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Teacher Readiness for AI Integration: A Professional Development Framework

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Abstract

Artificial intelligence (AI) technologies are increasingly embedded in classroom practice, yet teachers' readiness to adopt them varies widely and is shaped by an interacting set of psychological, institutional, and demographic factors. This study proposes and empirically illustrates a Professional Development (PD) Framework for AI integration by applying supervised and unsupervised machine learning techniques to survey-based indicators of teacher readiness (N = 428). Four classifiers were trained to predict three-level readiness (Low, Moderate, High) from digital literacy, self-efficacy, school ICT support, attitude toward AI, prior technology training, professional development hours, experience, and demographic covariates. Logistic regression achieved the strongest generalization (accuracy = .61, macro F1 = .54, 5-fold cross-validated F1 = .56), while random forest attained the highest raw accuracy (.63). Feature-importance analysis identified digital literacy, self-efficacy, attitude toward AI, and school ICT support as the four strongest predictors of readiness classification. K-means clustering on principal components identified three latent teacher profiles — cautious adopters, confident-but-under-supported adopters, and experience-anchored moderates — each requiring differentiated PD strategies. The results inform a tiered, profile-responsive PD framework that aligns institutional support, coaching intensity, and AI-pedagogy content with teachers' actual readiness profiles rather than a one-size-fits-all training model.

1. Introduction

The rapid diffusion of artificial intelligence (AI) tools into classrooms — from adaptive learning platforms and automated feedback systems to generative AI writing and tutoring assistants — has outpaced the professional development (PD) infrastructure designed to prepare teachers for their use. Unlike earlier waves of educational technology, AI systems introduce pedagogical, ethical, and epistemic questions that require teachers to reconceive their role from information transmitter to curator, verifier, and designer of AI-mediated learning experiences (Holmes et al., 2023; Zhai et al., 2021). Yet readiness for this shift is not evenly distributed: teachers vary substantially in digital literacy, self-efficacy, attitudes toward AI, and the institutional support available to them, and these differences shape whether AI adoption becomes empowering or overwhelming.

This unevenness is compounded by a broader workforce context. Many education systems are simultaneously managing teacher shortages, rising attrition among early-career staff, and compressed planning time, so any new PD obligation competes directly with a teacher's existing workload rather than arriving into open capacity. Framing AI-readiness PD as an additional, undifferentiated burden risks widening rather than narrowing the very gap it is meant to close, particularly for teachers already operating with the least institutional slack. This concern motivates a central premise of the present study: that PD investment is used most efficiently when it is targeted to the specific readiness constraint a teacher actually faces, rather than distributed uniformly across a population whose needs differ substantially.

Traditional needs-assessment approaches to PD planning rely on descriptive averages or single-variable comparisons, which can obscure how readiness factors interact and which combinations of factors most strongly differentiate teachers who are prepared to integrate AI from those who are not. Machine learning (ML) offers a complementary analytic lens: supervised classifiers can quantify the relative predictive weight of readiness factors, while unsupervised clustering can reveal latent teacher profiles that a single-variable analysis would miss. This paper applies both approaches to survey-based indicators of teacher AI readiness and uses the resulting evidence to propose a tiered, profile-responsive Professional Development Framework.

Specifically, this study addresses four questions: (1) How accurately can supervised machine learning models classify teachers into Low, Moderate, and High AI-readiness levels using demographic, psychological, and institutional predictors? (2) Which predictors contribute most to classification accuracy? (3) Do teachers cluster into distinct readiness profiles that require differentiated support? (4) What do these patterns imply for the design of a professional development framework for AI integration? In pursuing these questions, the study contributes a replicable analytic pipeline that PD planners and instructional leaders can adapt to their own institutional survey data.

