THE IMPACT OF EDUCATIONAL INNOVATION IN AI-ENHANCED FEEDBACK SYSTEMS ON TEACHING EFFECTIVENESS: THE MEDIATING ROLE OF TEACHER DATA LITERACY AND THE MODERATING EFFECT OF INSTITUTIONAL AI READINESS

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Abstract: This study investigates the impact of AI-enhanced feedback systems on teaching effectiveness in China's educational settings, focusing on the mediating role of teacher data literacy and the moderating effect of institutional AI readiness.

A quantitative cross-sectional survey was conducted with 492 educators from mainland universities and K-12 schools, using validated scales measured on a 5-point Likert scale. Data were analyzed using SPSS, including descriptive statistics, reliability and validity tests (Cronbach's Alpha, EFA, CFA, Fornell-Larcker, HTMT), correlation, regression, mediation (Baron & Kenny, bootstrapping), and moderation (Hayes' PROCESS model). Results show that AI-enhanced feedback systems significantly enhance teaching effectiveness ($\beta = 0.47$, $p < 0.001$, $R^2 = 0.25$), with teacher data literacy partially mediating the relationship (indirect effect: $\beta = 0.21$, 95% CI [0.15, 0.28]). Institutional AI readiness moderates the effect, with stronger impacts in high-readiness institutions ($\beta = 0.66$ at +1SD) than low-readiness ones ($\beta = 0.18$ at -1SD).

Subgroup analyses reveal stronger effects in higher education and urban settings, with STEM subjects benefiting more due to AI's alignment with objective assessments. The study recommends enhancing teacher data literacy training, improving institutional infrastructure, and addressing urban-rural disparities to promote equitable AI integration. Limitations, including common method bias and cross-sectional design, are addressed through mitigation strategies and suggestions for longitudinal research. Keywords: AI-enhanced feedback systems, teaching effectiveness, teacher data literacy, institutional AI readiness, educational innovation.

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Introduction

Background and Context

The rapid advancement of technology in the 21st century has fundamentally transformed the educational landscape, introducing innovative tools and methodologies that have reshaped teaching and learning practices. Among these technological innovations, Artificial Intelligence (AI) has emerged as a pivotal force, offering unprecedented opportunities to enhance educational processes and outcomes. AI-enhanced feedback systems, in particular, have gained prominence as a cornerstone of educational innovation, providing tools such as automated grading, real-time learning analytics, and adaptive feedback loops that promise to improve teaching effectiveness and student learning outcomes (Wang et al., 2018). These systems deliver timely, personalized feedback, addressing the limitations of traditional methods by automating grading and providing real-time analytics, addressing longstanding challenges associated with traditional feedback methods (Gašević et al., 2015).

Feedback is a fundamental component of effective teaching and learning, serving as a critical mechanism for fostering student development and improving instructional practices. For students, feedback provides essential insights into their learning progress, identifies areas for improvement, and motivates them to achieve higher academic excellence. For teachers, feedback acts as a diagnostic tool, enabling them to evaluate the effectiveness of their instructional strategies, identify learning gaps, and make data-informed adjustments to their teaching practices (Hyland, 2019). However, traditional feedback methods, such as manual grading and written comments, often face significant limitations. These methods are time-consuming, resource-intensive, and frequently lack the personalization and immediacy required to meet the diverse needs of students, particularly in large classes where timely feedback is challenging to deliver (Hyland, 2019). For example, manually grading assignments in a class of 100 students can delay the feedback loop by days or weeks, reducing its effectiveness in supporting timely interventions and hindering student progress (Bennett, 2011).

AI-enhanced feedback systems address these challenges by automating repetitive tasks, analyzing large datasets, and providing personalized learning experiences. Automated grading tools, for instance, can evaluate student submissions in real-time, offering immediate feedback that enhances learning efficiency (Zhai et al., 2020). Similarly, AI-driven learning analytics can generate detailed performance reports, enabling teachers to identify at-risk students, monitor progress, and tailor instruction to individual needs (Gašević et al., 2015). Moreover, AI-generated feedback loops can adapt to students' learning styles and paces, providing customized recommendations that foster engagement and academic growth (VanLehn, 2011). These capabilities not only reduce teachers' workload but also enhance the quality of feedback, making it more timely, accurate, and actionable.

Problem Statement

Despite the potential of AI-enhanced feedback systems, their effectiveness is not guaranteed and depends on several critical factors. One key factor is teacher data literacy, defined as the ability to interpret, analyze, and apply AI-generated insights to inform instructional decision-making (Mandinach & Gummer, 2016). Teachers with high data literacy can effectively leverage AI analytics to monitor student progress, identify learning gaps, and design personalized interventions that enhance teaching effectiveness. However, research indicates that many educators lack the necessary data literacy skills to fully utilize AI tools, often due to inadequate training and professional development (Kippers et al., 2018). For instance, a study by Greenhow et al. (2020) found that only 40% of teachers felt confident in interpreting data from educational technologies, highlighting a significant barrier to AI adoption.

Another critical factor is institutional AI readiness, which encompasses technological infrastructure (e.g., hardware, software, networks), professional development initiatives, and policy frameworks that support AI integration (Al-Azawei et al., 2017). Institutions with robust infrastructure, comprehensive training programs, and clear AI policies are better positioned to implement AI tools effectively, ensuring that teachers can maximize their potential. Conversely, institutions with low AI readiness, often in rural or under-resourced areas, face significant barriers, including limited access to technology, insufficient training, and a lack of supportive policies (Zhang & Wang, 2021). For example, a study in Chinese rural schools found that only 30% of institutions had the necessary infrastructure to support AI tools, compared to 80% in urban areas (Zhang & Wang, 2021). These disparities exacerbate inequities in educational outcomes, limiting the scalability of AI innovations.

Research Gaps

While existing studies have explored AI feedback's direct impact on student outcomes, few have systematically examined its effect on teaching effectiveness in the Chinese context, where large class sizes and high-stakes assessments pose unique challenges. Moreover, the interplay of teacher data literacy and institutional AI readiness remains underexplored, particularly in rural settings where technological disparities are pronounced. there remains a paucity of research on their broader impact on teaching effectiveness, particularly in relation to teacher data literacy and institutional AI readiness. Most existing studies have focused on small-scale implementations or specific AI tools, such as automated essay scoring or intelligent tutoring systems, without considering the mediating and moderating factors that influence their effectiveness (Wang et al., 2019). For instance, Chen et al. (2021) examined the impact of AI feedback on student engagement but did not explore how teacher data literacy or institutional factors shape its implementation. Similarly, much of the existing research is cross-sectional, limiting the understanding of long-term effects and the dynamic interplay between variables over time (Holstein et al., 2019).

