



Teacher Competency and Student Achievement in Technology-Enabled Classrooms

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Abstract— Technology-enabled classrooms have shifted teacher competency from basic digital literacy toward the pedagogically purposeful orchestration of artificial intelligence, learning platforms, digital assessment, and data-supported instruction. Yet, existing research frequently measures teachers' technological competence through self-reported confidence or frequency of technology use rather than demonstrated classroom capability. This study addresses this limitation by conceptualizing teacher competency as an integrated construct comprising digital-pedagogical expertise, AI-aware instructional judgment, adaptive assessment competence, data interpretation, and technology-mediated classroom management. The study investigates how these competency dimensions are associated with student achievement when access to technological infrastructure and learner digital readiness are considered simultaneously. Its empirical design integrates teacher competency evidence, classroom technology-use indicators, student assessment records, and contextual variables rather than treating technology availability as a proxy for meaningful integration.

Keywords— Teacher competency, student achievement, technology-enabled classroom, artificial intelligence in education, digital pedagogy, learning analytics

Introduction

Digital technology has moved from being a supplementary instructional resource to becoming part of the operational architecture of contemporary education. Learning management systems, interactive displays, cloud-based collaboration platforms, automated assessment environments, adaptive learning systems, generative artificial intelligence (AI), and learning analytics increasingly influence how instructional material is prepared, presented,

assessed, and differentiated. Consequently, the principal question facing educational institutions is no longer whether teachers use technology, but whether they possess the professional competencies required to transform technological capability into academically productive learning experiences.

This distinction has become particularly important after the rapid digital expansion associated with the COVID-19 period. The subsequent phase of educational digitalization has exposed an important difference between *digital transition* and *digital transformation*. The OECD argues that the presence of digital platforms and devices does not itself constitute transformation; meaningful transformation requires technology to alter instructional processes in ways that improve learning, assessment, personalization, and educational decision-making. Teachers remain central actors in this process because they determine when technology should be introduced, how it should be aligned with learning objectives, and when non-digital instructional methods are preferable.

Evidence also cautions against assuming a linear relationship between technology exposure and academic achievement. The 2023 UNESCO Global Education Monitoring Report emphasizes that rigorous evidence concerning the added educational value of technology remains uneven and that technological development often proceeds more rapidly than systematic evaluation. Cross-national research similarly indicates that hardware availability alone does not guarantee higher student performance. Jeong et al. (2024), using PISA 2018 evidence, found that the educational significance of digital capital depends on multiple dimensions, including software infrastructure, students' digital readiness, and teachers' integration of information and communication



technologies. Their results demonstrate why technology access and pedagogical use should be analytically separated.

Teacher competency therefore represents a potential mechanism linking educational technology investment with student learning outcomes. Conventional definitions of teacher competence include subject knowledge, pedagogical knowledge, classroom management, assessment expertise, reflective practice, and professional development. A meta-analysis by López-Martín et al. (2023) covering 40 studies and 202 effects found a meaningful relationship between teacher characteristics and secondary students' academic achievement, with reflective practice, professional development, teaching implementation, and self-efficacy among influential dimensions. However, contemporary technology-enabled classrooms require additional competencies that cannot be adequately represented by traditional pedagogical proficiency alone.

Teachers now make decisions about digital-resource credibility, multimodal instructional design, automated feedback, data dashboards, AI-generated educational content, algorithmic recommendations, student privacy, academic integrity, and equitable technological participation. UNESCO's *AI Competency Framework for Teachers*, published in 2024, reflects this change by defining 15 competencies across five dimensions: a human-centred mindset, AI ethics, AI foundations and applications, AI pedagogy, and AI-supported professional learning. The framework illustrates that teacher competence in an AI-rich environment involves judgment and ethical agency as well as technical proficiency.