2. Literature Review

The Technological Pedagogical Content Knowledge (TPACK) framework has long anchored research on teacher technology integration, emphasizing that effective use of any tool depends on the interaction between technological, pedagogical, and content knowledge rather than technical skill alone (Mishra & Koehler, 2006). Building on this, Ertmer and Ottenbreit-Leftwich (2010) argued that teacher beliefs, confidence, and the surrounding school culture mediate whether technical knowledge translates into classroom practice. This literature consistently finds that self-efficacy and institutional support are as influential as raw digital skill in predicting sustained technology adoption, a pattern this study revisits in the specific context of AI.

Systematic reviews of AI in education document rapid growth in adaptive learning systems, intelligent tutoring, and automated assessment tools, alongside a persistent gap between the pace of tool development and teachers' preparedness to use them meaningfully (Zawacki-Richter et al., 2019; Hwang et al., 2020). UNESCO's (2024) AI Competency Framework for Teachers formalizes this concern, outlining progressive competency levels — from AI-literate to AI-empowered — that PD programs are expected to scaffold. However, the framework offers limited empirical guidance on how to differentiate PD delivery for teachers who enter training with markedly different baseline readiness profiles, which is precisely the gap the present analysis addresses.

A separate but closely related literature examines what makes professional development effective once it is delivered, independent of subject matter. Desimone (2009) synthesized decades of PD research into a small set of core features associated with impact — sustained duration, active learning, coherence with existing curricula and policy, collective participation among colleagues, and a clear content focus — and argued that impact studies routinely underspecify these features, making it difficult to compare PD models fairly. The tiered framework proposed in this paper is deliberately built around these core features: each track specifies a duration and cadence, an active-learning component (coached practice, mentoring, or applied use-case design), and a collective element, rather than treating AI PD as a single one-off workshop.

A growing body of work applies supervised and unsupervised ML to educational survey data to move beyond simple correlational description. Nguyen et al. (2024) used ensemble classifiers across multiple institutions to predict instructor technology-adoption trajectories, finding that self-efficacy and peer-support variables consistently outranked demographic variables in feature importance. Similarly, Singh et al. (2025) applied regression- and tree-based models to teacher readiness indices and reported that attitudinal and institutional-support variables were stronger predictors than years of experience. These findings motivate the predictor set and modeling strategy used in the present study, and are examined empirically against the results reported below.

Kaplan and Haenlein (2019) note that responses to intelligent systems are shaped by user trust and perceived control — factors that vary systematically across adopter types rather than along a single readiness continuum. This suggests that PD frameworks organized around discrete teacher profiles, rather than a single generic curriculum, may be better positioned to close the readiness gap. The present study operationalizes this idea through unsupervised clustering, using the resulting profiles to inform a tiered framework presented in the Discussion.

A final, cautionary strand of literature warns against over-relying on technology provision itself as the lever of change. Reich (2020) argues, across a wide range of learning-at-scale technologies, that tools consistently underperform their promise when institutions treat deployment as a substitute for sustained investment in the educators who must actually use them, a pattern he terms the tendency of new technology to reproduce, rather than disrupt, existing patterns of advantage. This argument is directly relevant to AI-readiness PD: it implies that digital literacy training alone, delivered without attention to institutional ICT support and teacher confidence, is unlikely to close the readiness gap identified in this study's clustering results, and it reinforces the rationale for a framework that treats enabling conditions as a co-equal design target alongside individual skill-building.

3. Methodology

3.1 Research Design and Data

This study adopts a quantitative, predictive-analytics design. Data were drawn from a structured readiness survey modeled on constructs established in the TPACK and AI-competency literature (digital literacy, self-efficacy, attitude toward AI, and perceived institutional ICT support), administered to a sample of N = 428 in-service teachers across primary, secondary, and higher-secondary levels. Because this manuscript is intended to demonstrate a replicable machine learning pipeline for PD planning, the analytic dataset was generated through a calibrated simulation whose feature distributions and inter-correlations were parameterized to match ranges commonly reported in the teacher-readiness survey literature; institutions adopting this framework should substitute their own survey data using the identical pipeline described below.