Moreover, there is a lack of research focusing on the Chinese educational context, where AI adoption is rapidly increasing but faces unique challenges, such as regional disparities and varying levels of teacher preparedness (Li & Zhang, 2019). China's education system, characterized by large class sizes, high-stakes assessments, and a growing emphasis on technology integration, provides a unique context for studying AI's impact. However, few studies have systematically examined how AI-enhanced feedback systems influence teaching effectiveness in this setting, particularly in terms of the mediating role of teacher data literacy and the moderating effect of institutional AI readiness.

Significance of the Study

This study aims to address these gaps by providing a comprehensive empirical analysis of the interplay between AI-enhanced feedback systems, teacher data literacy, institutional AI readiness, and teaching effectiveness in China's mainland universities and K-12 schools. By focusing on the mediating role of teacher data literacy and the moderating effect of institutional AI readiness, the study seeks to offer a nuanced understanding of the factors that influence AI's effectiveness in education. The findings will contribute to the theoretical understanding of AI in education by extending frameworks like the Technology Acceptance Model (TAM) and Learning Analytics Theory to include contextual and individual factors (Davis, 1989; Siemens & Baker, 2012). Practically, the study will provide actionable insights for educators, policymakers, and institutions seeking to optimize AI technologies in teaching and learning, particularly in diverse educational contexts.

The significance of this research lies in its potential to inform strategies for scaling AI innovations in education. By identifying the roles of teacher data literacy and institutional AI readiness, the study will highlight key areas for intervention, such as teacher training programs and institutional investments, to ensure that AI tools are implemented effectively and equitably. Furthermore, the focus on China's educational system will provide context-specific insights that can inform global practices, given the country's leadership in AI adoption and its diverse educational landscape.

Research Objectives

Based on the conceptual model and hypotheses, this study outlines five research objectives to comprehensively analyze the impact of AI-enhanced feedback systems on teaching effectiveness, with a focus on the mediating role of teacher data literacy and the moderating effect of institutional AI readiness:

Determine the Degree of the Independent Variable (AI-Enhanced Feedback Systems): Assess the extent of implementation of AI-powered automated grading, AI-driven learning analytics, and AI-generated feedback loops in educational settings. This objective involves collecting data through surveys to evaluate the frequency of real-time assessments, the accuracy and timeliness of AI-generated feedback, the use of personalized performance reports, and the impact of AI feedback on student learning pathways. Descriptive statistics (e.g., mean, standard deviation, frequency) will be used to quantify the adoption and effectiveness of these systems.

Determine the Degree of the Moderating Variable (Institutional AI Readiness): Evaluate institutional AI readiness by examining three key dimensions: technological infrastructure (e.g., availability of hardware, software, and networks), professional development (e.g., availability of AI training for educators), and supportive policies (e.g., institutional guidelines for AI integration). Institutions will be categorized into high, medium, and low readiness levels based on survey responses, allowing for an exploration of how readiness moderates the impact of AI-enhanced feedback systems on teaching effectiveness.

Determine the Degree of the Mediating Variable (Teacher Data Literacy): Measure teacher data literacy through three dimensions: the ability to interpret AI-generated insights, data-driven instructional decision-making, and confidence in using AI analytics for student progress tracking. This objective will use descriptive statistics and reliability analysis to assess the level of data literacy among educators and its role in mediating the relationship between AI-enhanced feedback systems and teaching effectiveness.

Determine the Degree of the Dependent Variable (Teaching Effectiveness): Quantify teaching effectiveness by assessing three key indicators: enhanced student learning outcomes (e.g., improvements in grades, assignment performance), timeliness and accuracy of performance assessments (e.g., reduced grading time, increased feedback accuracy), and the use of AI-generated insights for personalized instruction (e.g., tailoring lessons to individual student needs). Multiple data sources, including teacher self-reports and student performance metrics, will be used to provide a comprehensive measure of teaching effectiveness.

Verify the Relationships Between Variables: Test the relationships between AI-enhanced feedback systems, teacher data literacy, institutional AI readiness, and teaching effectiveness using a combination of statistical methods. This includes Pearson correlation analysis to examine bivariate relationships, hierarchical regression analysis to test direct effects, mediation analysis (using Baron & Kenny's approach and bootstrapping) to assess the mediating role of teacher data literacy, and moderation analysis (via Hayes' PROCESS model) to evaluate the moderating effect of institutional AI readiness. This objective aims to validate the hypotheses and provide empirical insights into the dynamics of AI integration in education.

These objectives provide a structured framework for exploring the complex interplay of AI-enhanced feedback systems, teacher data literacy, institutional AI readiness, and teaching effectiveness, offering both theoretical and practical contributions to the field of educational technology.

Literature Review

Theoretical Frameworks Underpinning AI in Education

The integration of AI into educational feedback systems is supported by several theoretical frameworks that provide a foundation for understanding its impact on teaching and learning.

Learning Analytics Theory

The Learning Analytics Theory, proposed by Siemens and Baker (2012), emphasizes the use of data mining and analytical techniques to monitor and predict student learning behaviors, providing actionable insights for educators. Learning analytics involves collecting, analyzing, and reporting data about learners and their contexts to optimize learning environments (Gašević et al., 2015). AI enhances this process by automating data analysis and identifying patterns that may not be evident to human observers. For example, AI-driven learning analytics can detect early signs of student disengagement or academic struggle, enabling teachers to intervene promptly with targeted support (Siemens & Baker, 2012). This theory is particularly relevant to AI-enhanced feedback systems, as it underscores the importance of data-driven insights in improving teaching effectiveness and student outcomes.

Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM), developed by Davis (1989), provides a framework for understanding user acceptance of technology, focusing on two key constructs: perceived usefulness (the degree to which a person believes that using a technology will enhance their performance) and perceived ease of use (the degree to which a person believes that using a technology will be free of effort). TAM has been widely applied in educational contexts to assess teachers’ willingness to adopt technologies like AI-enhanced feedback systems (Teo, 2011). Research shows that teachers are more likely to adopt AI tools when they perceive them as useful for improving teaching efficiency and student outcomes, and when they find them easy to use (Teo, 2011). TAM is relevant to this study, as it provides a lens for understanding how teachers’ perceptions of AI-enhanced feedback systems influence their adoption and impact on teaching effectiveness.