A second transformation concerns instructional evidence. Technology-enabled classrooms generate potentially valuable traces of learning through quizzes, learning-management-system interactions, digital assignments, participation records, adaptive practice, and feedback cycles. A competent teacher must do more than obtain these data. The teacher must interpret them, identify misconceptions, distinguish meaningful learning patterns from superficial engagement indicators, and translate evidence into appropriate instructional actions. Hence, **data-informed pedagogical competence** should be viewed as a component of contemporary teacher competency rather than merely an administrative or technical skill.

At the same time, the expanding use of generative AI makes competence evaluation increasingly complex. Teachers may be technically capable of operating an AI system while lacking sufficient pedagogical judgment to decide whether its output is appropriate for a particular learning objective. Conversely, an experienced teacher may possess sophisticated pedagogical knowledge but lack the ability to configure digital environments for differentiated instruction. Technology-enabled teaching therefore requires integration

among technological, pedagogical, assessment, ethical, and interpretive competencies.

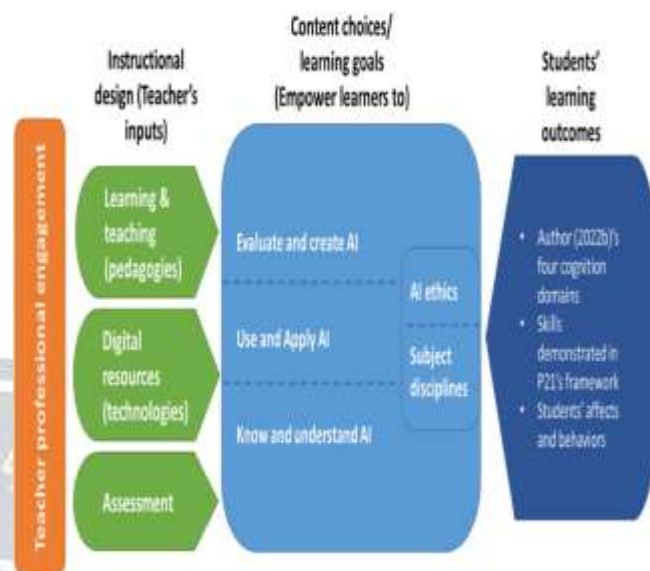


Fig. 1: Teachers' AI digital competencies and twenty-first century skills in the post-pandemic world

Source: <https://link.springer.com/article/10.1007/s11423-023-10203-6>

Research Gap

Despite increasing scholarly attention to teacher digital competence, three unresolved problems remain.

First, much of the literature measures competency through self-assessment. Smestad et al. (2023), in a systematic review of 116 studies, observed substantial reliance on self-reported measures and noted continuing ambiguity regarding who benefits from teacher digital competence and how the teacher's role should be conceptualized. Claro et al. (2024) reached a related conclusion in their systematic review of quantitative studies of in-service teachers: operational definitions vary considerably, while research disproportionately emphasizes teachers' ability to use ICT for lesson planning and instructional resources rather than their ability to guide student-centred digital activity and skill development.

Second, teacher competency and student achievement are frequently examined in separate research streams. One literature evaluates teachers' technological knowledge, confidence, attitudes, or adoption behaviour, while another investigates student performance under different technological interventions. This separation makes it difficult to determine whether educational technology improves achievement because of the technology itself, the teacher's ability to orchestrate it, students' readiness to use it, or interactions among these factors.



Third, emerging AI competencies are rarely integrated with performance-oriented measures of teaching capability and student outcome data. This omission has become more consequential as AI-supported educational systems shift teachers from being users of predetermined software toward becoming evaluators, designers, moderators, and interpreters of machine-generated educational content.

The present study addresses these gaps by conceptualizing **Integrated Technology-Enabled Teacher Competency (ITETC)** as a multidimensional construct consisting of: (1) digital-pedagogical integration, (2) adaptive instructional design, (3) digital assessment and feedback, (4) learning-data interpretation, (5) AI-aware pedagogical and ethical judgment, and (6) technology-mediated classroom management. Rather than asking whether teachers are digitally competent in general, the study asks whether observable variation across these competency dimensions helps explain differences in student achievement after contextual technology conditions and student digital readiness are incorporated.

