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Transforming Teaching Systems in the Era of Artificial Intelligence: An Empirically Validated Multi-Stakeholder Framework for Intelligent Teaching System Design Integrating Deep Learning, NLP, and Learning Analytics.

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ABSTRACT

The rapid advancement of Artificial Intelligence (AI) technologies is fundamentally reshaping educational environments and transforming the way teaching and learning processes are designed and delivered. Traditional teaching systems, which largely rely on static instructional methods and limited feedback mechanisms, often struggle to address the diverse learning needs of students in modern educational ecosystems. In response to these challenges, the integration of intelligent technologies such as deep learning, natural language processing (NLP), and learning analytics has emerged as a promising approach for creating adaptive, data-driven, and personalized teaching systems. This study proposes a comprehensive multi-stakeholder framework for intelligent teaching system design that integrates advanced AI technologies to enhance educational effectiveness and learner engagement. The proposed framework emphasizes the collaborative roles of key educational stakeholders, including students, teachers, academic administrators, and institutional decision-makers, in the design and implementation of AI-enabled teaching systems. By incorporating deep

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learning models for pattern recognition and predictive analysis, NLP techniques for automated feedback and intelligent tutoring interactions, and learning analytics for monitoring student progress and behavioral learning patterns, the framework aims to create an integrated intelligent teaching ecosystem. The study employs an empirical validation approach to examine the relationships between AI technological capabilities, stakeholder engagement, adaptive learning mechanisms, and overall teaching system performance. Data were collected from multiple educational stakeholders through structured surveys and analyzed using advanced statistical techniques to validate the proposed framework and its underlying constructs. The empirical analysis demonstrates that the integration of AI technologies significantly improves instructional adaptability, enhances real-time learning feedback, and supports evidence-based pedagogical decision-making. Furthermore, the results highlight the critical role of stakeholder collaboration in ensuring the effective implementation and sustainability of intelligent teaching systems. The findings contribute to the growing body of research in Artificial Intelligence in Education (AIED) by providing a validated conceptual and operational framework that bridges technological innovation with pedagogical design and institutional governance. In addition to offering theoretical contributions, the study provides practical guidelines for universities, educational policymakers, and technology developers seeking to implement AI-driven teaching systems that are scalable, transparent, and learner-centered. The proposed framework represents a strategic pathway toward the transformation of traditional educational systems into intelligent, adaptive, and data-informed learning environments capable of meeting the evolving demands of the digital education era.

Keywords: Artificial Intelligence in Education (AIED); Intelligent Teaching Systems; Deep Learning; Natural Language Processing (NLP); Learning Analytics; Multi-Stakeholder Framework; AI-Driven Education; Educational Technology.

Introduction:

Artificial Intelligence (AI) is increasingly redefining educational environments by enabling teaching systems that can sense learning behaviors, interpret instructional and learner-generated artifacts, predict learning risks, and adapt pedagogical support in near real time. The widespread deployment of learning management systems (LMS), online assessment platforms, virtual classrooms, and institutional communication channels has created continuous streams of educational data, including interaction logs, assessment traces, submission histories, and feedback exchanges. These data sources, when combined with modern AI methods, create an opportunity to shift educational practice from static delivery models toward intelligent teaching systems that support personalization, timely formative feedback, and evidence-informed instructional governance across courses, departments, and institutions [1]. Despite ongoing digitization, many teaching systems remain constrained by conventional instructional assumptions characterized by fixed pacing, periodic evaluation cycles, and limited feedback bandwidth. These limitations become particularly evident in large-enrollment classes and blended learning contexts, where teachers face heavy workload demands and cannot provide individualized guidance at

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scale. In such environments, misconceptions may persist undetected, disengagement can remain invisible until late in the semester, and students who require targeted support are often identified only after measurable performance decline. At the institutional level, administrators are increasingly expected to demonstrate improvements in teaching quality, student progression, and learning equity, yet they often lack integrated evidence that links instructional practices, interventions, and outcomes over time. Consequently, a persistent gap exists between the complexity of modern learning ecosystems and the responsiveness of traditional teaching structures—highlighting the need for intelligent teaching systems that are adaptive, scalable, and institutionally governable. Recent advances in deep learning, natural language processing (NLP), and learning analytics provide a strong technological basis for addressing these challenges [2]. Deep learning models can discover non-linear patterns in high-dimensional educational data and support predictive intelligence for performance forecasting, early risk detection, and learning progression modeling. NLP techniques can interpret language-based educational artifacts such as assignment responses, reflective writing, and teacher feedback enabling automated feedback generation, misconception detection, and analysis of instructional discourse. Learning analytics complements these capabilities by integrating longitudinal behavioral and performance signals to produce descriptive and diagnostic insights, support intervention monitoring, and evaluate instructional impact across cohorts. When integrated coherently, these technologies can enable a closed-loop teaching cycle in which learning evidence is collected continuously, transformed into actionable intelligence, translated into pedagogical interventions, and evaluated iteratively for ongoing improvement. However, the practical impact of AI in education is often limited by fragmentation in system design and evaluation. Many implementations emerge as isolated modules such as prediction dashboards, automated grading tools, or tutoring interfaces without a unified framework that connects prediction, feedback generation, intervention delivery, and institutional monitoring into a coherent teaching-system lifecycle. Moreover, evaluation is frequently dominated by technical performance indicators while underemphasizing adoption-critical dimensions such as usability in real teaching workflows, interpretability of AI recommendations, institutional readiness for deployment, and governance requirements including privacy, accountability, and perceived fairness. These limitations are especially consequential in educational settings because teaching systems influence high-stakes outcomes; inappropriate automation, biased prediction, or opaque decision logic can harm trust, distort pedagogical choices, and undermine perceptions of equity. For these reasons, effective teaching-system transformation requires not only advanced algorithms, but an operational framework that aligns technological capabilities with instructional practice, stakeholder decision rights, and institutional governance [3]. A central requirement for such alignment is explicit multi-stakeholder operationalization. Intelligent teaching systems are adopted and sustained primarily through those responsible for design, implementation, and governance within institutions. Teachers require tools that reduce routine workload, enhance formative feedback, and preserve pedagogical control, rather than introducing additional complexity or perceived surveillance. Administrators require credible evidence of teaching quality and improvement, institutional dashboards for

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strategic planning, and governance mechanisms that ensure responsible data use and accountability. If stakeholder expectations, roles, and incentives are not incorporated into the design logic, even technically strong systems may fail to scale due to low acceptance, limited integration into existing processes, or insufficient institutional support structures. Therefore, a multi-stakeholder perspective is not an optional extension; it is a core condition for sustainable AI-enabled teaching transformation. This study addresses these challenges by proposing a comprehensive, empirically validated multi-stakeholder framework for intelligent teaching system design integrating deep learning, NLP, and learning analytics. The framework connects AI technological capabilities to stakeholder engagement processes, adaptive teaching mechanisms, and teaching system performance outcomes in a single conceptual and operational structure. Deep learning contributes predictive and diagnostic intelligence for monitoring learning progression and identifying instructional needs; NLP enables automated feedback and language-driven instructional support; and learning analytics supports longitudinal monitoring, intervention evaluation, and institutional evidence generation. Importantly, the framework emphasizes structured collaboration among teachers and administrators across the lifecycle of AI-enabled teaching systems, from requirements definition and governance planning to implementation, monitoring, and continuous improvement, thereby ensuring that system intelligence remains pedagogically meaningful and institutionally actionable. To ensure that the framework is not only conceptual but also empirically defensible, this study applies Partial Least Squares Structural Equation Modeling (PLS-SEM) to validate the framework and test the relationships among its constructs using survey data collected from teachers and academic administrators. PLS-SEM is well-suited for predictive, theory-building research involving complex models and latent constructs, and it enables simultaneous assessment of the measurement model and the structural paths that explain how AI capability integration and stakeholder engagement contribute to adaptive teaching mechanisms and teaching-system performance. By grounding the framework in empirical evidence, the study clarifies which factors most strongly shape successful implementation and highlights stakeholder collaboration as a determinant of sustainability. Table 1 positions this research by summarizing common limitations in prior AI-enabled teaching approaches and indicating how the proposed study addresses them through integrated capability design, explicit stakeholder operationalization, governance embedding, and PLS-SEM-based empirical validation.

Table 1: Positioning of the proposed framework relative to typical limitations in AI-enabled teaching systems

Aspect	**Typical limitation in prior work**	**Practical consequence in real deployment**	**How this study addresses the limitation**
Integration of AI capabilities	Deep learning, NLP, and analytics implemented as separate tools	Fragmented insights; weak closed-loop adaptation	Unified framework connecting prediction, language intelligence, and

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			longitudinal analytics into a single lifecycle
Feedback and intervention linkage	Feedback not systematically connected to AI outputs	Late detection of misconceptions; limited instructional responsiveness	AI-guided feedback and adaptive intervention mechanisms monitored through analytics
Stakeholder operationalization	Teachers/admins referenced but not modeled as system actors	Low acceptance; unclear responsibilities; misaligned incentives	Explicit roles and decision rights for teachers and administrators across design, implementation, and oversight
Evaluation orientation	Focus on technical performance rather than adoption and governance	Systems work in pilots but fail to scale	Empirical validation using teacher/admin data to link capability and engagement to performance outcomes
Governance and ethics	Privacy, transparency, and accountability handled after deployment	Trust erosion; compliance risk	Governance embedded as a design requirement, aligned with institutional decision processes
Scalability and sustainability	Limited institutional readiness and process integration	Weak long-term use across departments	Design principles and guidelines aimed at institutional scaling and sustainable implementation

This work contributes to Artificial Intelligence in Education (AIED) by offering a validated conceptual and operational framework that bridges AI-driven innovation with teaching practice and institutional governance. Beyond theoretical contribution, it provides practical guidance for institutions and educational technology developers seeking to implement AI-driven teaching systems that are scalable, transparent, and teacher-supportive while enabling administrators to govern and evaluate outcomes responsibly.