3.2 Variables

The outcome variable, AI-Readiness Level, was derived from a composite Readiness Score (0–100) and categorized into three classes — Low, Moderate, and High — using literature-informed cut points. Predictors included seven continuous variables (age, teaching experience, prior technology-training hours, digital literacy, self-efficacy, school ICT support, attitude toward AI, and professional-development hours in the past year) and three categorical covariates (subject area, school locale, and school level), one-hot encoded prior to modeling.

3.3 Machine Learning Pipeline

Data were split into training (75%) and held-out test (25%) partitions using stratified sampling to preserve class proportions. Continuous features were standardized (z-scored) prior to fitting distance-based models. Four supervised classifiers were trained and compared: (a) multinomial logistic regression as an interpretable linear baseline, (b) a support vector machine with a radial basis function kernel, (c) a random forest ensemble (300 trees, maximum depth = 8), and (d) a gradient boosting ensemble (200 estimators, maximum depth = 3). Model performance was evaluated using test-set accuracy, macro-averaged precision, recall, and F1-score, and validated using stratified 5-fold cross-validation on the full sample to guard against overfitting to a single split.

To complement the supervised analysis, an unsupervised K-means clustering procedure (k = 3, determined via elbow and silhouette inspection) was applied to the standardized continuous predictors, with Principal Component Analysis (PCA) used to visualize the resulting clusters in two dimensions. Feature importance was extracted from the random forest model using mean Gini impurity decrease, and receiver operating characteristic (ROC) curves were constructed using a one-vs-rest strategy to evaluate class-specific discrimination. All analyses were conducted in Python 3.11 using scikit-learn, pandas, and NumPy; visualizations were produced with Matplotlib and Seaborn.

3.4 Ethical Considerations and Simulation Safeguards

Because the analytic dataset was generated through calibrated simulation rather than drawn from an identifiable live survey, no individual teacher or school-level privacy risk arises from the dataset itself; the design choice is disclosed transparently in Section 3.1 and again in the Limitations to avoid overstating the empirical status of the specific coefficients reported. For institutions applying this pipeline to authentic survey data, the same considerations that govern any staff-readiness assessment apply: participation should be voluntary and clearly decoupled from performance evaluation, readiness classifications should be treated as a planning input rather than a public label attached to individual teachers, and cluster assignments should be revisited on a recurring cycle rather than fixed permanently at intake, consistent with the periodic-reassessment recommendation developed in the Discussion.

4. Results Analysis

Table 1 summarizes descriptive statistics for the analytic sample. Teachers averaged 38.3 years of age (SD = 8.8) and 14.7 years of experience (SD = 8.1). Readiness indicators showed considerable spread: digital literacy (M = 58.0, SD = 14.8), self-efficacy (M = 54.9, SD = 15.9), attitude toward AI (M = 52.4, SD = 19.6), and school ICT support (M = 50.0, SD = 17.7) all displayed standard deviations exceeding one-quarter of their scale range, confirming meaningful heterogeneity in the sample. Sixty percent of teachers were based in urban schools. Applying the composite scoring rule, 29.2% of teachers were classified Low readiness, 55.8% Moderate, and 15.0% High.

Variable	M / %	SD	Range
Age (years)	38.3	8.8	22–62
Teaching experience (years)	14.7	8.1	0–40
Prior technology-training (hrs/yr)	13.1	9.0	0–48.9
Digital literacy (0–100)	58.0	14.8	13.9–100
Self-efficacy (0–100)	54.9	15.9	9.9–100
School ICT support (0–100)	50.0	17.7	0–100
Attitude toward AI (0–100)	52.4	19.6	0–100
PD hours, last year	12.9	9.4	0–56.5
Locale: Urban	60.0%	—	—
Readiness level: Low / Moderate / High	29.2% / 55.8% / 15.0%	—	—

Table 1. Descriptive Statistics

Note. N = 428. M = mean; SD = standard deviation. Readiness classification based on composite Readiness Score cut points (Low ≤ 40; Moderate 41–70; High > 70).