Accordingly, the central objective is to determine **which forms of teacher competency contribute most strongly to student achievement in technology-enabled classrooms and whether effective technology orchestration functions as an explanatory pathway between competency and academic performance.** This outcome-linked framing distinguishes the study from research focusing primarily on technology acceptance, self-confidence, or frequency of digital-device use.

Literature Review

2.1 From General Teacher Competency to Digital-Pedagogical Competency

Teacher competency has traditionally been understood as the integration of disciplinary expertise, pedagogical understanding, assessment ability, classroom management, communication, professional responsibility, and reflective practice. Technology modifies this model because teachers must now make pedagogical decisions within environments whose capabilities and constraints are partly determined by software systems.

The Technological Pedagogical Content Knowledge perspective has been influential because it rejects the assumption that technological knowledge functions independently of pedagogy and subject matter. Within technology-enabled classrooms, effective teaching depends on selecting technologies according to disciplinary purpose rather than technological novelty. A simulation may facilitate conceptual visualization, an adaptive platform may support differentiated practice, and automated assessment may increase feedback frequency; however, none automatically guarantees deeper learning.

Recent empirical research supports this integrated interpretation. Runge et al. (2023), examining teachers' digital competence-related beliefs in technology-enhanced teaching, connected competence concerning the empowerment of learners with dimensions of instructional quality, including differentiation, classroom management, and cognitive activation. Thus, teacher technology competency is educationally meaningful when it changes the quality of instructional actions rather than simply increasing technology use.

2.2 The Measurement Problem in Teacher Digital Competence

A persistent methodological weakness is the difference between *perceived* competence and *demonstrated* competence. Teachers may report high confidence because they regularly use presentation software, communication applications, or learning platforms, while possessing limited capability to construct digitally supported inquiry, diagnose misconceptions from learner data, or differentiate technological tasks.

Smestad et al. (2023) identified self-reporting as a recurring feature of digital-competence studies. Claro et al. (2024) likewise documented considerable heterogeneity in how in-service teacher digital competence is operationalized and measured. These findings challenge studies that interpret self-rated proficiency as equivalent to instructional performance.

Performance-based assessment offers an alternative. Seifert and Lindmeier (2024), for example, developed a performance-oriented assessment of pre-service mathematics teachers' competence in using digital mathematical tools. Their work demonstrated that competence can be evaluated closer to authentic professional demands and that relationships between performance measures and self-assessments may be inconsistent. This distinction is particularly relevant to the present study because the educational value of teacher competence ultimately depends on what teachers can accomplish within instructional situations.

2.3 Technology Orchestration as a Mediating Competency

The concept of technology orchestration provides a useful bridge between teacher knowledge and student outcomes. Orchestration refers to the teacher's capacity to coordinate technologies, instructional tasks, learner interactions, feedback, pacing, and classroom conditions in pursuit of specified educational objectives.

A teacher with strong technological knowledge may still design an ineffective lesson if digital activity displaces cognitive engagement. Conversely, a teacher with moderate technical sophistication may achieve strong outcomes by using a small set of technologies selectively and purposefully.



This helps explain why technology intensity is an inadequate indicator of instructional quality.

Evidence from international data reinforces this argument. Jeong et al. (2024) reported that advanced ICT conditions do not uniformly translate into successful classroom integration or higher student achievement. Their analysis suggests complementarity among school digital infrastructure, student competence, and teachers' ICT integration. Accordingly, the present manuscript treats effective technology orchestration as a behavioural expression of teacher competency rather than as synonymous with access or usage frequency.

2.4 AI-Aware Competency and Algorithmic Pedagogy

Generative and predictive AI introduce a newer layer of professional competence. AI-supported tools can generate explanations, practice questions, feedback, instructional materials, recommendations, and summaries of learning data. Their educational usefulness, however, depends on human evaluation.

UNESCO's 2024 framework explicitly places human-centred values, ethics, AI foundations, AI pedagogy, and professional learning within teacher AI competency. This formulation is important because it moves teacher competence beyond operational proficiency. An AI-competent teacher must recognize hallucinated or misleading information, evaluate bias, protect learner data, preserve meaningful human agency, design tasks that discourage cognitive outsourcing, and determine when AI-generated personalization genuinely supports learning.