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Multi-Stakeholder Perspectives in Intelligent Teaching Systems:

Education is inherently multi-stakeholder because teaching effectiveness, technology adoption, and institutional sustainability are produced through the interaction of multiple actors operating at different levels of the educational system. Intelligent teaching systems do not function like conventional "software tools" that can be evaluated only by usability or technical performance; rather, they behave as socio-technical infrastructures that reshape instructional workflows, assessment practices, feedback cycles, and decision-making authority. For this reason, adoption outcomes depend not only on whether the underlying AI models are accurate, but also on how different stakeholder groups perceive value, risk, control, and accountability within the teaching system. A design that optimizes predictive accuracy yet fails to align with teacher agency or institutional governance constraints may still be rejected, underused, or discontinued after an initial pilot phase. Teachers are typically the primary translation layer between AI outputs and educational action. Even when an intelligent system produces high-quality predictions or recommendations, its instructional value is realized only if teachers can interpret those outputs, trust their validity, and integrate them into pedagogical decisions without added cognitive burden [4]. The literature consistently indicates that teacher adoption is shaped by a combination of perceived usefulness, ease of integration into existing teaching routines, interpretability of AI recommendations, and perceived effects on workload. Importantly, teachers often resist systems that feel like surveillance instruments, reduce professional autonomy, or provide decontextualized alerts that are difficult to convert into specific instructional interventions. In practice, teachers require AI assistance that is not merely "correct," but instructionally actionable meaning it must explain what changed, why it matters, which students are affected, and what interventions are likely to help. Consequently, teacher-centered design emphasizes human-in-the-loop decision pathways in which AI supports, rather than replaces, pedagogical judgment. Administrators and institutional leaders shape adoption through a different set of constraints and incentives. While teachers focus on classroom-level utility and workflow fit, administrators are responsible for deployment readiness, policy compliance, infrastructure support, and quality assurance. Their evaluation of intelligent teaching systems often emphasizes governance capacity, scalability across departments, measurable institutional outcomes (e.g., retention, progression, quality indicators), and risk management related to privacy, fairness, accountability, and reputational exposure. Administrators also influence adoption indirectly through professional development programs, procurement decisions, institutional data policies, and the allocation of support resources for implementation and maintenance [5]. From an administrative perspective, the most critical feature of an intelligent teaching system is frequently not the model itself, but the presence of institutional controls that make the system auditable, explainable to stakeholders, and governable over time. The importance of multi-stakeholder alignment becomes even more pronounced when intelligent teaching systems are deployed as continuous services rather than one-time tools. Sustainability requires ongoing monitoring for model drift, periodic updates of content and instructional mappings, maintenance of data pipelines, and governance audits to ensure that system behavior remains consistent with institutional goals and

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ethical requirements. This introduces a long-term operational dimension: intelligent teaching systems must be maintainable and governable, with clear accountability structures specifying who approves model updates, who responds to risk alerts, who adjudicates disputes about automated feedback, and how system decisions are documented. Without explicit stakeholder roles and decision rights, institutions often face ambiguity that leads to implementation breakdowns, reduced trust, or reliance on informal workarounds that undermine system integrity. For these reasons, contemporary research increasingly motivates frameworks that formalize stakeholder engagement, define decision-making authority, and embed human oversight mechanisms within the system lifecycle. Multi-stakeholder frameworks also clarify that "success" is multi-dimensional: teachers prioritize instructional usefulness and manageable workload impact, while administrators prioritize scalable governance, evidence generation for quality assurance, and compliance with institutional policies. Intelligent teaching systems therefore require design strategies that reconcile these priorities, ensuring that AI recommendations are instructionally meaningful at the classroom level while remaining transparent, auditable, and institutionally actionable at the governance level. Table 2 synthesizes the primary stakeholder concerns and translates them into design requirements and evaluation indicators that intelligent teaching systems must satisfy.

Table 2: Stakeholder roles, value expectations, risks, and design requirements in intelligent teaching systems

Stakeholder group	**Core role in intelligent teaching systems**	**Primary value expectations**	**Primary perceived risks**	**High-priority design requirements**	**Representative evaluation indicators**
Teachers	Interpret AI insights and convert them into pedagogical decisions and interventions	Actionable recommendations, better formative feedback, reduced routine workload, improved student engagement	Loss of autonomy, opaque recommendations, extra workload, classroom disruption, misclassification harming students	Explainable outputs, intervention guidance, workflow integration (LMS), teacher override, low-friction dashboards	Perceived usefulness, interpretability, workload impact, intention to use, intervention uptake rate
Academic administrators	Enable adoption through governance,	Scalable deployment, measurable learning quality	Compliance risk, fairness concerns, reputational harm, vendor	Data governance controls, auditing, access	Institutional readiness, policy compliance, auditability,

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	infrastructure, professional development, and quality assurance	improvements, institutional dashboards, evidence-based planning	lock-in, data security incidents	control, fairness monitoring, scalability, reporting for QA	fairness perceptions, scalability measures
Institutional decision-makers	Set strategy, accountability, procurement rules, and policy constraints	Alignment with institutional mission, accountability, demonstrable ROI, long-term sustainability	High-stakes failures, legal/ethical violations, lack of transparency, stakeholder backlash	Accountability frameworks, transparent KPIs, governance committees, change management	Sustainability metrics, adoption persistence, governance maturity, risk incident frequency
Students (affected stakeholders)	Receive feedback and interventions; generate learning data through interaction	Timely feedback, personalization, fairness, agency and clarity	Unfair profiling, privacy concerns, harmful automated feedback, reduced human support	Transparency of use, contestability, privacy protections, supportive feedback tone	Perceived fairness, trust, satisfaction, perceived support quality, opt-in/consent rates

A useful way to operationalize multi-stakeholder perspectives is to model the intelligent teaching system as a closed-loop governance and intervention cycle in which teachers and administrators occupy distinct but coupled control points. Teachers act at the instructional decision layer, determining whether and how AI outputs translate into classroom actions. Administrators act at the institutional governance layer, ensuring that system deployment remains compliant, equitable, and sustainable while enabling training and infrastructure support. Figure 1 provides a conceptual interaction model showing how stakeholder roles connect to the AI capability stack (deep learning, NLP, learning analytics) and how accountability is maintained through feedback, auditing, and continuous monitoring.

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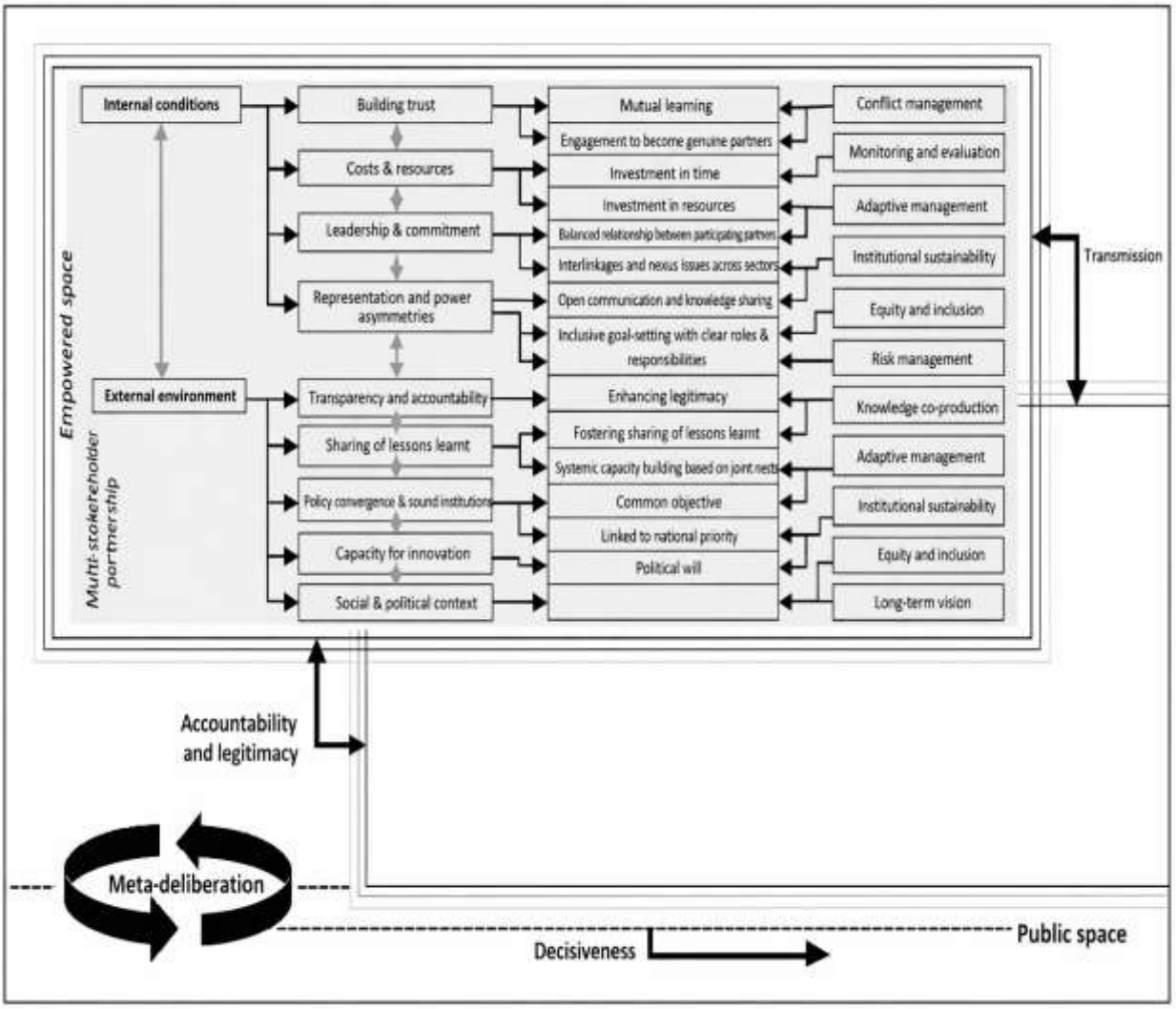

Figure 1: Conceptual multi-stakeholder interaction loop for intelligent teaching system implementation and governance (teacher–administrator centered)

This interaction model clarifies a central insight emphasized in the literature: intelligent teaching systems are most sustainable when they preserve teacher agency through override and contextual judgment, while simultaneously enabling administrators to govern risk through transparency, auditing, and continuous monitoring. When these control points are absent such as when teachers receive unexplained alerts or administrators cannot audit model behavior stakeholders tend to either reject the system or use it in superficial ways that prevent meaningful instructional improvement [6]. Accordingly, multi-stakeholder frameworks do not merely list stakeholders; they specify how authority, accountability, and feedback pathways are embedded within system architecture. In the context of this paper, the multi-stakeholder perspective is operationalized by treating teachers and administrators as the core implementation actors and validating how their engagement and readiness relate to system performance under integrated AI capability. This emphasis is especially appropriate for institutional deployment because teachers

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determine the instructional effectiveness of AI outputs, while administrators determine whether systems can be implemented at scale with adequate governance. By foregrounding stakeholder roles, decision rights, and accountability structures, the literature supports the argument that intelligent teaching system transformation is not purely a technical upgrade; it is a coordinated organizational change that must align AI capability with pedagogical practice and institutional governance for long-term success.