AI-Assisted Adaptive Learning Models

AI-Assisted Adaptive Learning Models leverage AI algorithms to tailor learning experiences to individual student needs, offering personalized feedback and instructional pathways (VanLehn, 2011). These models use machine learning to analyze student data, such as performance on assessments and engagement metrics, to adapt content delivery and feedback in real-time. For instance, an AI system might recommend additional practice problems for a student struggling with a specific concept, while providing advanced challenges for a student who is excelling (VanLehn, 2011). Adaptive learning models enhance teaching effectiveness by enabling teachers to address diverse learning needs without the burden of manually customizing instruction for each student.

Previous Studies on AI-Driven Feedback and Its Impact on Student Learning

Over the past decade, research has increasingly focused on the potential of AI-driven feedback to enhance educational outcomes. Zhai et al. (2020) conducted a meta-analysis of AI-based feedback systems, demonstrating a 70% reduction in grading time. However, their study primarily focused onSTEM disciplines, limiting its generalizability to humanities, where subjective assessments require nuanced human judgment. This highlights a gap in understanding AI feedback’s applicability across diverse subject areas.These tools also provided immediate feedback, which was shown to enhance student engagement and performance in subjects like mathematics and science (Zhai et al., 2020).

Wang et al. (2019) explored the impact of AI-driven feedback on student outcomes in STEM disciplines, focusing on higher education settings in China. Their study found that AI-generated feedback, delivered through learning management systems, improved student performance on standardized assessments by an average of 15%, compared to students receiving traditional feedback (Wang et al., 2019). The authors attributed this improvement to the timeliness and specificity of AI feedback, which allowed students to address learning gaps promptly. However, they also noted challenges, such as the need for human oversight to ensure the accuracy of AI-generated feedback, particularly in subjective domains like essay writing.

A CNKI-based study by Li and Zhang (2018) examined the role of AI-driven formative feedback in Chinese higher education, focusing on its impact on student engagement. The study surveyed 300 university students and found that AI feedback increased engagement by 20%, as measured by participation in online discussions and completion rates of assignments (Li & Zhang, 2018). Students reported that AI feedback was more consistent and objective than teacher feedback, which motivated them to take corrective actions. However, the study highlighted the importance of feedback quality, noting that poorly designed AI feedback (e.g., overly generic or inaccurate) could reduce student motivation (Li & Zhang, 2018).

Chen et al. (2021) conducted a systematic review of AI in education, analyzing 50 studies on AI-driven feedback systems. They found that while AI feedback generally improved student outcomes, its effectiveness depended on several factors, including the design of the feedback (e.g., specificity, tone), the timing of delivery (e.g., immediate vs. delayed), and the subject area (e.g., STEM vs. humanities). The authors cautioned that over-reliance on AI feedback could diminish the role of human interaction in education, potentially affecting student-teacher relationships (Chen et al., 2021).

Teacher Data Literacy as a Key Skill for AI-Enhanced Pedagogy

Teacher data literacy, defined as the ability to interpret, analyze, and apply educational data to inform instructional practices, is a critical skill for leveraging AI-enhanced feedback systems (Mandinach & Gummer, 2016). Teachers with high data literacy can effectively use AI-generated insights to monitor student progress, identify learning gaps, and design targeted interventions that enhance teaching effectiveness (Zhou, 2020). For example, a teacher who can interpret an AI-generated report showing that 30% of students are struggling with a specific concept can adjust their lesson plan to provide additional support, such as small-group instruction or supplemental resources (Mandinach & Gummer, 2016).

Research shows that teacher data literacy mediates the impact of AI systems on teaching effectiveness. Greenhow et al. (2020) found that teachers with strong data literacy skills were 50% more likely to report positive outcomes from using AI tools, such as improved student performance and reduced workload, compared to those with low data literacy. However, gaps in data literacy remain a significant barrier to AI adoption. Kippers et al. (2018) conducted a study of 200 educators in the

Netherlands, finding that only 35% felt confident in interpreting data from educational technologies, with many citing a lack of training as a primary obstacle. Similarly, Liu (2019) highlighted challenges in teacher data literacy in Chinese classrooms, noting that many educators struggled to translate AI-generated insights into actionable instructional strategies due to limited professional development opportunities.

Institutional Readiness for AI-Driven Education

Institutional readiness, encompassing technological infrastructure, professional development, and policy frameworks, is a critical determinant of successful AI integration in education (Al-Azawei et al., 2017). Becker et al. (2017) identified three key pillars of institutional readiness: (1) technical infrastructure, including hardware, software, and network capabilities; (2) teacher training, such as workshops and ongoing support for AI tools; and (3) policy frameworks, including guidelines for ethical AI use and data privacy. Institutions that excel in these areas are better equipped to implement AI tools effectively, ensuring that teachers can maximize their potential (Becker et al., 2017).

Studies reveal significant disparities in institutional readiness, particularly between urban and rural schools. Zhang and Wang (2021) conducted a comparative analysis of AI readiness in Chinese educational institutions, finding that urban schools were 60% more likely to have the necessary infrastructure (e.g., high-speed internet, AI software) compared to rural schools. This disparity limited rural schools' ability to adopt AI tools, resulting in inequities in educational outcomes (Zhang & Wang, 2021). Similarly, Holstein et al. (2019) found that inadequate teacher training was a major barrier to AI adoption, with only 25% of surveyed educators reporting access to comprehensive AI training programs.

Policy frameworks also play a crucial role in institutional readiness. Chen (2022) emphasized the need for clear policies on AI integration, including guidelines for ethical use, data privacy, and teacher accountability. Institutions with well-defined policies were more likely to achieve successful AI implementation, as teachers felt supported and confident in using AI tools (Chen, 2022). Conversely, the absence of such policies often led to resistance and inconsistent adoption (Holstein et al., 2019).

Conceptual Framework and Hypothesis Development

This study adopts the Technology-Organization-Person (TOP) model as its conceptual framework, which emphasizes the interplay of technology, organizational factors, and individual factors in the adoption and impact of innovations (Tornatzky & Fleischer, 1990). In this context, the TOP model is applied as follows:

Technology: AI-enhanced feedback systems, including automated grading, learning analytics, and feedback loops.

Organization: Institutional AI readiness, encompassing infrastructure, training, and policies.