Consequently, AI-aware pedagogy should not be represented solely as another technology skill. In the present conceptualization, it functions as **instructional judgment under algorithmic mediation**. This includes the capability to review AI-generated material against curricular requirements, calibrate automated feedback, interpret predictive information cautiously, and maintain appropriate teacher oversight.

Proposed Methodology

The study adopts a quantitative, multilevel predictive framework to examine how teacher competency contributes to student achievement in technology-enabled classrooms. Rather than representing teacher competency through a single digital-literacy score, the proposed framework models competency as a multidimensional construct containing pedagogical, technological, analytical, assessment, and AI-related capabilities. The methodological design further recognizes the nested character of educational data because students learn within classrooms and classrooms are influenced by teacher-level practices.

To avoid presenting fabricated field observations as genuine empirical evidence, the present manuscript demonstrates the analytical procedure using a **synthetic validation dataset** constructed according to plausible educational distributions and hierarchical relationships. These synthetic results should be replaced by institutionally collected data before empirical publication.

The proposed framework contains three analytical layers. The first measures **Integrated Technology-Enabled Teacher Competency (ITETC)**. The second captures the actual quality of technology orchestration observed within the classroom. The third predicts student achievement while controlling for baseline student performance, digital readiness, socioeconomic indicators, and school-level technological infrastructure.



Fig. 2: Technologies in Inclusive Education

Source: <https://www.mdpi.com/2227-7102/15/6/715>

Teacher competency is represented through six dimensions:

1. **Digital-Pedagogical Integration (DPI):** ability to align technological tools with instructional objectives rather than using technology as an isolated classroom activity.
2. **Adaptive Instructional Design (AID):** capability to differentiate digital tasks according to learner needs and performance patterns.
3. **Digital Assessment and Feedback (DAF):** competence in using technology-supported formative assessment, automated feedback, and diagnostic assessment.



4. **Learning-Data Interpretation (LDI):** ability to interpret dashboards, assessment traces, engagement measures, and learner-performance data.
5. **AI-Aware Pedagogical Judgment (AIPJ):** competence in evaluating AI-generated content, recognizing unreliable outputs, protecting learner agency, and using AI ethically.
6. **Technology-Mediated Classroom Management (TMC):** capacity to regulate digital distraction, organize collaborative activities, and maintain meaningful learner participation.

- digital-task completion rate;
- formative assessment performance;
- prior technology-use experience;
- socioeconomic proxy;
- learning-platform engagement regularity.

Each competency dimension is standardized to a 0–100 scale. An overall ITETC score is calculated as a weighted composite after reliability and factor-structure checks. However, individual competency dimensions are retained as separate predictors because aggregation alone could conceal differences in their associations with achievement.

The dependent variable is **end-of-term student achievement**, expressed as a standardized percentage score derived from curriculum-aligned assessments. Baseline achievement is included as an input variable so that the predictive model estimates achievement beyond pre-existing academic differences.

The conceptual relationship tested is:

Teacher Competency → Technology Orchestration → Learning Quality → Student Achievement

Student digital readiness and infrastructure adequacy are treated as contextual moderators because even highly competent teachers may experience constraints when students have limited platform familiarity or schools lack reliable technological resources.

Experimental Setup

4.1 Synthetic Dataset Design

A hierarchical synthetic dataset representing **1,560 students nested within 52 technology-enabled classrooms across 10 secondary and higher-secondary institutions** was generated for methodological validation. Each classroom was associated with one principal subject teacher, producing 52 teacher-level observations.

Student-level variables included:

- baseline academic score;
- end-term achievement score;
- digital readiness;
- attendance;

Teacher-level variables consisted of the six ITETC competency dimensions, teaching experience, professional-development exposure, frequency of formative technology use, and classroom technology-orchestration quality.