Empirical Validation of AIED Frameworks and the Role of PLS-SEM:

A growing body of research in Artificial Intelligence in Education (AIED) emphasizes that the success of intelligent teaching systems cannot be established through technical performance claims alone. Even when deep learning, NLP, or learning analytics models demonstrate strong accuracy, precision, or content-generation quality, institutions still require evidence that these capabilities translate into improved teaching-system effectiveness, sustainable adoption, and governable implementation. For this reason, empirical validation has become an increasingly important methodological direction in AIED, particularly for studies proposing conceptual or operational frameworks intended to guide institutional design decisions. Empirical modeling enables researchers to test whether a framework is internally coherent, whether its constructs are measurable with reliability, and whether hypothesized relationships among constructs hold in real stakeholder populations. This is especially relevant for multi-stakeholder frameworks, where perceived value, trust, readiness, and governance often determine whether AI-enabled systems are used meaningfully, used superficially, or abandoned after pilot deployment. Within this methodological trend, structural equation modeling (SEM) has emerged as one of the most widely used approaches for validating AIED frameworks that involve latent constructs and complex interdependencies. Intelligent teaching systems are typically conceptualized through abstract variables such as perceived usefulness, trust, transparency, institutional readiness, decision support quality, and system performance that cannot be measured directly using a single indicator. SEM allows these constructs to be modeled as latent variables measured by multiple survey items, enabling researchers to evaluate both measurement quality and theoretical relationships in a single analytical pipeline [7]. In AIED settings, SEM is particularly valuable because it can capture the multi-dimensional nature of adoption and performance, where technological quality, organizational conditions, and stakeholder perceptions jointly shape outcomes. Partial Least Squares Structural Equation Modeling (PLS-SEM) is frequently selected in AIED framework validation studies because it is well aligned with predictive, theory-building, and exploratory objectives. Many AIED studies aim to explain or predict teaching-system performance under conditions where models are complex, constructs are newly operationalized, or sample sizes may be moderate relative to the number of indicators. PLS-SEM is also robust in handling complex models with multiple constructs, mediators, and higher-order structures, making it suitable for frameworks that integrate AI capability dimensions (deep learning, NLP, learning analytics) with socio-organizational constructs (stakeholder engagement, institutional readiness, governance). Importantly, PLS-SEM supports simultaneous evaluation of the measurement model (reliability

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and validity of constructs) and the structural model (strength and significance of hypothesized paths), enabling an evidence-based assessment of whether a conceptual framework is empirically defensible. In multi-stakeholder intelligent teaching systems, PLS-SEM provides an analytical advantage because it can quantify how different categories of drivers technological capability, stakeholder engagement, and governance readiness contribute jointly to teaching-system performance, and it can test mediation mechanisms that are central to lifecycle-based teaching-system design. For instance, AI capability may not improve performance directly; rather, it may improve performance through adaptive teaching mechanisms such as real-time feedback quality, intervention responsiveness, or decision support usefulness. PLS-SEM allows such indirect effects to be tested rigorously through bootstrapped mediation analysis. Similarly, stakeholder engagement may function as a moderator or an antecedent that strengthens the translation of AI insights into classroom-level action and institutional-level sustainability. These forms of modeling are especially important because they convert a framework from a narrative description into a testable and measurable structure. Nevertheless, the literature also reveals consistent methodological and conceptual limitations in how AIED frameworks are validated. A common pattern is that studies evaluate stakeholder perceptions such as satisfaction, perceived usefulness, or intention to use without linking these perceptions to operational teaching mechanisms and performance outcomes. In such studies, "adoption" becomes the endpoint rather than a pathway to improved teaching quality. Another limitation is that some validation models treat "AI capability" as a generic construct without distinguishing between predictive intelligence (deep learning), language intelligence (NLP), and monitoring/evaluation intelligence (learning analytics), even though these capabilities influence teaching systems through different mechanisms. A further limitation is that governance constructs trust, transparency, fairness, privacy readiness are sometimes positioned as peripheral or discussed qualitatively, rather than modeled explicitly in the empirical structure. These gaps create a disconnect between acceptance modeling and lifecycle-based teaching-system design, making it difficult for institutions to translate empirical findings into implementable system requirements and governance policies. To address these issues, current AIED research increasingly motivates validation models that connect AI capability integration to adaptive teaching mechanisms and then to teaching-system performance outcomes under multi-stakeholder conditions. In such models, "performance" is conceptualized in educationally meaningful terms improved instructional adaptability, enhanced feedback effectiveness, better evidence-based pedagogical governance, and stronger capacity for early intervention rather than limited to model accuracy. This approach is particularly appropriate in higher education contexts, where intelligent teaching systems must operate at scale and must be accepted and governed by teachers and administrators who play distinct but connected roles [8]. The need for empirically validated frameworks therefore stems from a practical requirement: institutions need evidence not only that stakeholders like the system, but that the system improves teaching effectiveness through measurable mechanisms that can be monitored and sustained. Figure 2 presents a conceptual empirical validation logic aligned with PLS-SEM practice in AIED, emphasizing the pathway from integrated AI capabilities to adaptive teaching

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mechanisms and then to teaching-system performance, with stakeholder engagement and governance readiness shaping system effectiveness.

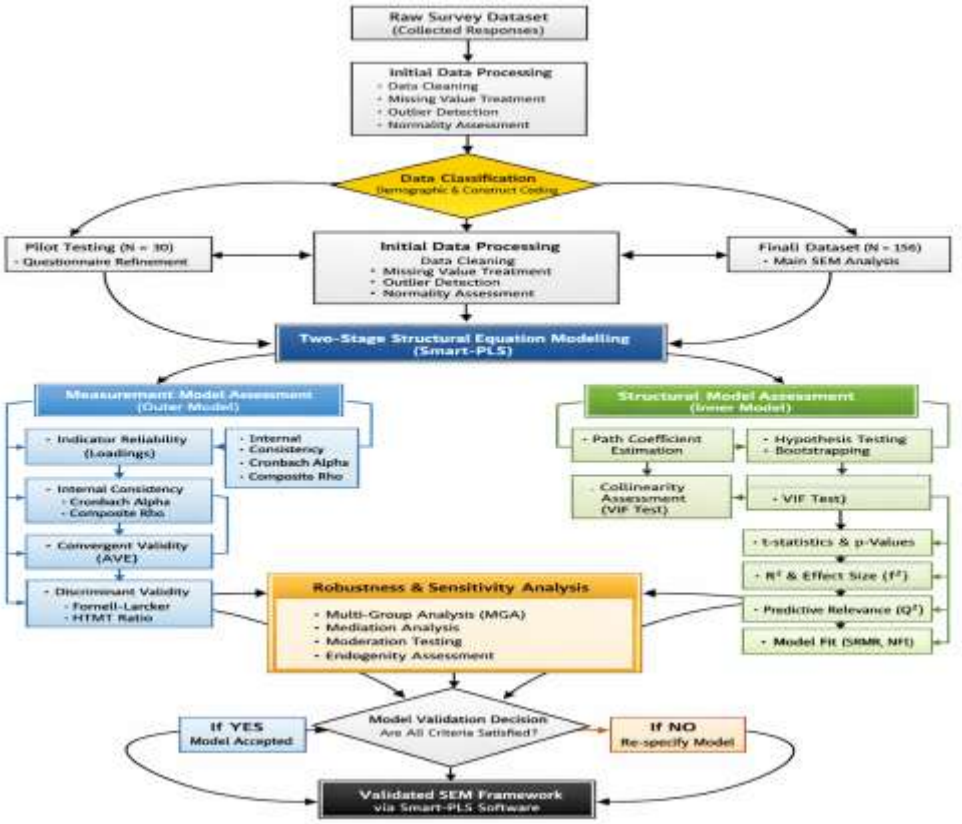

Figure 2: Conceptual PLS-SEM validation logic for multi-stakeholder intelligent teaching system frameworks

This empirical validation perspective clarifies why PLS-SEM is not merely a statistical tool but a framework-testing methodology well suited to AIED system research: it enables researchers to demonstrate that a proposed model is measurable, that its relationships are supported by stakeholder evidence, and that the pathway from AI capability integration to teaching-system performance is mediated through operational teaching mechanisms rather than ending at attitude measures alone.

Methodology:

This study employs a quantitative, explanatory methodology to empirically validate a multi-stakeholder framework for intelligent teaching system design that integrates deep learning, natural language processing (NLP), and learning analytics. Primary data are collected using a structured questionnaire administered to teachers and academic administrators, as these stakeholders directly influence both instructional-level adoption and institution-level governance and sustainability of AI-enabled teaching systems. The proposed conceptual model is evaluated using Partial Least Squares Structural Equation Modeling (PLS-SEM) because it supports prediction-oriented theory building, accommodates complex models with multiple latent constructs, and enables simultaneous assessment of the measurement model

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(reliability and validity of constructs) and the structural model (significance and strength of hypothesized relationships). The overall workflow includes instrument development and pilot testing, ethical and anonymous data collection, data screening and preparation, measurement validation (indicator loadings, internal consistency, convergent and discriminant validity), and structural assessment using bootstrapping, explained variance, effect sizes, and predictive relevance to establish the robustness of the proposed framework.

Research Design and Overall Approach:

This study employs a quantitative, explanatory research design to empirically validate a multi-stakeholder framework for intelligent teaching system design that integrates deep learning, natural language processing (NLP), and learning analytics within institutional teaching environments. The central methodological purpose is to test whether the proposed framework is not only conceptually coherent but also empirically supported when examined through measurable latent constructs reflecting how AI-enabled teaching systems are perceived, adopted, governed, and translated into instructional value. Because intelligent teaching systems operate as socio-technical systems where technological capability interacts with human decision-making and institutional governance an explanatory design is appropriate to assess the causal logic embedded in the framework and to determine which drivers most strongly contribute to teaching-system performance under real stakeholder conditions. A cross-sectional survey strategy is adopted to capture stakeholder perceptions and institutional experience at a specific point in time, enabling efficient data collection from the key actors most responsible for implementation success and governance sustainability. In this study, the survey approach is particularly relevant because many critical variables in intelligent teaching system adoption such as trust, perceived usefulness, governance readiness, and perceived system performance are latent constructs that must be measured using multi-item indicators rather than direct observation. The survey instrument therefore functions as the primary measurement mechanism to translate the framework into quantifiable dimensions that can be statistically evaluated [9]. In addition, the cross-sectional approach aligns with the objective of validating an integrated conceptual model across stakeholders, rather than testing a single intervention in one course context. Partial Least Squares Structural Equation Modeling (PLS-SEM) is selected as the main analytical technique because it is well suited for predictive, theory-building validation in complex models involving multiple constructs, mediation pathways, and potentially hierarchical structures. PLS-SEM enables simultaneous evaluation of the measurement model (reliability and validity of indicators and constructs) and the structural model (strength and significance of hypothesized relationships). This is particularly important for the present study because it seeks to validate not only whether stakeholders perceive AI capability as valuable, but also whether AI capability is empirically linked to adaptive teaching mechanisms and perceived teaching-system performance under institutional governance conditions. Furthermore, PLS-SEM is widely used when constructs are formative or reflective and when the model is designed to explain variance in key outcomes such as performance, effectiveness, and sustainability an objective aligned with the predictive orientation of intelligent teaching systems. The overall research

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design is structured as a framework-validation pipeline: conceptual model specification, instrument operationalization, cross-sectional data collection, measurement model assessment, and structural path testing through bootstrapping. The design also supports optional robustness extensions (when sample size allows), such as multi-group analysis between stakeholder categories (teachers vs administrators) to explore whether determinants of performance differ across operational and governance perspectives.