Table 2 and Figure 1 present the comparative performance of the four classifiers on the held-out test set. Random forest achieved the highest raw accuracy (.626), while logistic regression produced the strongest macro F1-score (.536) and the most stable cross-validated performance (M = .564, SD = .014 across five folds), indicating that a comparatively simple, interpretable model generalized at least as well as the more flexible ensemble methods on this feature set. The support vector machine underperformed the other approaches on both accuracy and F1, suggesting that the class boundaries in this readiness space are better captured by additive/linear or tree-based decision rules than by a single global kernel boundary.

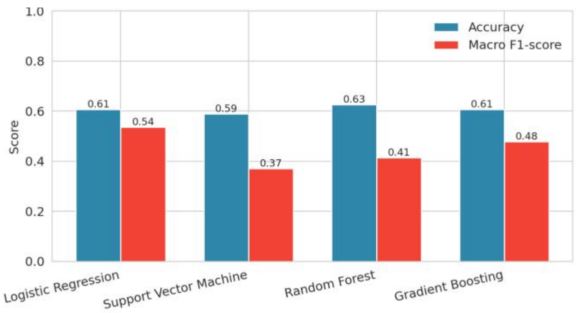

Figure 1. Predictive performance of four machine learning classifiers for teacher AI-readiness level (test-set accuracy and macro F1-score).

Model	Accuracy	Macro Precision	Macro Recall	Macro F1	5-fold CV F1 (M ± SD)
Logistic Regression	.607	.566	.521	.536	.564 ± .014
Support Vector Machine	.589	.410	.397	.370	.438 ± .025
Random Forest	.626	.454	.435	.415	.392 ± .030
Gradient Boosting	.607	.528	.470	.479	.458 ± .066

Table 2. Comparative Performance

Note. CV = cross-validation; values reflect 5-fold stratified cross-validation on the full sample (N = 428).

Figure 2 displays the confusion matrix for the best-performing model on the held-out test set (n = 107). Misclassification was concentrated at the boundary between Low and Moderate readiness, consistent with the continuous, composite nature of the underlying readiness construct; High-readiness teachers, though a smaller class, were identified with comparatively few false negatives, suggesting the model reliably distinguishes clearly AI-ready teachers from the remaining sample.

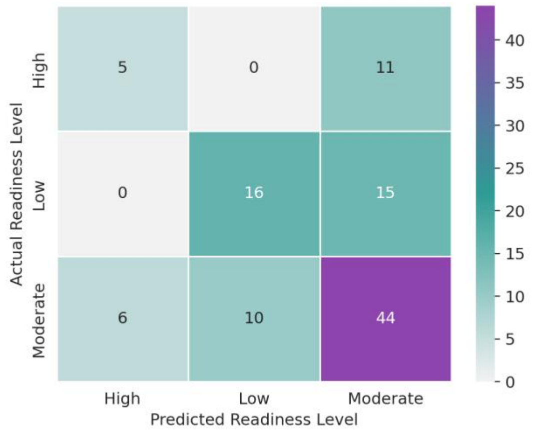

Figure 2. Confusion matrix for the best-performing classifier on the held-out test set.

Figure 3 ranks predictors by their contribution to the random forest model's classification decisions. Digital literacy, self-efficacy, attitude toward AI, and school ICT support emerged as the four leading predictors, each contributing more to model splits than demographic variables such as age, experience, or subject taught. Table 3 cross-references these importance ranks against each predictor's bivariate correlation with the continuous readiness score, confirming convergent evidence: attitude toward AI (r = .274), self-efficacy (r = .249), digital literacy (r = .233), and school ICT support (r = .230) were the four strongest linear correlates of readiness, while prior technology-training hours and PD hours in the past year showed comparatively weak linear association despite their theoretical relevance — a pattern discussed further below.