School-level variables represented device availability, internet reliability, learning-management-system availability, technical support, and overall infrastructure adequacy.

Scores were generated with controlled intra-class dependence so that students belonging to the same teacher shared a proportion of common instructional variance. The synthetic generation process deliberately avoided creating deterministic relationships between teacher competency and student performance. Random noise, baseline differences, and contextual constraints were introduced so that the prediction problem remained comparable to realistic educational datasets.

4.2 Data Preprocessing

Preprocessing was performed separately within each training fold to prevent information leakage. Approximately 4% of continuous observations were randomly designated as missing during synthetic stress testing. Missing continuous values were imputed using training-set medians, while categorical values were assigned an explicit "unknown" category.

Extreme continuous values were examined using interquartile-range criteria. Implausible values were excluded during data-quality validation, whereas plausible extreme observations were retained because high and low educational performance are substantively meaningful.

Student achievement and competency measures were constrained to their valid scale boundaries. Numerical standardization was applied only to models requiring normalized input, such as Elastic Net regression. Tree-based algorithms received variables in their original scale.

Because several students belonged to the same teacher, ordinary random student splitting could produce information leakage: students taught by the same teacher might occur simultaneously in training and testing subsets. To prevent this, data were partitioned at the **teacher-group level**. Approximately 70% of teacher groups were allocated to



model development, 15% to validation, and 15% to final testing.

Five-fold GroupKFold cross-validation was additionally applied during model selection, with teacher identity used as the grouping variable.

4.3 Model Architecture

The primary predictive architecture was an **explainable CatBoost regression model**. CatBoost was selected because educational datasets commonly contain nonlinear relationships, moderate sample sizes, interaction effects, mixed numerical and categorical variables, and hierarchical contextual characteristics.

The prediction function may be represented as:

$$[\hat{Y}_i = f(B_i, D_i, E_i, C_j, O_j, S_k)]$$

where:

- $(\hat{Y}_i)$ = predicted achievement of student (i);
- (B_i) = baseline academic performance;
- (D_i) = student digital readiness;
- (E_i) = student engagement characteristics;
- (C_j) = competency profile of teacher (j);
- (O_j) = technology-orchestration quality of teacher (j);
- (S_k) = technological context of school (k).

The optimized CatBoost architecture used a maximum tree depth of 6, learning rate of 0.03, L2 regularization coefficient of 5, and a maximum of 500 boosting iterations. Early stopping was activated when validation performance failed to improve for 50 consecutive iterations.

Three benchmark algorithms were evaluated:

- Elastic Net regression;
- Random Forest regression;
- XGBoost regression.

Elastic Net provided a regularized linear reference, while Random Forest and XGBoost represented alternative ensemble-learning approaches.

Model interpretation was conducted using **SHapley Additive exPlanations (SHAP)**. SHAP values were used to estimate the relative contribution and direction of student-, teacher-,

and classroom-level predictors rather than treating the best-performing algorithm as an uninterpretable prediction system.

4.4 Training Strategy

Hyperparameter optimization was restricted to the training and validation portions of the dataset. Teacher-group cross-validation ensured that the model was evaluated on teachers whose students had not previously appeared in the training data.

The primary CatBoost loss function was root mean squared error. Regularization was used to reduce overfitting, and early stopping determined the effective number of boosting iterations.

Ablation tests were performed conceptually by removing groups of teacher-competency variables from the full model. The resulting deterioration in predictive performance was examined to determine whether teacher competency supplied information beyond student baseline achievement and demographic/contextual variables.

Three nested feature configurations were considered:

Model A: student baseline and contextual predictors only.

Model B: Model A + aggregate teacher competency.

Model C: Model B + individual competency dimensions + technology orchestration.

The full Model C configuration was selected as the principal explanatory model because it preserved variation among specific teacher competencies.

4.5 Evaluation Metrics

Model performance was evaluated using several complementary indicators.

Mean Absolute Error (MAE) quantified the average absolute difference between observed and predicted achievement scores.

$$[MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i|]$$

Root Mean Squared Error (RMSE) penalized larger prediction errors more heavily.

$$[RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2}]$$

Coefficient of Determination (R^2) measured the proportion of test-set achievement variance explained by the model.