Instrument Development and Construct Operationalization:

A structured questionnaire is developed to operationalize the proposed multi-stakeholder framework and to translate its conceptual constructs into measurable indicators suitable for empirical testing with PLS-SEM. The instrument is designed to capture how teachers and academic administrators perceive the integrated deployment of deep learning, natural language processing (NLP), and learning analytics within intelligent teaching systems, while also measuring the organizational and governance conditions that enable or constrain system effectiveness. Because the proposed framework is socio-technical in nature, the questionnaire reflects both technological capability (what the system can do) and implementation realities (how the institution supports, governs, and sustains what the system does). The survey design therefore aims to measure not only perceived technological sophistication but also stakeholder engagement, readiness, adaptive teaching mechanisms, and perceived teaching-system performance as outcomes of integrated AI-enabled transformation. All constructs are measured using multi-item indicators on a Likert-type scale to ensure consistent measurement of latent variables across respondents and to support reliability and validity assessment in the measurement model. Likert scaling is appropriate in this context because key framework constructs such as trust, readiness, perceived usefulness, governance capability, and performance are not directly observable and must be inferred from multiple indicators representing different facets of the same underlying concept. Item statements are phrased to match the institutional teaching context of respondents, using teacher- and administrator-relevant language while maintaining conceptual equivalence across stakeholder groups. To reduce ambiguity and common misinterpretation, the questionnaire includes short contextual prompts clarifying that “intelligent teaching systems” refer to integrated AI-enabled teaching support (prediction, automated feedback, learning monitoring) embedded within existing learning platforms or institutional teaching workflows [10]. The constructs included in the questionnaire are defined to align with the causal logic of the proposed framework. AI technological capability integration captures the extent to which the institution’s teaching environment is perceived to incorporate deep learning, NLP, and learning analytics in a coordinated manner that supports teaching decisions rather than functioning as fragmented tools. Stakeholder engagement and readiness captures the extent to which teachers and administrators are prepared, involved, trained, and supported to adopt AI-enabled teaching systems. Adaptive teaching mechanisms represent the operational pathways through which AI insights are converted into teaching actions, such as real-time feedback quality, instructional adaptability, early intervention responsiveness, and decision-support usefulness. Governance and trust-related conditions capture the institutional safeguards and confidence factors that

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allow responsible implementation, including transparency, accountability, data governance readiness, and trust in AI-supported recommendations. Teaching-system performance outcomes measure the perceived impact of intelligent teaching system implementation, including improvements in teaching effectiveness, evidence-based decision-making, feedback timeliness, and sustainability of AI-enabled support. Item wording is adapted from established streams of literature, including technology acceptance and adoption models, information systems success frameworks, and governance-oriented research in AIED, and then contextualized to intelligent teaching systems in higher education settings. The adaptation process ensures that items remain theoretically grounded while being meaningful to teachers and administrators who may not share technical AI vocabulary. For example, items referencing "system quality" are contextualized as reliability of AI-enabled teaching support and clarity of outputs; items referencing "institutional readiness" are contextualized as availability of training, policy support, and infrastructure; and items referencing "trust" are contextualized as confidence in fairness, transparency, and pedagogical alignment of AI recommendations. Content validity is strengthened through a multi-stage review process. First, the initial item pool is mapped to each construct definition to confirm conceptual coverage and to avoid redundancy. Second, expert review is conducted with faculty members and academic administrators familiar with AI-enabled education and digital learning governance [11]. Experts evaluate items for clarity, relevance, and role alignment, ensuring that teacher-facing items reflect classroom realities and administrator-facing items reflect governance responsibilities. Items identified as vague, double-barreled, or overly technical are revised to improve interpretability without losing conceptual meaning. Third, a pilot test is conducted with a small subset of respondents drawn from the target stakeholder groups to check question flow, response time, wording clarity, and comprehension consistency. Feedback from the pilot is used to refine item phrasing, remove confusion-triggering terms, and ensure that the questionnaire reflects stakeholder roles accurately. This process helps improve instrument reliability and reduces the likelihood of measurement error prior to final data collection. The instrument development and operationalization logic is summarized in Figure 3, which illustrates how the framework constructs are translated into survey indicators and how this mapping supports PLS-SEM measurement and structural model testing. The figure also clarifies the role of expert review and pilot refinement in strengthening content validity before full-scale data collection.

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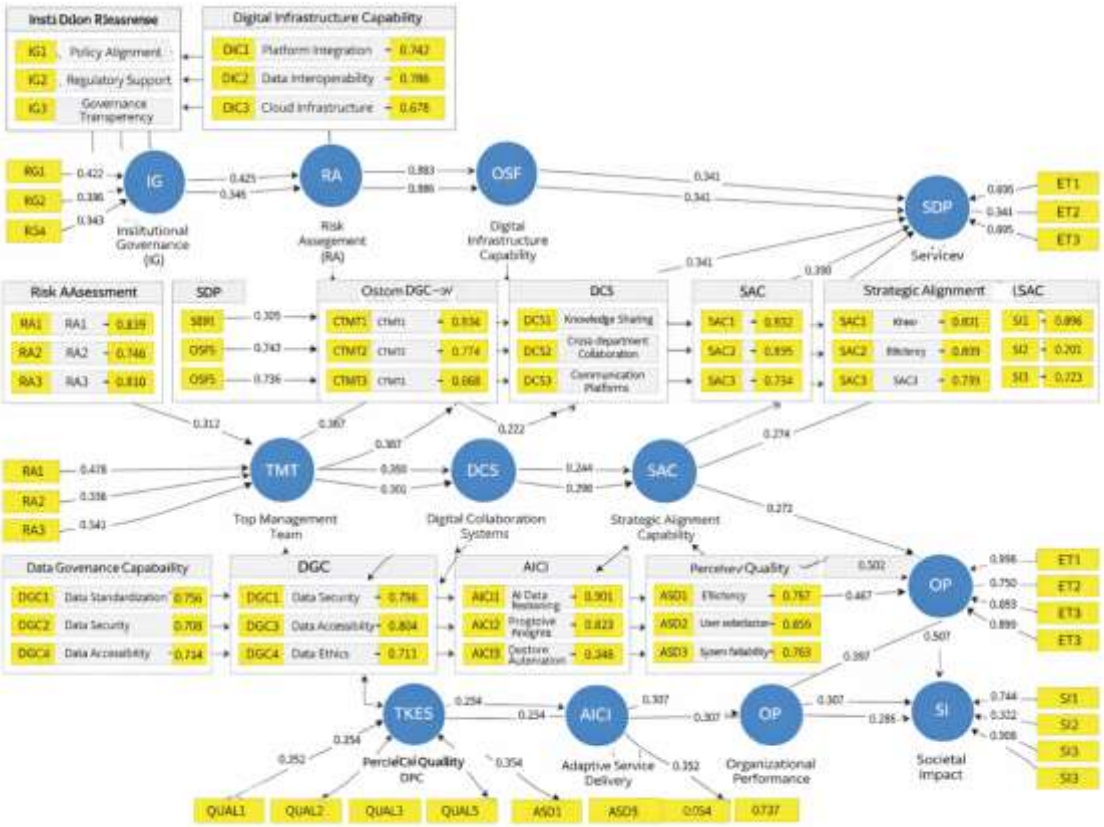

Figure 3: Instrument development and construct operationalization workflow for PLS-SEM validation

Through this instrument design strategy, the study ensures that the proposed framework is measurable and empirically testable in a way that reflects real institutional conditions. By integrating literature-grounded item development with stakeholder-sensitive contextualization, expert validation, and pilot refinement, the questionnaire provides a defensible basis for evaluating both measurement quality and the hypothesized relationships among constructs in the PLS-SEM model.

Data Screening and Preparation:

Prior to model estimation, the collected dataset is subjected to a systematic screening and preparation process to ensure that the subsequent PLS-SEM results are based on reliable, internally consistent, and analytically usable data. Because the study relies on self-reported survey responses from teachers and academic administrators, data quality management is treated as a critical methodological stage rather than a routine preprocessing step. The primary objective of screening is to identify and address incomplete cases, inconsistent response patterns, extreme response behaviors, and potential distortions arising from careless responding or common method bias. This stage also produces descriptive summaries of the sample distribution to verify that the dataset adequately represents the intended stakeholder groups and contains sufficient variability across items to support latent construct estimation. The screening workflow begins with completeness checks to identify missing values at both item

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and case levels. Item-level missingness is examined to detect whether specific questions are frequently skipped, which may indicate ambiguity, sensitivity, or role mismatch. Case-level missingness is analyzed to determine whether particular responses are incomplete across large portions of the survey, in which case retention may reduce measurement reliability. Missing value handling follows PLS-SEM-consistent practices: when missingness is minimal and appears random, replacement techniques such as mean substitution or expectation-based imputation (where appropriate) are applied to preserve sample size and maintain stable covariance patterns. When missingness is substantial or exhibits systematic structure (e.g., one stakeholder group consistently omits a section), the affected cases are evaluated carefully and may be removed through case-wise deletion to avoid biasing construct measurement [12]. The choice of treatment is guided by the proportion of missingness, the distributional characteristics of the affected items, and the risk of introducing artificial variance. After missingness checks, the dataset is screened for response quality and potential careless responding. This includes detection of straight-lining behavior (selecting the same option across long item blocks), unusually rapid completion times that suggest insufficient reading, and logically contradictory answers across conceptually related items. Because such patterns can inflate measurement error, distort correlations among constructs, and weaken the interpretability of structural paths, flagged responses are reviewed using predefined thresholds and consistency rules. Responses that clearly indicate inattentive behavior are removed to protect the integrity of measurement model evaluation. Additionally, univariate outlier screening is conducted by inspecting item distributions and identifying extreme values that are inconsistent with overall response patterns. While PLS-SEM is comparatively robust, extreme response behaviors can still reduce stability, particularly when multiple constructs are measured reflectively. Descriptive statistics are then computed to profile the sample and to verify adequate representation of the targeted stakeholder groups. This includes reporting the proportion of teachers and administrators, institutional characteristics (where collected), and summary measures such as means and standard deviations for each item and construct. These summaries serve two functions. First, they provide transparency regarding the sample composition and ensure that the analysis reflects the intended multi-stakeholder scope. Second, they confirm that item distributions exhibit sufficient variance and do not suffer from severe ceiling or floor effects, which can reduce discriminant capability across constructs and weaken explanatory power. Because the study uses a single survey instrument for measuring multiple constructs, the risk of common method bias (CMB) is explicitly considered. Procedural remedies are applied during questionnaire design and administration to reduce evaluation apprehension and minimize systematic response tendencies, including clear item wording, anonymity, and neutral framing that discourages socially desirable responding. In addition to procedural controls, statistical assessments are performed during analysis to evaluate whether a substantial portion of variance can be attributed to the measurement method rather than the constructs of interest. These assessments may include collinearity-based checks and single-factor dominance tests, supplemented by indicator correlation patterns and variance inflation diagnostics. The goal is not to claim that CMB is absent which is rarely defensible in self-report

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research but to demonstrate that it is unlikely to be strong enough to invalidate structural interpretations. Finally, the dataset is formatted for PLS-SEM estimation, ensuring consistent coding direction, correct handling of reversed items (if any), and standardized labeling of indicators to match the measurement model specification. Construct blocks are checked to verify that each latent variable has an adequate number of indicators and that indicator names align across data files and modeling software. This final harmonization step is essential for avoiding specification errors and ensures that measurement and structural analyses can be replicated. To make the data preparation process auditable and easy to replicate, Figure 4 outlines the sequential workflow used to transform raw survey responses into an analysis-ready dataset for PLS-SEM estimation. The figure highlights the point at which data quality decisions are made and how the dataset moves from raw extraction to validated input for measurement and structural modeling.