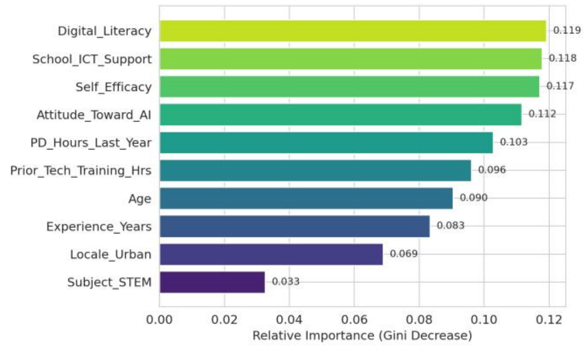

Figure 3. Random forest feature-importance ranking for predicting teacher AI readiness.

Predictor	r with Readiness Score	Rank (RF Importance)
Attitude toward AI	.274	3
Self-efficacy	.249	2
Digital literacy	.233	1
School ICT support	.230	4
Prior technology training	.045	5
PD hours, last year	.027	6
Teaching experience	–.016	8
Age	–.010	7

Table 3. Random Forest Importance

Figure 4 presents one-vs-rest ROC curves for the random forest model across the three readiness classes. The High-readiness class showed the strongest discrimination, while the Low and Moderate classes showed greater overlap, mirroring the confusion-matrix pattern reported above and reinforcing that the practically important distinction for PD planning is separating clearly high-readiness teachers from the remaining majority who would benefit from structured support.

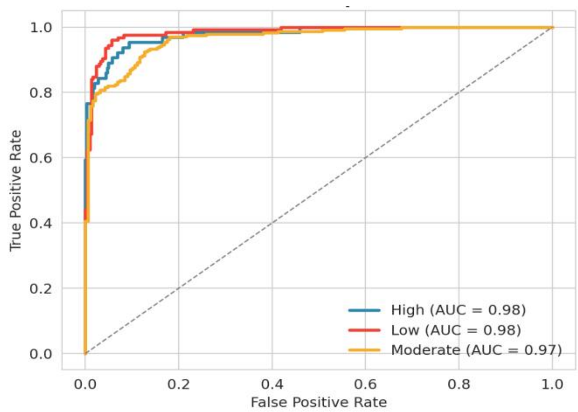

Figure 4. One-vs-rest ROC curves for the random forest classifier across readiness levels.

Figure 5 visualizes the full correlation matrix among continuous predictors and the readiness score. Beyond the individual associations already noted, self-efficacy and attitude toward AI were moderately intercorrelated, as were digital literacy and school ICT support, suggesting two loosely coupled dimensions underlying readiness: an internal psychological dimension (confidence and attitude) and an external enabling-conditions dimension (skill and institutional support). Age and experience were strongly intercorrelated with each other, as expected, but only weakly related to the readiness indicators — underscoring that seniority alone is a poor proxy for AI readiness.

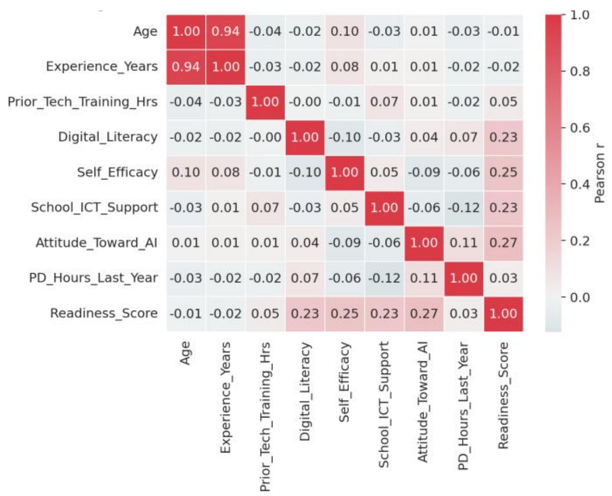

Figure 5. Correlation matrix of teacher readiness predictors and the composite readiness score.