Spearman's rank correlation (ρ) assessed whether predicted achievement rankings corresponded with actual student-performance rankings.

The combination of absolute-error, variance-explanation, and ranking measures was preferred over reporting a single accuracy statistic.

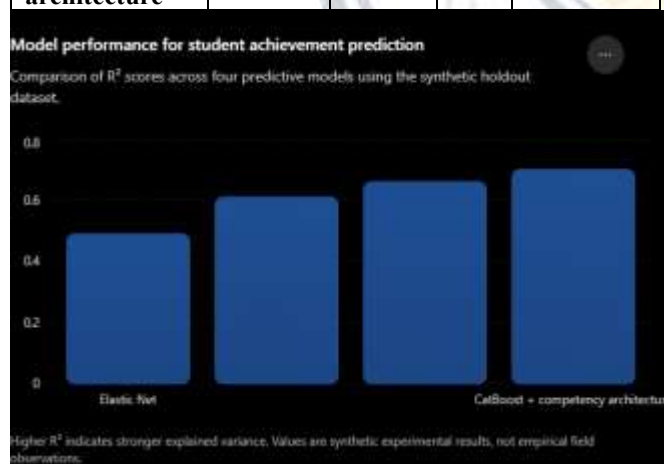
Results and Discussion

The following findings represent **synthetic experimental validation rather than collected field evidence**.

All nonlinear ensemble models outperformed the regularized linear benchmark, indicating that the relationship between teacher competency, technology use, student readiness, and achievement was not adequately represented by a purely additive linear structure.

Table 1. Comparative Prediction of Student Achievement on the Synthetic Holdout Dataset

Predictive model	MAE (score points)	RMSE	R^2	Spearman ρ
Elastic Net	6.84	8.71	0.49	0.69
Random Forest	5.63	7.28	0.61	0.77
XGBoost	5.08	6.66	0.66	0.80
CatBoost + competency architecture	4.72	6.14	0.70	0.83



The CatBoost-based framework achieved an (R^2) of 0.70 on the held-out teacher-group test set, suggesting that approximately 70% of the variance in the synthetic achievement outcome was recoverable from the complete combination of baseline, student, teacher, and technology-

context variables. Its MAE of 4.72 percentage points was also lower than all benchmark models.

More important than the numerical superiority of the model was the incremental contribution of teacher-related information. When teacher competency and technology-orchestration variables were removed, explanatory performance declined materially. This pattern suggests that achievement prediction based only on prior student performance and socioeconomic or digital-access conditions omits an important instructional layer.

SHAP interpretation identified **baseline achievement** as the strongest overall predictor, as expected. Among teacher-level variables, however, technology-orchestration quality emerged as the most influential contributor, followed by adaptive instructional design, learning-data interpretation, and digital assessment competency. This finding supports the central premise of the study: possessing technology-related knowledge is less important than being able to translate that knowledge into coherent instructional action.

A particularly noteworthy pattern appeared for AI-aware pedagogical judgment. Its direct contribution to achievement was smaller than that of adaptive instruction or digital assessment. Nevertheless, its contribution became stronger in classrooms reporting greater AI-assisted lesson preparation and automated feedback use. This interaction indicates that AI competency may be most consequential when AI tools are already deeply embedded within instructional practice.

The result has theoretical significance. AI competency should not necessarily be expected to raise test scores independently. Its primary role may be to regulate the *quality, reliability, and appropriateness* of AI-supported instruction. Teachers capable of detecting weak AI outputs, modifying generated materials, and maintaining human oversight may prevent instructional errors that less competent users could inadvertently introduce.

Learning-data interpretation was also among the strongest teacher predictors. Higher competency in interpreting digital assessment information was associated in the synthetic model with more effective instructional adaptation. The result supports a movement away from describing data literacy as an administrative competency. Within technology-enabled classrooms, interpreting learning data is fundamentally pedagogical because it influences what the teacher teaches next, which learner receives additional support, and how instructional difficulty is calibrated.