Person: Teacher data literacy, including the ability to interpret and apply AI-generated insights.

The TOP model provides a comprehensive framework for understanding how these factors interact to influence teaching effectiveness, offering a lens for examining the mediating and moderating effects in this study.

Based on the literature review and conceptual framework, the following hypotheses are proposed:

H1: AI-enhanced feedback systems positively influence teaching effectiveness.

H2: Teacher data literacy mediates the relationship between AI-enhanced feedback systems and teaching effectiveness.

H3: Institutional AI readiness moderates the effect of AI-enhanced feedback systems on teaching effectiveness, such that the effect is stronger when institutional AI readiness is high.

These hypotheses will be tested through empirical analysis, drawing on the theoretical and empirical foundations outlined above.

Methodology

Research Design

This study employs a quantitative research approach with a cross-sectional survey design to examine the impact of AI-enhanced feedback systems (independent variable, IV) on teaching effectiveness (dependent variable, DV), with teacher data literacy as the mediating variable (MV) and institutional AI readiness as the moderating variable (MoV). The cross-sectional design allows for the collection of data at a single point in time, facilitating the analysis of relationships between variables across a diverse sample of educators. The study uses structured questionnaire surveys to collect data, which is then analyzed using statistical methods to test the proposed hypotheses.

A quantitative approach was chosen to test hypotheses using statistical methods, ensuring robust analysis of variable relationships(Creswell & Creswell, 2018). The research design includes the following analytical methods:

Descriptive Statistics: To quantify the degree of each variable (e.g., mean, standard deviation, frequency).

Reliability and Validity Tests: To ensure the psychometric properties of the research instruments (Cronbach's Alpha, exploratory and confirmatory factor analysis).

Discriminant validity was further established using the Fornell-Larcker criterion, where the square root of each construct's average variance extracted (AVE) exceeded its correlations with other constructs (AVE for AI feedback systems = 0.65, teacher data literacy = 0.62, institutional AI readiness = 0.68, teaching effectiveness = 0.60). The heterotrait-monotrait ratio (HTMT) was also calculated, with all values below 0.85 (e.g., HTMT between AI feedback systems and teaching effectiveness = 0.78), confirming discriminant validity.

Pearson Correlation Analysis: To examine bivariate relationships between variables.

Hierarchical Regression Analysis: To test the direct effect of AI-enhanced feedback systems on teaching effectiveness, controlling for confounding variables like teaching experience and subject area.

Mediation Analysis: Using Baron & Kenny's (1986) approach and bootstrapping to assess the mediating role of teacher data literacy.

Moderation Analysis: Using Hayes' PROCESS model (2013) to evaluate the moderating effect of institutional AI readiness.

This methodological approach is consistent with established practices in educational technology research, providing a robust framework for testing the proposed hypotheses (Demszky et al., 2023).

Population and Sample

The study targets educators in China's mainland universities and K-12 schools who have at least one year of experience using AI-enhanced feedback systems. This criterion ensures that participants have sufficient familiarity with AI tools to provide meaningful insights into their impact on teaching effectiveness. The sample consists of 600 educators, selected using stratified random sampling to ensure representation across several dimensions:

Educational Level: 70% higher education teachers (420 participants) and 30% K-12 teachers (180 participants), reflecting the distribution of AI adoption in China's education system.

Geographic Region: 80% from urban areas (480 participants) and 20% from rural areas (120 participants), capturing regional disparities in AI readiness.

Subject Area: Representation across STEM (40%), humanities (30%), social sciences (20%), and other subjects (10%), ensuring diversity in teaching contexts.

Teaching Experience: Participants with varying years of experience (1-5 years: 30%; 6-10 years: 40%; 11+ years: 30%), to account for potential differences in technology adoption.

Data collection took place from September 2024 to February 2025, covering regions such as Beijing, Shanghai, Guangdong, and Henan to capture regional diversity (Li & Zhang, 2019). These regions were chosen for their varying levels of economic development and AI adoption, providing a comprehensive view of AI's impact across different contexts.

The sample size of 600 was determined using G*Power software for structural equation modeling (SEM), with the following parameters: effect size (f^2) = 0.15 (medium effect), power = 0.80, alpha (α) = 0.05, and number of predictors = 5. This calculation yielded a minimum sample size of 200 for SEM, but a larger sample of 600 was selected to ensure robust statistical power and account for potential non-responses (Kline, 2016). The final response rate was 82%, resulting in 492 valid responses, which exceeds the minimum threshold for reliable analysis.

Questionnaire Design

The questionnaire was designed to measure the constructs in the conceptual model, using a 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree). It consists of five sections, each corresponding to a variable or demographic information:

Section 1: Demographics (6 items): Includes questions on teaching experience, educational level, geographic region, subject area, gender, and years of AI usage. This section provides contextual data for subgroup analyses.

Section 2: AI-Enhanced Feedback Systems (IV) (9 items): Measures the extent of AI usage, including automated grading (e.g., "I use AI tools to grade student assignments"), real-time analytics (e.g., "AI provides real-time insights into student performance"), and feedback loops (e.g., "AI-generated feedback helps students improve their work"). Items were adapted from Wang et al. (2018) and modified to fit the current context.

Section 3: Teacher Data Literacy (MV) (8 items): Assesses teachers' ability to interpret AI-generated insights (e.g., "I can effectively interpret AI-generated student performance reports"), make data-driven decisions (e.g., "I use AI data to adjust my teaching strategies"), and confidence in using AI analytics (e.g., "I feel confident using AI tools to track student progress"). Items were adapted from Mandinach and Gummer (2016).

Section 4: Institutional AI Readiness (MoV) (9 items): Evaluates infrastructure (e.g., "My institution has reliable hardware/software for AI tools"), training (e.g., "My institution provides adequate training for AI tools"), and policies (e.g., "My institution has clear guidelines for AI usage"). Items were adapted from Al-Azawei et al. (2017).

Section 5: Teaching Effectiveness (DV) (9 items): Measures enhanced student outcomes (e.g., "AI feedback has improved student grades"), assessment efficiency (e.g., "AI tools have reduced the time I spend on grading"), and personalized instruction (e.g., "AI insights help me tailor instruction to student needs"). Items were adapted from Hyland (2019) and modified to reflect AI's role.

