change or only short-term experimentation. Multilevel research can distinguish school-level digital transformation from teacher-level enactment. Qualitative work can reveal how teachers negotiate professional identity when AI systems enter lesson planning, assessment and workshop practice. Comparative studies can examine whether industrial regions, service-oriented regions and digitally advanced metropolitan areas show different patterns of teacher role reconfiguration.

7. Conclusion

This article explains TVET teacher role reconfiguration as a sociotechnical process in which perceived institutional digital transformation becomes professionally meaningful through teacher-level AI application. The framework moves beyond the assumption that digital transformation automatically changes teacher work. It argues instead that teacher AI application is the mediating practice through which institutional digital conditions are translated into learning design, data-informed mentoring, smart skills coaching, industry-education brokerage and AI ethics stewardship.

Because the article is conceptual, it does not claim that the proposed mediation pathway has already been empirically confirmed. Its value lies in offering a clearer mechanism, a measurable role-centred construct and a validation protocol for future studies. For Liaoning and comparable industrial regions, the framework suggests that AI-enabled TVET reform needs to be judged by teacher role expansion, not by infrastructure provision or tool availability alone.

Declarations

Ethics approval: Not applicable. This conceptual framework article did not involve human participants or empirical data collection.

Informed consent: Not applicable. No participants were recruited for the present article.

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