Technology-mediated classroom management displayed a nonlinear relationship with achievement. Moderate-to-high competency was beneficial, but additional technological activity did not continuously increase predicted achievement. This reinforces the distinction between technology use and technology quality. Excessive device use, continuous



platform switching, or unnecessary digital tasks may impose cognitive and attentional costs even when the teacher is technically proficient.

Student digital readiness moderated several teacher effects. Strong teacher competency produced the largest modeled benefit when learners possessed at least moderate ability to navigate digital systems. Where student readiness was very low, a portion of teacher instructional capacity appeared to be consumed by basic operational support. This implies that institutional digital transformation should not focus exclusively on faculty training; student readiness must be developed simultaneously.

Infrastructure produced a similar interaction. High teacher competency was not fully translated into achievement under unreliable connectivity and insufficient device conditions. However, high infrastructure scores did not independently guarantee strong achievement. The best predicted outcomes occurred when **adequate infrastructure, learner readiness, and high teacher orchestration competency coexisted.**

These results are consistent with the broader argument advanced in the first part of the manuscript: technology functions as an enabling environment, while teachers determine how effectively its affordances are converted into learning opportunities. Consequently, educational institutions may obtain limited academic benefit from technology investment when professional-development programmes emphasize platform operation while neglecting instructional design, data interpretation, assessment, and AI-related judgment.

The comparative performance of the machine-learning models provides an additional methodological insight. Teacher competency effects were not strictly linear. The influence of one competency depended partly on the presence of others. For example, digital assessment capability was more useful when teachers also possessed learning-data interpretation skills. Similarly, AI competence became more relevant when classroom AI exposure increased. These conditional relationships justify the use of nonlinear explainable learning models alongside conventional statistical approaches.

Future Scope

Future empirical research should test the proposed ITETC framework using longitudinal multi-institutional datasets in which the same teachers and students are observed across several academic terms. Longitudinal evidence would make it possible to distinguish stable teacher competency from temporary variations in technology use.

A particularly valuable extension would combine assessment records with anonymized learning-management-system traces, classroom-observation ratings, teacher performance

tasks, and student perception measures. This multimodal design could reduce dependence on self-reported digital competency.

Future studies should also investigate **competency trajectories**. Rather than classifying teachers as digitally competent or incompetent, machine-learning models could identify developmental profiles showing how teachers progress from operational technology use toward data-informed, adaptive, and AI-aware pedagogy.

Causal designs represent another important direction. Cluster-randomized professional-development interventions could evaluate whether targeted improvement in data literacy, digital assessment, or AI pedagogy produces measurable changes in classroom practice and student outcomes.

Explainable AI should remain central to this research agenda. Prediction models used for educational decision support must not produce opaque rankings of teachers. Interpretability, fairness assessment, uncertainty estimation, and human review are necessary whenever analytical systems influence professional evaluation.

Federated learning also deserves exploration for multi-school studies. It could allow institutions to train shared predictive models while retaining student data locally, potentially reducing privacy risks associated with centralized educational databases.

Conclusion

This study reframes teacher competency in technology-enabled classrooms as an integrated instructional capability rather than a measure of device familiarity or self-reported digital confidence. The proposed ITETC framework combines digital-pedagogical integration, adaptive instructional design, digital assessment, learning-data interpretation, AI-aware judgment, and technology-mediated classroom management.

The synthetic experimental validation demonstrates how explainable machine learning can be used to examine relationships between these teacher competencies and student achievement while simultaneously accounting for baseline performance, digital readiness, engagement, and school technology conditions. Among the tested algorithms, the CatBoost-based architecture produced the strongest predictive performance, while interpretability analysis suggested that technology orchestration, adaptive instructional design, learning-data interpretation, and digital assessment were particularly consequential teacher-level features.