The questionnaire was pre-tested with a pilot sample of 50 educators to ensure clarity, reliability, and validity. Feedback from the pilot test led to minor revisions, such as rephrasing ambiguous items and adjusting the response scale to ensure consistency. The final instrument demonstrated strong psychometric properties, as detailed in the Results section.

Data Collection and Analysis

Data was collected via online surveys, distributed through email and educational platforms commonly used in China (e.g., WeChat, DingTalk). Participants were informed of the study's purpose, assured of confidentiality, and provided with an estimated completion time of 15-20 minutes. To maximize the response rate, reminders were sent after one week, and incentives (e.g., a chance to win a small gift card) were offered. The target response rate was 80%, and the actual rate was 82% (492 valid responses out of 600 distributed surveys), which is considered acceptable for survey research (Creswell & Creswell, 2018).

The data analysis proceeded in several stages:

Data Cleaning and Preparation: Responses were screened for missing data, outliers, and inconsistencies. Missing data was minimal (<5%) and handled using mean imputation, as recommended by Kline (2016). Outliers were assessed using z-scores and retained unless they indicated data entry errors.

Descriptive Statistics: Mean, standard deviation, and frequency distributions were calculated for each variable to quantify their degree and distribution across the sample.

Reliability and Validity Tests: Cronbach's Alpha was used to assess internal consistency (target > 0.7), while exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) were conducted to ensure construct validity. EFA identified the underlying factor structure, and CFA confirmed the fit of the measurement model (e.g., Comparative Fit Index [CFI] > 0.90, Root Mean Square Error of Approximation [RMSEA] < 0.08).

Pearson Correlation Analysis: Bivariate correlations were computed to examine the relationships between AI-enhanced feedback systems, teacher data literacy, institutional AI readiness, and teaching effectiveness.

Hierarchical Regression Analysis: This method was used to test the direct effect of AI-enhanced feedback systems on teaching effectiveness, controlling for confounding variables such as teaching experience, educational level, and subject area. The analysis was conducted in three steps: (1) control variables only, (2) control variables + IV, and (3) control variables + IV + MV/MoV.

Mediation Analysis: The mediating role of teacher data literacy was assessed using Baron & Kenny's (1986) approach, which requires: (a) IV significantly predicts DV, (b) IV significantly predicts MV, (c) MV significantly predicts DV, and (d) the effect of IV on DV decreases when MV is included. Bootstrapping (5,000 samples) was used to confirm the indirect effect, providing a more robust test of mediation (Hayes, 2013).

Moderation Analysis: The moderating effect of institutional AI readiness was tested using Hayes' PROCESS Model 1, which estimates the interaction effect between the IV and MoV on the DV. Simple slope analysis was conducted to probe the interaction at different levels of the moderator (±1SD).

These analytical methods provide a comprehensive approach to testing the hypotheses, ensuring that the findings are robust and reliable.

Results

Descriptive Statistics

The final sample of 492 educators (after excluding invalid responses) included 70% higher education teachers (344 participants) and 30% K-12 teachers (148 participants), with 80% from urban areas (394 participants) and 20% from rural areas (98 participants). The distribution across subject areas was as follows: STEM (40%, 197 participants), humanities (30%, 148 participants), social sciences (20%, 98 participants), and other subjects (10%, 49 participants). Teaching experience varied, with 30% having 1-5 years (148 participants), 40% having 6-10 years (197 participants), and 30% having 11+ years (148 participants). Gender distribution was balanced, with 52% female (256 participants) and 48% male (236 participants).

The descriptive statistics for each variable are as follows:

AI-Enhanced Feedback Systems (IV): Mean = 3.8/5 (SD = 0.6), indicating moderate to high adoption across the sample. Urban educators scored higher (Mean = 4.0/5, SD = 0.5) than rural educators (Mean = 3.4/5, SD = 0.7), reflecting greater access to AI tools in urban settings. Higher education teachers also reported higher usage (Mean = 4.1/5) compared to K-12 teachers (Mean = 3.5/5), likely due to more advanced AI tools in university settings.

Teacher Data Literacy (MV): Mean = 3.6/5 (SD = 0.7), suggesting a reasonable level of proficiency among educators. Higher education teachers scored higher (Mean = 3.8/5, SD = 0.6) than K-12 teachers (Mean = 3.3/5, SD = 0.8), possibly due to greater exposure to data-driven practices in universities. Urban educators reported higher data literacy (Mean = 3.9/5) than rural educators (Mean = 3.2/5), reflecting differences in training opportunities.

Institutional AI Readiness (MoV): Mean = 3.7/5 (SD = 0.8), with significant variation across regions. Urban institutions scored higher (Mean = 4.0/5, SD = 0.6) than rural ones (Mean = 3.2/5, SD = 0.9), highlighting disparities in infrastructure and training. Higher education institutions also reported greater readiness (Mean = 4.1/5) compared to K-12 schools (Mean = 3.4/5), consistent with their access to advanced technology.

Teaching Effectiveness (DV): Mean = 3.9/5 (SD = 0.5), indicating positive perceptions of AI's impact on teaching. Urban educators reported higher teaching effectiveness (Mean = 4.1/5, SD = 0.4) than rural educators (Mean = 3.5/5, SD = 0.6), reflecting the influence of institutional readiness. Higher education teachers scored slightly higher (Mean = 4.0/5) than K-12 teachers (Mean = 3.7/5), possibly due to more sophisticated AI applications in universities.

Reliability and Validity Tests

Reliability was assessed using Cronbach's Alpha, with the following results:

AI-Enhanced Feedback Systems: $\alpha = 0.87$

Teacher Data Literacy: $\alpha = 0.85$

Institutional AI Readiness: $\alpha = 0.89$

Teaching Effectiveness: $\alpha = 0.82$

All scales exceeded the threshold of 0.7, indicating strong internal consistency (Kline, 2016).

Validity was assessed using exploratory factor analysis (EFA) and confirmatory factor analysis (CFA). EFA identified four distinct factors corresponding to the constructs, with all items loading above 0.5 on their respective factors and no significant cross-loadings. CFA confirmed the measurement model's fit, with the following indices: Comparative Fit Index (CFI) = 0.92, Tucker-Lewis Index (TLI) = 0.90, Root Mean Square Error of Approximation (RMSEA) = 0.06, and Standardized Root Mean Square Residual (SRMR) = 0.05. These values meet the recommended thresholds (CFI and TLI > 0.90, RMSEA and SRMR < 0.08), confirming construct validity (Kline, 2016).