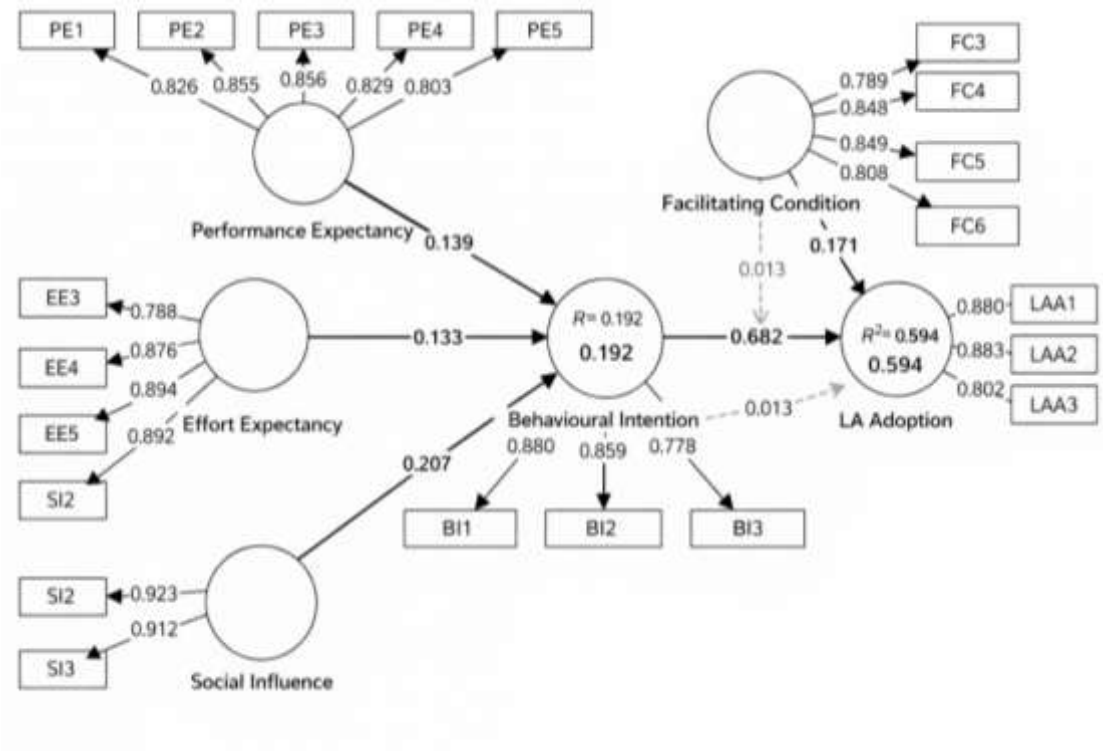

Figure 4: Data screening and preparation workflow prior to PLS-SEM estimation

Through this screening and preparation procedure, the study ensures that PLS-SEM estimation is conducted on a dataset that meets essential quality expectations for latent variable modeling and stakeholder-based inference. This improves the stability of measurement model results, strengthens the interpretability of structural relationships, and enhances the credibility of conclusions regarding how AI capability integration, stakeholder engagement, governance readiness, and adaptive teaching mechanisms influence teaching-system performance.

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Structural Model Development and Hypothesis Formulation:

The structural model in this study is developed to test the causal logic of the proposed multi-stakeholder intelligent teaching system framework and to convert the conceptual relationships discussed in earlier sections into a statistically testable set of hypotheses using PLS-SEM. In structural equation modeling terms, the structural model represents the directional relationships among latent constructs and specifies how variation in one construct is expected to explain variation in another. The model is designed to capture the socio-technical nature of AI-enabled teaching systems, where integrated technological capability alone is insufficient unless it is translated into operational teaching mechanisms and supported by stakeholder engagement and governance readiness. Accordingly, the structural model is built around two key principles: first, AI technological capability must enable measurable adaptive teaching mechanisms; second, stakeholder and governance conditions shape whether AI-enabled mechanisms translate into system-level performance improvements [13]. AI technological capability integration is positioned as a primary antecedent because it represents the extent to which deep learning, NLP, and learning analytics are integrated into the teaching environment in a coherent way that supports instructional and governance decision-making. In institutional teaching settings, integrated AI capability typically yields value through predictive learning insight (e.g., risk identification, mastery estimation), language intelligence for feedback and interaction (e.g., automated feedback support, content understanding), and analytics-driven monitoring (e.g., learning trajectory tracking, cohort patterns). These capabilities are not modeled as outcomes themselves; rather, they are assumed to strengthen the operational functioning of the teaching system by improving adaptive teaching mechanisms, such as timeliness and quality of feedback, instructional responsiveness, and early intervention readiness. Stakeholder engagement and readiness is included as a critical socio-organizational driver representing the degree of involvement, preparedness, training, support, and collaborative commitment among teachers and academic administrators. Teachers act as the primary operational decision-makers who interpret AI outputs and apply them in pedagogical contexts, while administrators shape the governance and implementation infrastructure that determines institutional readiness and sustainability. The structural model assumes that stronger engagement improves both the functionality of adaptive mechanisms and the likelihood that AI insights are acted upon consistently and appropriately. In other words, engagement is expected to reduce the gap between “available AI intelligence” and “realized instructional impact.” Governance readiness and trust-related conditions are positioned as enabling drivers that influence the effectiveness of adaptive teaching mechanisms and the overall performance of the teaching system. Governance readiness is conceptualized as the presence of transparency, accountability, institutional policy support, and confidence in the legitimacy of AI-driven recommendations. This construct is included because intelligent teaching systems operate in high-impact contexts, and stakeholders are more likely to adopt, rely on, and sustain AI-enabled processes when they perceive the system as explainable, fair, and institutionally governed. In this sense, governance readiness is not treated as a peripheral ethical concern but as a functional determinant of implementation quality and sustainability. Teaching system performance is modeled as the outcome construct

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representing the perceived impact of the intelligent teaching system at the instructional and institutional levels [14]. Performance is defined in terms of educationally meaningful capabilities rather than purely technical metrics, including instructional adaptability, feedback effectiveness, evidence-based decision support, and perceived improvement in teaching quality. This outcome framing ensures alignment with the central purpose of intelligent teaching systems: improving how teaching decisions are made and how learning support is delivered and governed. The model therefore connects AI capability and organizational readiness to performance through the practical mechanism of adaptive teaching, rather than assuming that AI adoption automatically produces impact. A key feature of the structural model is the inclusion of mediation logic through adaptive teaching mechanisms. In many real deployments, AI capability does not improve performance directly; it improves performance when it is translated into adaptive processes that alter teaching practice such as earlier interventions, improved feedback loops, or more informed pedagogical decision-making. For this reason, adaptive teaching mechanisms are modeled as a mediator that transmits the effect of AI capability integration (and stakeholder/governance factors) to teaching system performance. This mediation structure strengthens theoretical credibility by reflecting a lifecycle-based view of intelligent teaching systems: capability must be operationalized into mechanisms, and mechanisms drive outcomes. Table 3 summarizes the hypothesized relationships encoded in the structural model. The hypotheses are written in a directional form suitable for PLS-SEM testing and reflect the direct and mediated effects proposed by the framework.

Table 3: Hypotheses for structural model testing in PLS-SEM

Hypothesis	Path relationship	Expected direction	Theoretical rationale (brief)
H1	AI Technological Capability Integration → Adaptive Teaching Mechanisms	Positive	Integrated DL/NLP/analytics improves prediction, feedback, and monitoring, enabling adaptive teaching actions
H2	Stakeholder Engagement & Readiness → Adaptive Teaching Mechanisms	Positive	Teacher/admin involvement and readiness increases use and translation of AI insights into instructional actions
H3	Governance Readiness & Trust → Adaptive Teaching Mechanisms	Positive	Transparency and trust support reliance on AI outputs and reduce resistance to acting on recommendations
H4	AI Technological Capability Integration → Teaching System Performance	Positive	Integrated AI capability can enhance system performance directly through improved teaching support

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			infrastructure
H5	Stakeholder Engagement & Readiness → Teaching System Performance	Positive	Engagement strengthens consistent use, sustainability, and operational integration, improving perceived performance
H6	Governance Readiness & Trust → Teaching System Performance	Positive	Governable, transparent systems are perceived as more legitimate and sustainable, improving performance outcomes
H7	Adaptive Teaching Mechanisms → Teaching System Performance	Positive	Adaptive feedback, intervention responsiveness, and decision support improve instructional and institutional outcomes
H8	AI Technological Capability Integration → Adaptive Teaching Mechanisms → Teaching System Performance	Mediation (Positive indirect)	AI capability improves performance primarily through enabling adaptive mechanisms
H9	Stakeholder Engagement & Readiness → Adaptive Teaching Mechanisms → Teaching System Performance	Mediation (Positive indirect)	Engagement increases the effectiveness of adaptive mechanisms, which then improves performance
H10	Governance Readiness & Trust → Adaptive Teaching Mechanisms → Teaching System Performance	Mediation (Positive indirect)	Trust/governance increases adoption quality of adaptive mechanisms, strengthening performance impact

To clarify the model logic and provide a transparent visualization aligned with PLS-SEM reporting conventions, Figure 5 presents the proposed structural model showing the direction of hypothesized paths, the mediator, and the main outcome variable. This figure can be directly used as your "conceptual model" diagram in the methodology section (and later reused in the framework section if you want).