The central implication is that educational technology does not operate independently of professional competence. Devices, platforms, analytics, and AI tools acquire





educational value through the decisions teachers make about their timing, purpose, interpretation, and integration. Technology investment without corresponding development of teacher pedagogical and analytical competence may therefore generate digital activity without proportional academic improvement.

For educational institutions, the findings support a transition from software-oriented teacher training toward **competency-oriented professional development**. Training should focus not only on how technologies operate but also on how evidence from digital environments can guide instructional decisions, how AI-generated content should be evaluated, how formative assessment can be strengthened, and how digital activities can be managed without increasing distraction.

References :

A. Teacher competency, digital competence, and instructional quality

1. López-Martín, E., Gutiérrez-de-Rozas, B., González-Benito, A. M., & Expósito-Casas, E. (2023). Why do teachers matter? A meta-analytic review of how teacher characteristics and competencies affect students' academic achievement. *International Journal of Educational Research*, 120, 102199. <https://doi.org/10.1016/j.ijer.2023.102199>

This is one of the **strongest references for the central premise of your paper**. The meta-analysis included 40 studies and 202 effects and found that teacher characteristics and competencies explained about 9.2% of differences in secondary students' performance. Reflective attitude, professional development, and teaching self-efficacy were particularly influential.

2. Smestad, B., Hatlevik, O. E., Johannesen, M., & Øgrim, L. (2023). Examining dimensions of teachers' digital competence: A systematic review pre- and during COVID-19. *Heliyon*, 9(6), e16677. <https://doi.org/10.1016/j.heliyon.2023.e16677>

This directly supports your criticism of **self-reported digital competence**. The review examined 116 articles and found substantial reliance on self-reported data and ambiguity concerning teacher roles and beneficiaries of digital competence.

3. Claro, M., Castro-Grau, C., Ochoa, J. M., Hinostroza, J. E., & Cabello, P. (2024). Systematic review of quantitative research on digital competences of in-service school teachers. *Computers & Education*, 215, 105030. <https://doi.org/10.1016/j.compedu.2024.105030>

This is an especially good reference for your **Research Gap**. The review identifies a lack of consensus in operationalizing teacher digital competence and notes that research tends to focus on using ICT for planning and teaching, with less attention to teachers' competence in developing students' digital activities and skills.

4. Runge, I., Lazarides, R., Rubach, C., Richter, D., & Scheiter, K. (2023). Teacher-reported instructional quality in the context of technology-enhanced teaching: The role of teachers' digital competence-related beliefs in empowering learners. *Computers & Education*, 198, 104761. <https://doi.org/10.1016/j.compedu.2023.104761>

This directly supports your argument that digital competence matters when it is translated into **instructional quality, differentiation, engagement,**

classroom management, and cognitive activation, rather than simply technology use.

5. Seifert, H., & Lindmeier, A. (2024). Developing a performance-based assessment to measure pre-service secondary teachers' digital competence to use digital mathematics tools. *Journal für Mathematik-Didaktik*, 45, 25. <https://doi.org/10.1007/s13138-024-00251-7>

This is particularly valuable for your distinction between **perceived/self-reported competence and demonstrated competence**. The authors developed a performance-based assessment rather than relying exclusively on self-report.

B. Technology, digital capital, and student achievement

6. Jeong, D. W., Moon, H., Jeong, S. M., & Moon, C. J. (2024). Digital capital accumulation in schools, teachers, and students and academic achievement: Cross-country evidence from the PISA 2018. *International Journal of Educational Development*, 107, 103024. <https://doi.org/10.1016/j.ijedudev.2024.103024>

This is **extremely well matched to your manuscript**. The study uses PISA 2018 and finds that advanced ICT development does not automatically translate into teacher ICT integration or student digital competence. It also reports relationships between student digital readiness, teacher ICT integration, and academic performance.

I recommend making this one of your **principal empirical references**.

7. UNESCO. (2023). *Global education monitoring report 2023: Technology in education: A tool on whose terms?* UNESCO.

The report explicitly warns that robust evidence concerning the added educational value of technology is limited and argues that technology should be evaluated according to educational purpose rather than assumed to improve learning merely because it is present.