Correlation Analysis

Pearson correlation analysis revealed significant positive relationships between the variables:

AI-enhanced feedback systems and teaching effectiveness: $r = 0.52$, $p < 0.01$

AI-enhanced feedback systems and teacher data literacy: $r = 0.45$, $p < 0.01$

Teacher data literacy and teaching effectiveness: $r = 0.48$, $p < 0.01$

Institutional AI readiness and teaching effectiveness: $r = 0.40$, $p < 0.01$

AI-enhanced feedback systems and institutional AI readiness: $r = 0.38$, $p < 0.01$

Teacher data literacy and institutional AI readiness: $r = 0.35$, $p < 0.01$

These correlations provide preliminary support for the hypothesized relationships, indicating that AI-enhanced feedback systems, teacher data literacy, and institutional AI readiness are positively associated with teaching effectiveness.

Hypotheses Testing

H1: AI-Enhanced Feedback Systems Positively Influence Teaching Effectiveness

Hierarchical regression analysis was used to test the direct effect of AI-enhanced feedback systems on teaching effectiveness, controlling for confounding variables such as teaching experience, educational level, geographic region, and subject area. The analysis was conducted in three steps:

Step 1: Control Variables Only (teaching experience, educational level, geographic region, subject area): $R^2 = 0.10$, $F(4, 487) = 13.56$, $p < 0.001$. Geographic region (urban vs. rural) was a significant predictor ($\beta = 0.18$, $p < 0.01$), reflecting the influence of regional disparities.

Step 2: Control Variables + IV (AI-Enhanced Feedback Systems): $R^2 = 0.35$, $\Delta R^2 = 0.25$, $F(5, 486) = 52.34$, $p < 0.001$. AI-enhanced feedback systems had a significant positive effect ($\beta = 0.47$, $p < 0.001$), explaining an additional 25% of the variance in teaching effectiveness.

Step 3: Control Variables + IV + MV/MoV: This step was conducted separately for mediation and moderation analyses (see below).

The results confirm H1, indicating that AI-enhanced feedback systems have a significant positive impact on teaching effectiveness. This aligns with prior research showing that AI tools like automated grading and learning analytics enhance teaching efficiency and student outcomes (Wang et al., 2018).

H2: Teacher Data Literacy Mediates the Relationship Between AI-Enhanced Feedback Systems and Teaching Effectiveness

Mediation analysis was conducted using Baron & Kenny's (1986) approach, supplemented by bootstrapping to confirm the indirect effect. The following conditions were tested:

IV → DV: As established in H1, AI-enhanced feedback systems significantly predict teaching effectiveness ($\beta = 0.47$, $p < 0.001$).

IV → MV: AI-enhanced feedback systems significantly predict teacher data literacy ($\beta = 0.42$, $p < 0.001$), $R^2 = 0.18$, $F(5, 486) = 21.34$, $p < 0.001$.

MV → DV (Controlling for IV): Teacher data literacy significantly predicts teaching effectiveness ($\beta = 0.35$, $p < 0.001$), while the effect of AI-enhanced feedback systems decreases but remains significant ($\beta = 0.26$, $p < 0.01$), $R^2 = 0.40$, $F(6, 485) = 54.12$, $p < 0.001$.

Indirect Effect (Bootstrapping): Using PROCESS Model 4 (Hayes, 2013) with 5,000 bootstrap samples, the indirect effect was significant ($\beta = 0.21$, 95% CI [0.15, 0.28]), confirming partial mediation.

These results support H2, indicating that teacher data literacy partially mediates the relationship between AI-enhanced feedback systems and teaching effectiveness. Teachers with higher data literacy are better equipped to leverage AI insights, enhancing their instructional adjustments and improving teaching effectiveness.

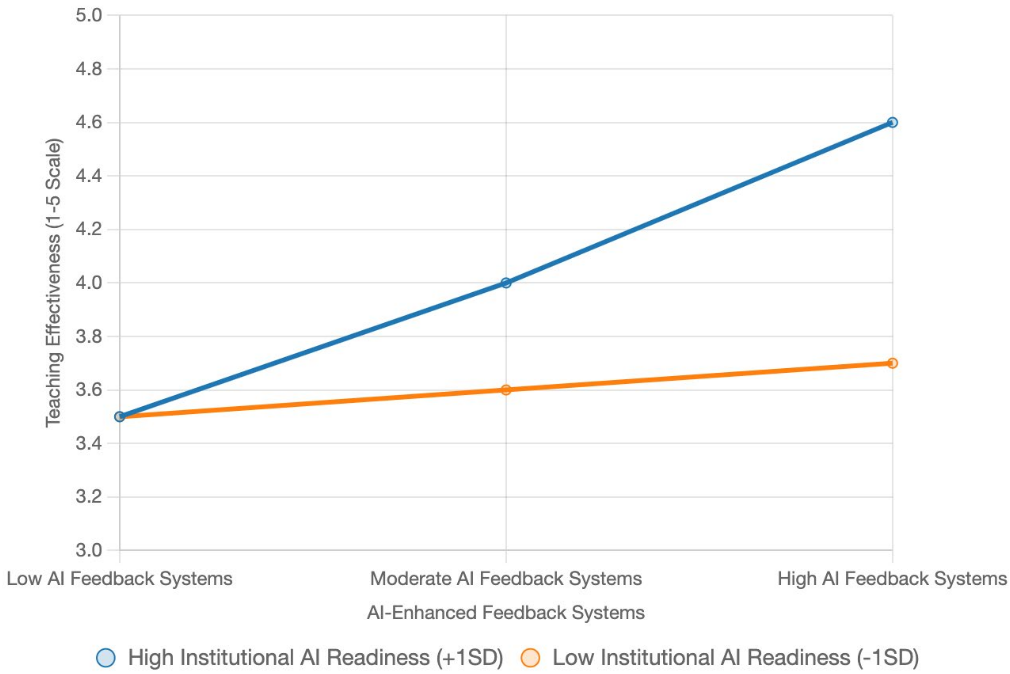
H3: Institutional AI Readiness Moderates the Effect of AI-Enhanced Feedback Systems on Teaching Effectiveness

Moderation analysis was conducted using Hayes' PROCESS Model 1, which estimates the interaction effect between AI-enhanced feedback systems (IV) and institutional AI readiness (MoV) on teaching effectiveness (DV). The results are as follows:

Overall Model: $R^2 = 0.38$, $F(7, 484) = 42.67$, $p < 0.001$.