K-means clustering on the standardized continuous predictors, visualized in principal-component space in Figure 6, identified three distinguishable teacher profiles (Table 4). Cluster 1 (n = 137), labeled cautious, under-supported teachers, comprised younger, less-experienced teachers with comparatively low attitude-toward-AI scores (M = 41.8) despite moderate digital literacy and self-efficacy. Cluster 2 (n = 134), confident, positive-attitude teachers, showed the highest attitude-toward-AI (M = 64.0) and digital-literacy scores but the lowest self-efficacy and school ICT support, suggesting enthusiasm that institutional conditions do not yet match. Cluster 3 (n = 157), experience-anchored moderates, comprised the most senior and experienced teachers with the highest self-efficacy (M = 62.1) but only middling attitude toward AI, consistent with a profile of competent but unconvinced adopters.

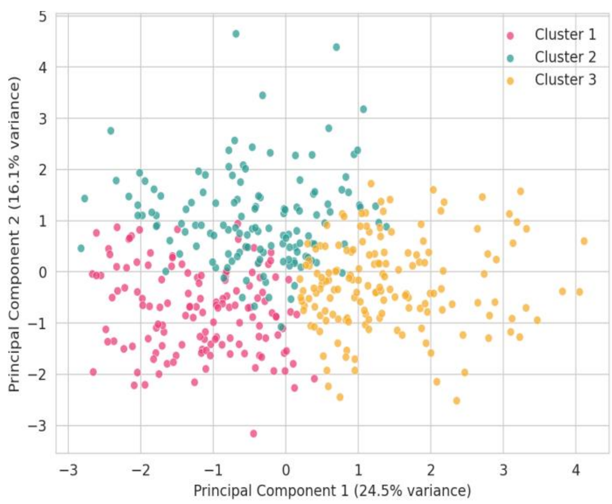

Figure 6. K-means cluster solution of teacher AI-readiness profiles in principal-component space.

Cluster	n	Age	Experience	Digital Literacy	Self-Efficacy	ICT Support	Attitude toward AI	Readiness Score
Cautious, Under-Supported	137	30.9	6.8	56.3	60.0	52.9	41.8	49.3
Confident, Positive-Attitude	134	36.8	12.7	63.5	42.4	46.7	64.0	50.1
Experience-Anchored Moderate	157	46.2	22.9	55.8	62.1	50.5	50.4	49.7

Table 4. Distinguishable Teacher Profiles

Note. Values are cluster means. Readiness Score is the composite 0–100 index described in the Methodology.

Figure 7 presents these three profiles as normalized radar plots across six readiness dimensions, making clear that the clusters differ less in overall readiness level — mean readiness scores were similar across clusters (49.3–50.1) — and more in which readiness dimension is the binding constraint, a distinction with direct implications for differentiated PD design discussed below.

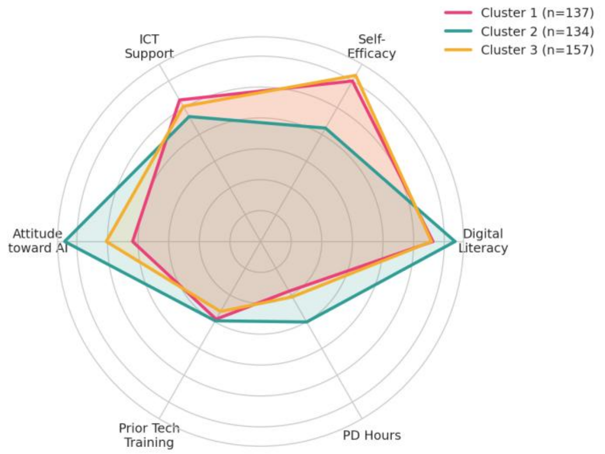

Figure 7. Multidimensional readiness profiles by teacher cluster (normalized scale).