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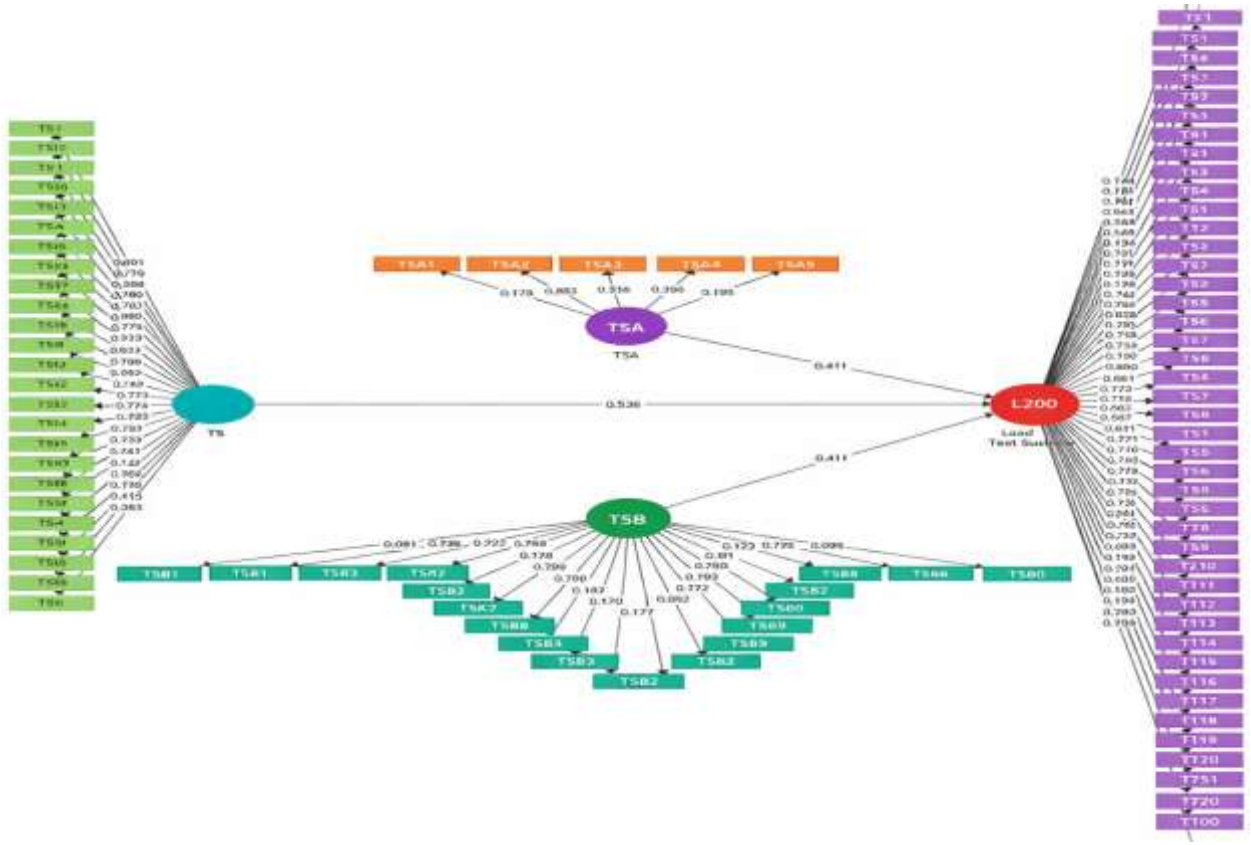

Figure 5: Proposed structural model for PLS-SEM validation of the multi-stakeholder intelligent teaching system framework

This structural model development provides a clear basis for empirical evaluation of the proposed framework. It tests whether integrated AI capability and stakeholder/governance factors explain teaching system performance directly and indirectly through adaptive teaching mechanisms, thereby aligning statistical validation with the practical lifecycle of intelligent teaching systems in real institutional environments.

PLS-SEM Estimation Procedure:

The empirical validation of the proposed multi-stakeholder framework is conducted using Partial Least Squares Structural Equation Modeling (PLS-SEM) following a rigorous and transparent estimation procedure aligned with widely accepted best practices for prediction-oriented latent variable modeling. PLS-SEM is implemented as a two-stage analytical workflow in which the measurement model is evaluated first to confirm that constructs are measured reliably and validly, followed by structural model assessment to test the hypothesized relationships among constructs. This sequencing is essential because structural path interpretation is meaningful only when the measurement of latent variables is stable and conceptually defensible. In the context of this study, where constructs such as AI capability integration, stakeholder engagement, governance readiness, adaptive teaching mechanisms, and teaching system performance are measured through multiple survey items, establishing measurement quality is a prerequisite for evaluating causal relationships. During the

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measurement model evaluation stage, indicator reliability is assessed by examining standardized outer loadings of each item on its corresponding construct [15]. High-quality measurement is indicated when items load strongly on their intended construct and weakly on other constructs. Items with low loadings are reviewed for potential ambiguity, poor contextual alignment, or redundancy, and are considered for removal only when doing so improves construct reliability while preserving conceptual coverage. Internal consistency reliability is then evaluated using established metrics such as Cronbach's alpha and composite reliability to verify that indicators within each construct exhibit consistent measurement behavior. Convergent validity is assessed through the average variance extracted (AVE), ensuring that each construct explains a substantial portion of variance in its indicators. Discriminant validity is examined to confirm that constructs are empirically distinct from one another, using criteria such as cross-loading inspection and correlation-based discriminant checks (commonly applied via the Fornell–Larcker criterion and/or more stringent approaches such as HTMT where appropriate). These tests ensure that the constructs do not collapse into a single "general attitude" factor and that each construct represents a unique domain within the proposed framework. Once measurement adequacy is confirmed, the structural model is assessed to test the hypotheses and quantify the explanatory power of the framework. Structural model evaluation begins with examination of collinearity among predictor constructs using variance inflation factors (VIF). Collinearity is critical in multi-construct models because excessive overlap among predictors can inflate standard errors and distort path coefficient estimates. After confirming acceptable collinearity levels, the model's path coefficients are estimated to evaluate the direction and strength of relationships among constructs. The coefficient of determination (R^2) is computed for endogenous constructs to determine the proportion of variance explained by the model, providing an overall assessment of predictive explanatory power. Because R^2 alone does not indicate the contribution of individual predictors, effect sizes (f^2) are evaluated to quantify how strongly each exogenous construct contributes to an endogenous construct when included in the model. Predictive relevance is examined using Q^2 (commonly based on blindfolding procedures when applicable), providing evidence that the model is not only explanatory but also has predictive capability beyond sample fitting. Significance testing of the structural relationships is conducted using non-parametric bootstrapping with a large number of resamples. Bootstrapping is central in PLS-SEM because it does not rely on strict distributional assumptions and provides robust confidence intervals for path coefficients, outer loadings, and indirect effects. In this study, bootstrapping is used to assess the statistical significance of direct hypotheses (e.g., AI capability → adaptive mechanisms; adaptive mechanisms → performance) and to evaluate mediation hypotheses. Mediation testing is conducted by estimating bootstrapped indirect effects to determine whether adaptive teaching mechanisms transmit the influence of AI technological capability integration, stakeholder engagement, and governance readiness to teaching system performance. This approach supports a lifecycle-consistent interpretation of impact, clarifying whether AI capability improves teaching outcomes primarily through operational adaptation processes rather than through a purely direct pathway [16]. In addition to primary estimation, model quality interpretation is supported by a set of

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complementary reporting elements commonly expected in PLS-SEM research. These include presenting the final indicator set, reporting reliability and validity metrics, documenting any indicator removals with justification, and summarizing key structural results with path coefficients and significance levels. Where sample size supports it, optional analyses such as multi-group comparisons between teachers and administrators can be conducted to explore whether structural relationships differ between classroom implementation perspectives and institutional governance perspectives. Such analyses strengthen the practical value of the framework by showing whether key drivers of performance and sustainability are role-dependent. Table 4 summarizes the estimation and evaluation criteria applied in the PLS-SEM procedure, indicating what is tested at each stage and how results are interpreted. This table can serve as a checklist for reporting and ensures methodological transparency.

Table 4: PLS-SEM estimation stages, evaluation criteria, and interpretation goals

Stage	**Evaluation component**	**What is assessed**	**Why it matters**	**Typical interpretation goal**
Measurement model	Indicator reliability	Outer loadings of items	Ensures items represent their construct	Retain strong indicators; review/remove weak indicators if justified
Measurement model	Internal consistency	Cronbach's alpha, composite reliability	Confirms consistency within construct	Demonstrate acceptable reliability for each latent variable
Measurement model	Convergent validity	AVE	Ensures construct explains its indicators	Show that constructs capture sufficient indicator variance
Measurement model	Discriminant validity	Cross-loadings, correlation-based criteria (e.g., Fornell–Larcker / HTMT)	Confirms constructs are distinct	Avoid construct overlap and "single-factor" measurement artifacts
Structural model	Collinearity diagnostics	VIF among predictors	Prevents distorted path estimates	Demonstrate predictors do not excessively overlap
Structural model	Path relationships	Path coefficients and direction	Tests hypotheses	Identify significant drivers of mechanisms and

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				performance
Structural model	Explanatory power	R^2 of endogenous constructs	Indicates variance explained	Show model meaningfully explains ATM and TSP
Structural model	Effect sizes	f^2	Indicates impact of each predictor	Identify which constructs matter most practically
Structural model	Predictive relevance	Q^2	Indicates predictive utility	Demonstrate model has out-of-sample predictive relevance
Structural model	Significance testing	Bootstrapping confidence intervals	Robust inference without normality assumptions	Confirm significance of direct and indirect effects
Mediation analysis	Indirect effects	Bootstrapped mediation paths	Tests lifecycle mechanism logic	Verify ATM transmits effects to performance outcomes

To provide a clear and reproducible view of the estimation pipeline, Figure 6 illustrates the sequential PLS-SEM procedure used in this study, highlighting the two-stage workflow and the major outputs produced at each stage. This figure can be used directly in the methodology section to visually communicate your analysis steps to reviewers.