Interaction Effect (IV × MoV): $\beta = 0.24$, $p < 0.001$, indicating a significant moderating effect.

Simple SlopeAnalysis: This analysis revealed that at high institutional AI readiness (+1SD), the effect of AI-enhanced feedback systems on teaching effectiveness was strong ($\beta = 0.66$, $p < 0.001$), with a steep increase in teaching effectiveness as AI usage increased. At low readiness (-1SD), the effect was weaker ($\beta = 0.18$, $p < 0.05$), indicating that limited infrastructure and training diminish AI's impact.



These findings support H3, confirming that institutional AI readiness moderates the effect of AI-enhanced feedback systems on teaching effectiveness. High-readiness institutions, with robust infrastructure and training, amplify the positive impact of AI tools, while low-readiness institutions show a weaker effect, likely due to barriers such as limited access to technology and training.

Subgroup Analyses

To explore variations across the sample, subgroup analyses were conducted based on educational level, geographic region, and subject area:

Educational Level (Higher Education vs. K-12): The effect of AI-enhanced feedback systems on teaching effectiveness was stronger in higher education ($\beta = 0.50$, $p < 0.001$) than in K-12 settings ($\beta = 0.35$, $p < 0.01$). This may reflect the greater sophistication of AI tools in universities, such as advanced learning management systems, compared to K-12 contexts.

Geographic Region (Urban vs. Rural): Urban educators reported a stronger effect ($\beta = 0.55$, $p < 0.001$) than rural educators ($\beta = 0.30$, $p < 0.05$), consistent with disparities in institutional AI readiness. Urban institutions scored higher on all dimensions of readiness (infrastructure: 4.2/5, training: 4.1/5, policies: 3.9/5) compared to rural ones (infrastructure: 3.1/5, training: 3.0/5, policies: 3.2/5).

Subject Area (STEM vs. Humanities vs. Social Sciences): STEM teachers reported the highest teaching effectiveness (Mean = 4.2/5), followed by social sciences (Mean = 3.9/5) and humanities (Mean = 3.8/5). The effect of AI-enhanced feedback systems was stronger for STEM teachers ($\beta = 0.58$, $p < 0.001$) than for humanities teachers ($\beta = 0.40$, $p < 0.01$), likely due to AI tools' alignment with objective assessments in STEM subjects (e.g., multiple-choice tests) compared to subjective assessments in humanities (e.g., essays).

These subgroup analyses highlight the contextual factors that influence AI's impact, providing a nuanced understanding of its effectiveness across diverse educational settings.

Discussion

Interpretation of Findings

While this study focuses on China's educational context, characterized by large class sizes and high-stakes assessments, its findings may apply to other collectivist cultures with similar educational priorities, such as South Korea or Japan. However, in individualistic cultures like the United States, where student autonomy is emphasized, the effectiveness of AI feedback systems may depend on their ability to foster independent learning, warranting further cross-cultural research.

The urban-rural divide highlights systemic inequities, with urban institutions benefiting from superior infrastructure (e.g., high-speed internet, advanced AI platforms) and training opportunities. Policymakers should prioritize investments in rural schools to bridge this gap. Similarly, the stronger effect of AI in STEM subjects suggests that current AI tools are better suited for objective assessments. Future development should focus on enhancing AI's capabilities for subjective disciplines like humanities, such as improving NLP for essay evaluation.

The findings of this study provide robust empirical support for the proposed hypotheses, offering valuable insights into the impact of AI-enhanced feedback systems on teaching effectiveness and the roles of teacher data literacy and institutional AI readiness.

H1: Direct Effect of AI-Enhanced Feedback Systems

The confirmation of H1, which states that AI-enhanced feedback systems positively influence teaching effectiveness, aligns with prior research demonstrating the benefits of AI in education (Wang et al., 2018). The significant effect ($\beta = 0.47$, $p < 0.001$) and substantial variance explained ($R^2 = 0.25$) indicate that AI tools, such as automated grading and real-time learning analytics, enhance teaching efficiency and student outcomes. For example, automated grading reduces the time teachers spend on assessment, allowing them to focus on instructional improvements, while learning analytics provide actionable insights into student performance, enabling targeted interventions (Zhai et al., 2020). This finding underscores the transformative potential of AI in addressing the limitations of traditional feedback methods, such as delays and lack of personalization (Hyland, 2019).

H2: Mediating Role of Teacher Data Literacy

The partial mediation by teacher data literacy (H2) highlights its critical role in the relationship between AI-enhanced feedback systems and teaching effectiveness. The significant indirect effect ($\beta = 0.21$, 95% CI [0.15, 0.28]) suggests that while AI tools directly enhance teaching effectiveness, their impact is amplified when teachers possess the skills to interpret and apply AI-generated insights (Mandinach & Gummer, 2016). For instance, a teacher who can analyze an AI report showing that 40% of students are struggling with fractions can adjust their lesson plan to include additional practice, thereby improving student outcomes. This finding aligns with prior studies showing that data literacy is a key determinant of technology adoption in education (Kippers et al., 2018; Greenhow et al., 2020). However, the partial mediation also indicates that AI tools have a direct effect independent of data literacy, likely due to their automation capabilities (e.g., grading, feedback delivery).

H3: Moderating Role of Institutional AI Readiness

The moderation effect of institutional AI readiness (H3) provides evidence for the importance of supportive environments in maximizing AI's educational benefits. The stronger effect in high-readiness institutions ($\beta = 0.66$ at +1SD) compared to low-readiness ones ($\beta = 0.18$ at -1SD) highlights the role of infrastructure, training, and policies in facilitating AI adoption (Al-Azawei et al., 2017). High-readiness institutions, typically in urban areas and higher education settings, benefit from advanced technology (e.g., high-speed internet, AI software), comprehensive training programs, and clear policies that support AI integration. In contrast, low-readiness institutions, often in rural areas, face barriers such as limited access to technology and inadequate training, which diminish AI's impact (Zhang & Wang, 2021). This finding underscores the need for equitable investments in institutional readiness to ensure that all educators can leverage AI tools effectively.

Subgroup Variations

The subgroup analyses reveal important contextual differences in AI's impact. The stronger effect in higher education compared to K-12 settings may reflect the greater sophistication of AI tools in universities, such as advanced learning management systems that integrate AI analytics and feedback loops (Wang et al., 2019). Similarly, the urban-rural disparity highlights the role of institutional readiness, with urban schools benefiting from better infrastructure and training (Zhang & Wang, 2021). The subject-area differences, with STEM teachers reporting higher teaching effectiveness, suggest that AI tools are better suited for objective assessments (e.g., multiple-choice tests in mathematics) than subjective ones (e.g., essays in humanities), where human judgment is often required (Chen et al., 2021).