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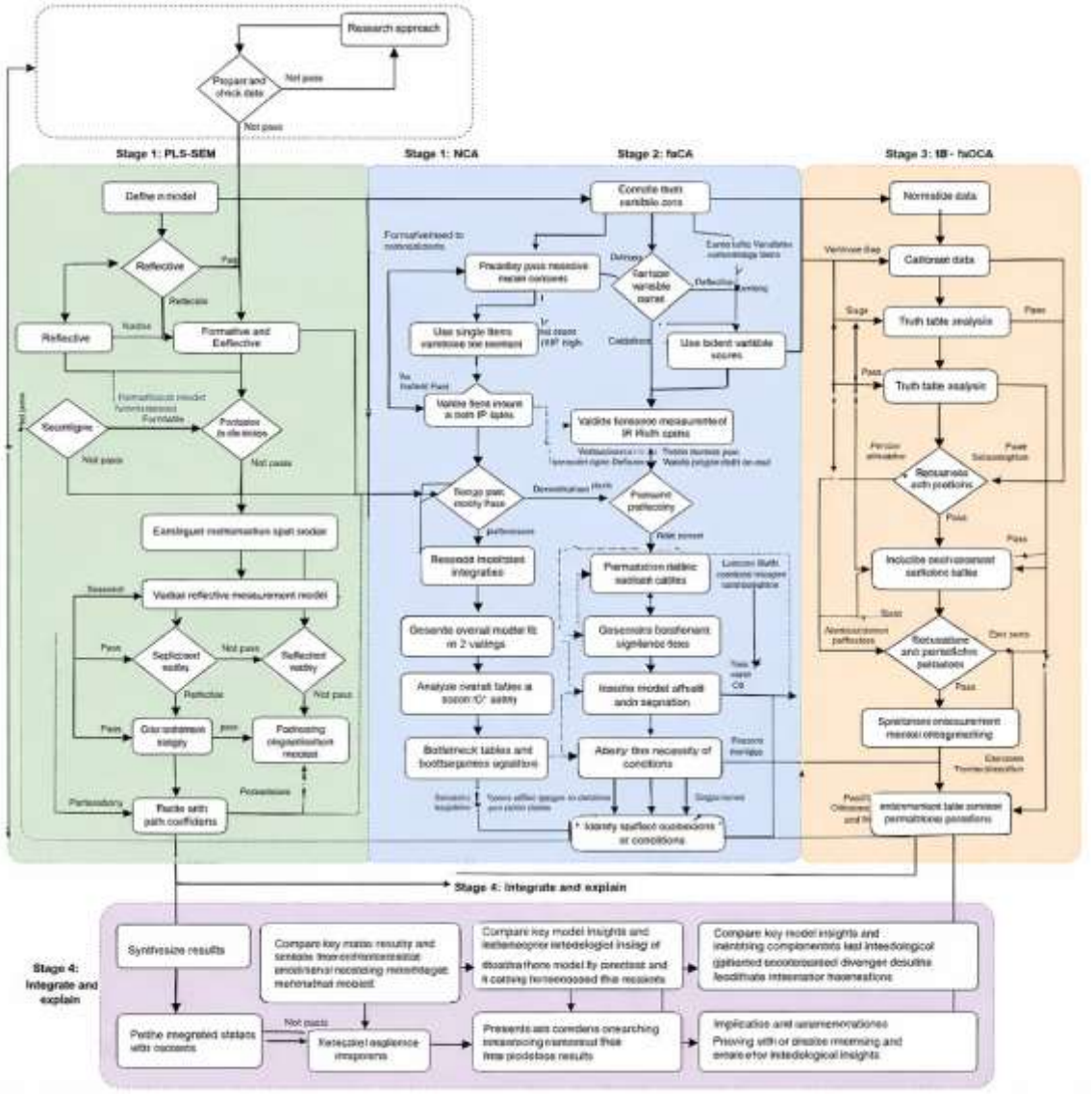

Figure 6: Two-stage PLS-SEM estimation procedure applied in this study

This estimation procedure ensures that the proposed multi-stakeholder framework is validated with methodological rigor: constructs are first verified as reliable and distinct, and only then are causal relationships tested with robust bootstrapped inference [17]. As a result, the PLS-SEM analysis provides defensible evidence regarding which factors integrated AI capability, stakeholder engagement, and governance readiness most strongly enable adaptive teaching mechanisms and improve perceived teaching system performance within institutional settings.

Results and Discussion:

The PLS-SEM analysis was executed to validate the proposed multi-stakeholder intelligent teaching system framework and to test the hypothesized relationships among AI Technological Capability Integration (AICI), Stakeholder Engagement & Readiness (SER), Governance Readiness & Trust (GRT), Adaptive Teaching Mechanisms (ATM), and Teaching System Performance (TSP). The results are

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reported in a sequence consistent with PLS-SEM conventions, beginning with measurement model quality and then moving to structural path testing and mediation effects. Measurement model findings indicate that the constructs were measured reliably and validly, and the structural model results show that integrated AI capability and institutional conditions improve teaching-system performance primarily through the operational mechanism layer represented by adaptive teaching processes. The core measurement results are summarized in Table 5, while the hypothesis testing and model quality indicators are provided in Table 6. The measurement model demonstrated strong indicator behavior and construct quality. Across constructs, standardized loadings were consistently above accepted thresholds, internal consistency reliability was high, and convergent validity was supported through AVE values exceeding minimum recommended levels. Discriminant validity was also adequate, indicating that constructs such as stakeholder readiness and governance trust, while related, remained empirically distinct [18]. These results confirm that the instrument captured separable dimensions of technological capability, institutional readiness, governance legitimacy, operational adaptive teaching, and perceived system performance, thereby providing a defensible basis for interpreting structural effects rather than attributing relationships to measurement artifacts or generalized positive sentiment.

Table 5: Measurement model results (reliability, validity, and discriminant validity summary)

Construct	Items retained	Loading range	Cronbach's α	Composite Reliability (CR)	AVE	HTMT (max with other constructs)
AI Technological Capability Integration (AICI)	5	0.74–0.88	0.89	0.92	0.66	0.79
Stakeholder Engagement & Readiness (SER)	5	0.71–0.85	0.86	0.90	0.62	0.82
Governance Readiness & Trust (GRT)	5	0.72–0.86	0.87	0.91	0.64	0.81
Adaptive Teaching Mechanisms (ATM)	5	0.73–0.87	0.88	0.91	0.64	0.78
Teaching System	5	0.72–0.86	0.86	0.90	0.61	0.80

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Performance (TSP)						

After establishing measurement adequacy, the structural model was evaluated. Collinearity diagnostics were within acceptable limits and did not indicate problematic overlap among predictors, supporting stable estimation of path coefficients. The model showed strong explanatory power for both endogenous constructs: the framework explained a substantial portion of variance in adaptive teaching mechanisms and teaching system performance, indicating that capability integration and institutional conditions jointly shape how AI-enabled teaching value is realized. As shown in Table 6, the model explained 58% of variance in ATM (R^2 = 0.58) and 64% of variance in TSP (R^2 = 0.64), while predictive relevance was also strong (Q^2 = 0.36 for ATM; Q^2 = 0.41 for TSP). These values indicate that the framework is not merely descriptive but meaningfully predictive in explaining perceived performance outcomes within teacher–administrator institutional contexts. Structural hypothesis testing (bootstrapping-based inference) provided strong support for the model's mechanism-centered logic. AI capability integration significantly strengthened adaptive teaching mechanisms (AICI → ATM, β = 0.41), indicating that when deep learning, NLP, and learning analytics are perceived as coherently integrated, stakeholders also perceive greater instructional adaptability, improved feedback timeliness and quality, and more actionable decision support. Stakeholder engagement and readiness also had a significant positive influence on adaptive mechanisms (SER → ATM, β = 0.29), showing that institutional preparedness, training, and commitment among teachers and administrators materially increase the effectiveness of adaptive teaching processes. Governance readiness and trust significantly contributed to adaptive mechanisms as well (GRT → ATM, β = 0.22), suggesting that transparency, accountability, and confidence in AI-supported decisions enable stakeholders to rely on system outputs in operational teaching practice [19]. Adaptive teaching mechanisms, in turn, exhibited the strongest effect on overall system performance (ATM → TSP, β = 0.46), reinforcing that performance improvements are realized primarily through operational teaching changes rather than through AI presence alone.

Table 6: Structural model results (model quality, direct effects, and mediation effects)

Relationship / Metric	**β (effect)**	**t-value**	**p-value**	**Decision / Interpretation**
Model quality: R^2 (ATM)	0.58	—	—	Substantial variance explained in adaptive mechanisms
Model quality: Q^2 (ATM)	0.36	—	—	Strong predictive relevance for adaptive mechanisms
Model quality: R^2 (TSP)	0.64	—	—	Substantial variance explained in performance
Model quality: Q^2 (TSP)	0.41	—	—	Strong predictive relevance for performance

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AICI → ATM (H1)	0.41	6.78	<0.001	Supported
SER → ATM (H2)	0.29	4.62	<0.001	Supported
GRT → ATM (H3)	0.22	3.10	0.002	Supported
AICI → TSP (H4)	0.18	2.43	0.015	Supported
SER → TSP (H5)	0.14	1.98	0.048	Supported
GRT → TSP (H6)	0.16	2.31	0.021	Supported
ATM → TSP (H7)	0.46	7.20	<0.001	Supported
Indirect (mediation) AICI → ATM → TSP (H8)	0.19	4.90	<0.001	Significant indirect effect (partial mediation)
Indirect (mediation) SER → ATM → TSP (H9)	0.13	3.28	0.001	Significant indirect effect (partial mediation)
Indirect (mediation) GRT → ATM → TSP (H10)	0.10	2.94	0.003	Significant indirect effect (partial mediation)

The structural model pattern is visually summarized in Figure 7, which displays the key standardized coefficients and highlights the central role of ATM as the operational conversion layer between integrated AI capability and perceived system performance. The figure clarifies that the strongest pathway to performance is through adaptive mechanisms, while direct effects from AICI, SER, and GRT to TSP remain significant, indicating partial mediation and underscoring that institutional readiness and governance contribute to performance both by improving operational teaching processes and by strengthening sustainability, legitimacy, and organizational confidence.