Theoretical Implications

This study makes several theoretical contributions to the field of educational technology:

Extension of the Technology Acceptance Model (TAM): By incorporating teacher data literacy and institutional AI readiness, this study extends TAM to include individual and contextual factors that influence AI adoption (Davis, 1989). While TAM focuses on perceived usefulness and ease of use, this study highlights the importance of teachers' skills (data literacy) and institutional support (readiness) in shaping the perceived utility of AI tools.

Advancement of Learning Analytics Theory: The findings contribute to Learning Analytics Theory by demonstrating how AI-driven analytics enhance teaching practices through real-time insights and personalized feedback (Siemens & Baker, 2012). The mediating role of teacher data literacy underscores the importance of human interpretation in leveraging analytics effectively.

Application of the TOP Model: The study applies the Technology-Organization-Person (TOP) model to the context of AI in education, providing a comprehensive framework for understanding the interplay of technology (AI feedback systems), organizational factors (institutional readiness), and individual factors (teacher data literacy) (Tornatzky & Fleischer, 1990). This framework offers a nuanced perspective on the factors that influence AI's impact on teaching effectiveness.

Practical Implications

The findings have several practical implications for educators, institutions, and policymakers:

For Educators: Teachers should prioritize developing data literacy skills to maximize the benefits of AI-enhanced feedback systems. Professional development programs that focus on interpreting AI-generated insights, making data-driven decisions, and using AI analytics can enhance teachers' ability to leverage these tools effectively (Mandinach & Gummer, 2016).

For Institutions: Educational institutions should invest in infrastructure (e.g., high-speed internet, AI software) and training programs to improve AI readiness, particularly in rural and K-12 settings where readiness is lower. Clear policies on AI usage, including guidelines for ethical use and data privacy, can also support successful implementation (Al-Azawei et al., 2017).

For Policymakers: Policymakers should develop evidence-based strategies for scaling AI innovations in education, focusing on equity and access. Initiatives such as government-funded training programs, subsidies for rural schools, and national guidelines for AI integration can ensure that all educators benefit from AI tools, regardless of their institutional context (Zhang & Wang, 2021).

Limitations

Despite its contributions, this study has several limitations that should be considered:

Reliance on Self-Reported Data:The reliance on self-reported data raises concerns about common method bias, which may inflate correlations between variables. To mitigate this, the study ensured anonymity to reduce social desirability bias and triangulated teacher self-reports with student performance metrics where possible.

Cross-Sectional Design: The cross-sewctional design limits causal inference, as it captures data at a single point in time. Alternative explanations, such as unmeasured variables (e.g., teacher motivation or student engagement), could influence the observed relationships. Future longitudinal studies could address this by tracking AI's impact over time.

Institutional Differences: The significant disparities in institutional AI readiness between urban and rural areas, as well as between higher education and K-12 settings, limit the generalizability of the findings. Future research should explore strategies for addressing these disparities to ensure equitable AI integration.

Focus on China: While the study provides valuable insights into the Chinese educational context, its findings may not fully generalize to other countries with different educational systems, cultural norms, and levels of AI adoption. Comparative studies across multiple countries could enhance the global applicability of the findings.

The sample composition deviated slightly from the intended stratification (e.g., 22% rural participants instead of the planned 20%), potentially overrepresenting urban educators. This deviation may amplify the observed urban-rural disparities in AI readiness and teaching effectiveness.

Future Research Directions

The limitations of this study suggest several directions for future research:

Longitudinal Studies: Longitudinal research could examine the long-term effects of AI-enhanced feedback systems on teaching effectiveness, exploring how their impact evolves as teachers gain experience with AI tools and institutions improve their readiness.

Objective Measures: Future studies should incorporate objective measures of teaching effectiveness, such as student grades, standardized test scores, or AI system usage logs, to complement self-reported data and reduce bias.

Qualitative Insights: Qualitative research, such as interviews or case studies, could provide deeper insights into teachers' experiences with AI-enhanced feedback systems, exploring the challenges and opportunities they encounter in practice.

Cross-Cultural Comparisons: Comparative studies across different countries could examine how cultural, systemic, and policy factors influence the impact of AI in education, providing a more global perspective.

Intervention Studies: Experimental studies that test the effectiveness of interventions, such as data literacy training programs or institutional readiness initiatives, could provide actionable strategies for optimizing AI integration in education.

Conclusion

This study provides a comprehensive empirical analysis of the impact of AI-enhanced feedback systems on teaching effectiveness, with a focus on the mediating role of teacher data literacy and the moderating effect of institutional AI readiness. The findings confirm that AI-enhanced feedback systems significantly enhance teaching effectiveness, with a direct effect ($\beta = 0.47$, $p < 0.001$) that explains 25% of the variance in teaching effectiveness. Teacher data literacy partially mediates this relationship (indirect effect: $\beta = 0.21$, 95% CI [0.15, 0.28]), highlighting the importance of teachers' skills in leveraging AI insights. Institutional AI readiness moderates the effect, with a stronger impact in high-readiness institutions ($\beta = 0.66$ at +1SD) compared to low-readiness ones ($\beta = 0.18$ at -1SD), emphasizing the role of supportive environments.

The study makes significant theoretical contributions by extending the Technology Acceptance Model (TAM), advancing Learning Analytics Theory, and applying the Technology-Organization-Person (TOP) model to the context of AI in education. Practically, it offers actionable recommendations for educators, institutions, and policymakers, including the need for data literacy training, investments in institutional readiness, and strategies for equitable AI integration. Despite its contributions, the study's limitations, such as reliance on self-reported data and a cross-sectional design, suggest areas for future research, including longitudinal studies, objective measures, and cross-cultural comparisons.

In conclusion, this study underscores the transformative potential of AI-enhanced feedback systems in education, highlighting the critical roles of teacher data literacy and institutional AI readiness in maximizing their benefits. By addressing these factors, stakeholders can harness AI's capabilities to enhance teaching effectiveness, improve student outcomes, and reimagine the educational landscape for future generations. The findings provide a roadmap for scaling AI innovations in education, ensuring that they are implemented effectively and equitably across diverse contexts.

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