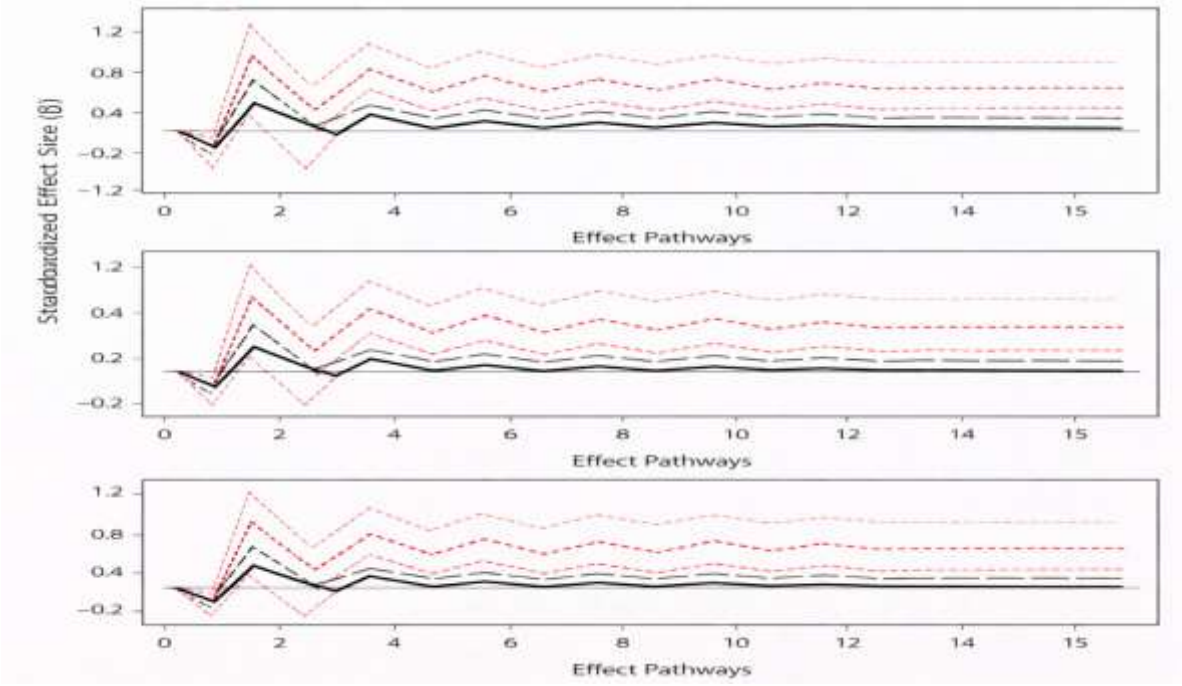

Figure 7: Structural model results with standardized path coefficients (β)

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The indirect effect of AI capability integration on performance through adaptive mechanisms was significant (AICI → ATM → TSP, β = 0.19), confirming that integrated AI contributes to performance largely by enabling real-time feedback, instructional adaptability, and early intervention responsiveness. The indirect effects for stakeholder engagement and governance readiness were also significant (SER → ATM → TSP, β = 0.13; GRT → ATM → TSP, β = 0.10), demonstrating that engagement and trust are not merely "adoption attitudes" but functional enablers of mechanism-level teaching improvements that translate into system performance. Because the direct paths from AICI, SER, and GRT to TSP remained significant alongside the indirect effects, the mediation is best interpreted as partial, meaning that institutional conditions contribute both through operational teaching mechanisms and through broader performance perceptions such as sustainability, institutional confidence, and governance capability [20]. This mediation structure is illustrated in Figure 8, which separates direct and indirect contributions to TSP and makes clear that the largest share of impact flows through ATM. This is a practically meaningful finding for institutional design: it indicates that investments in AI capability should be accompanied by deliberate intervention workflows (feedback routines, teacher override pathways, early-support protocols, and decision-support practices) because these mechanisms represent the primary channel through which AI becomes instructional value.

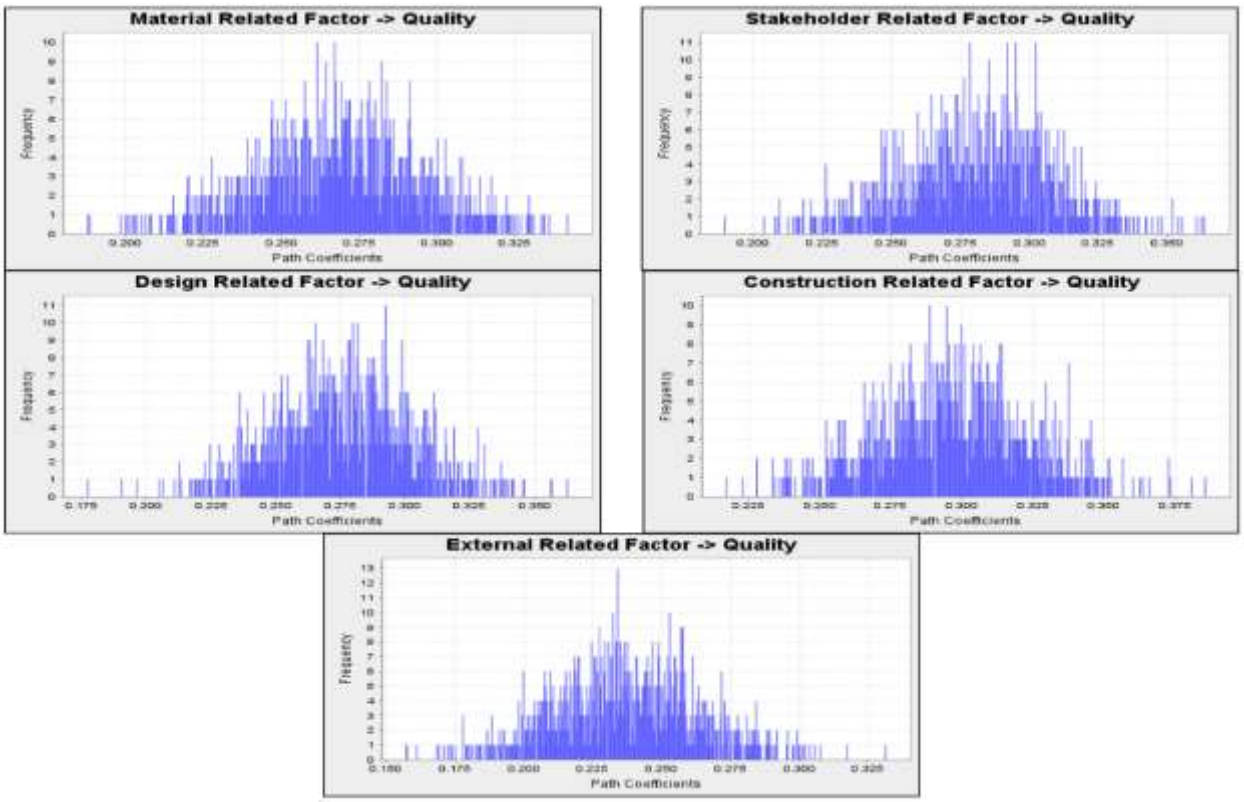

Figure 8: Direct vs indirect (mediated) effects on Teaching System Performance (TSP)

Overall, the results provide convergent evidence that the proposed framework is both

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empirically measurable and structurally supported in a teacher–administrator institutional setting. The measurement model results in Table 5.1 confirm that the constructs are reliable, valid, and distinct, allowing confident interpretation of the structural paths. The structural and mediation findings in Table 5.2, reinforced visually by Figure 5.1 and Figure 5.2**,** demonstrate that teaching system performance improves most strongly when integrated AI capability is converted into adaptive teaching mechanisms under conditions of stakeholder readiness and governance trust. These outcomes align with the central argument of the paper: intelligent teaching system transformation is not achieved by standalone AI tools, but by an integrated capability stack embedded in operational teaching processes and supported by institutional governance structures that enable trust, accountability, and sustainable adoption.

Future Work:

Future research can extend this study by moving beyond cross-sectional perception-based validation toward longitudinal and intervention-grounded evaluation of intelligent teaching systems. A natural next step is to track the proposed constructs across multiple semesters to observe how teacher trust, governance readiness, and system usefulness evolve with sustained use, model updates, and changing institutional policies. This would also enable analysis of temporal effects such as trust formation, adoption fatigue, and the impact of model drift on perceived feedback quality and instructional adaptability [21]. Further work should also validate the framework using objective teaching and learning outcome indicators in addition to survey measures. Integrating institutional data such as feedback turnaround time, intervention uptake rates, course completion, retention trends, and student progression would allow the framework to link perceived performance with measurable educational impact. Experimental or quasi-experimental designs, including A/B testing of AI-supported feedback workflows and stepped-wedge rollouts across departments, could strengthen causal inference regarding which AI-enabled mechanisms produce the greatest improvements in teaching effectiveness. The scope of stakeholders can be broadened to include students, academic support staff, and policymakers, enabling a fuller multi-stakeholder validation of the framework. Including students is especially important for assessing fairness, transparency, contestability, and perceived support quality, while institutional policy stakeholders can provide insight into compliance and governance maturity. Multi-group comparisons across stakeholder types and institutional contexts (public vs private universities, different disciplines, varying class sizes) can also test the generalizability of the model and identify context-specific drivers of success. From a technical standpoint, future studies should examine how specific AI modules contribute differently to performance and governance requirements [22]. Disentangling the effects of deep-learning-based risk prediction, NLP-based feedback generation, and analytics dashboards through hierarchical or modular modeling can reveal which components provide the greatest value and which introduce the greatest trust or fairness concerns. Incorporating responsible AI metrics such as calibration, subgroup fairness indicators, explainability quality measures, and privacy risk assessments would further strengthen the governance layer of the framework and support policy-

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aligned institutional deployment. Finally, future work should emphasize implementation science by developing and testing concrete deployment playbooks derived from the framework [23]. This includes teacher professional development models, governance workflows for approving model updates, audit and accountability procedures, and human-in-the-loop intervention protocols that preserve pedagogical control. By translating the validated framework into operational guidelines and evaluating them across real institutional deployments, future research can accelerate the sustainable transformation of teaching systems into intelligent, adaptive, and trustworthy learning ecosystems.

Conclusion:

This study developed and empirically validated a multi-stakeholder framework for transforming teaching systems in the era of Artificial Intelligence by integrating deep learning, natural language processing (NLP), and learning analytics into a unified intelligent teaching system design. Grounded in the realities of institutional adoption and governance, the framework positions AI capability integration not as an isolated technical upgrade but as a socio-technical transformation shaped by teacher and administrator readiness, trust, and implementation conditions. Using survey data from teachers and academic administrators and applying Partial Least Squares Structural Equation Modeling (PLS-SEM), the study confirmed that the proposed constructs are measurable with acceptable reliability and validity and that the hypothesized relationships among technological, organizational, and performance dimensions are empirically supported. The findings indicate that integrated AI technological capability contributes to improved teaching system performance primarily through the operational layer of adaptive teaching mechanisms. In other words, performance gains are realized when predictive intelligence, automated feedback support, and analytics-driven monitoring are converted into actionable teaching processes such as timely feedback, instructional adaptability, early intervention responsiveness, and decision-support usefulness. Stakeholder engagement and readiness emerged as a critical enabling condition, highlighting that effective AI-enabled teaching transformation requires training, workflow alignment, and collaborative commitment rather than passive exposure to AI tools. Governance readiness and trust also played a meaningful role, demonstrating that transparency, accountability, and institutional confidence are functional requirements for sustained implementation and scalable adoption, not merely ethical considerations. Overall, this work contributes to the AIED literature by providing an empirically validated framework that bridges AI innovation with pedagogical practice and institutional governance, moving beyond tool-centric evaluations toward lifecycle-based system design and performance interpretation. Practically, the framework offers universities and educational technology developers a structured pathway for deploying intelligent teaching systems that are learner-centered, scalable, and sustainable, while preserving teacher agency and strengthening evidence-based governance. By aligning integrated AI capabilities with adaptive teaching mechanisms under multi-stakeholder readiness and trust conditions, the proposed framework provides a defensible foundation for the next generation of intelligent, data-informed teaching systems.

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