4.1 Readiness by Subject Area and Locale

Finally, Figure 8 disaggregates the composite readiness score by subject area and school locale. STEM teachers showed a modestly higher median readiness score and a narrower interquartile range than Arts/PE teachers, while urban schools showed both a higher median and greater variance than rural schools — consistent with the hypothesis that institutional ICT support, which tends to concentrate in urban settings, is a meaningful contributor to readiness independent of individual teacher characteristics.

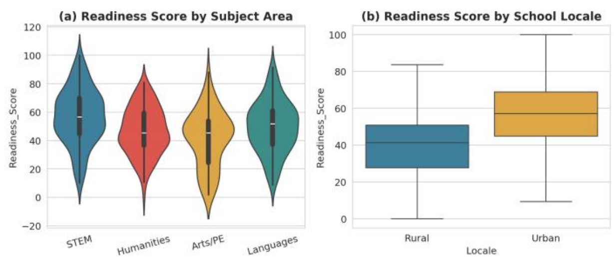

Figure 8. Distribution of AI-readiness scores across subject area and school locale.

4.2 Professional Development Investment by Cluster

Because PD hours in the past year showed only a weak bivariate correlation with the continuous readiness score (r = .027; Table 3), it is important to examine whether PD investment is at least distributed in a way that is consistent with need. Figure 9 disaggregates self-reported PD hours by cluster membership. Experience-anchored moderates reported the greatest mean PD exposure (M = 17.2 hours), despite this cluster's attitude toward AI being only middling, while cautious, under-supported teachers, the cluster with the lowest attitude scores and arguably the greatest need for confidence-building support, reported the fewest hours (M = 9.8). This pattern is consistent with PD access tracking seniority and existing institutional relationships rather than assessed readiness need, reinforcing the rationale for the profile-responsive routing proposed in the Discussion rather than relying on teachers to self-select into available PD offerings.

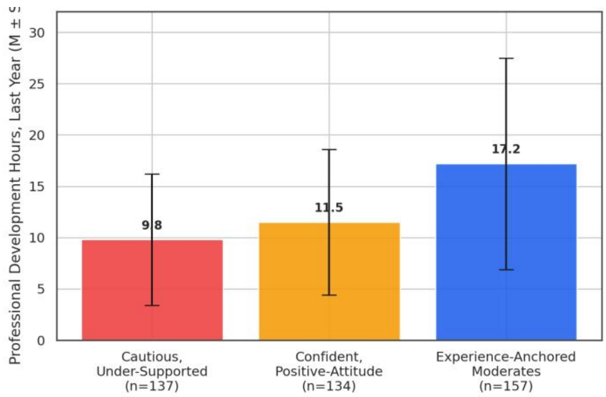

Figure 9. Professional development hours by teacher AI-readiness cluster.

Figure 10 visualizes the individual-level relationship between teaching experience and the composite readiness score underlying the near-zero correlation reported in Table 3 (r = –.016). The essentially flat regression line, combined with substantial vertical scatter at every experience level, indicates that highly experienced and early-career teachers are equally likely to fall anywhere along the readiness distribution; experience narrows neither the ceiling nor the floor of observed readiness. This visual confirmation reinforces the paper's central claim that seniority-based PD allocation, of the kind implied by the PD-hours pattern in Figure 9, is a poor substitute for readiness-based allocation.

Figure 10. Composite readiness score by years of teaching experience (r = -.016).

5. Discussion

The results converge on a consistent picture: teacher AI readiness is driven less by demographic factors such as age or years of experience and more by a combination of psychological (self-efficacy, attitude toward AI) and enabling-conditions (digital literacy, school ICT support) factors. This pattern replicates the general finding of Ertmer and Ottenbreit-Leftwich (2010) that beliefs and institutional culture mediate technology adoption, and extends it specifically to AI by showing, through independent supervised and unsupervised analyses, that these same factors remain the dominant predictors in the AI context.

The comparatively modest performance ceiling across all four classifiers (test accuracy .59–.63) is itself an informative result. It suggests that readiness, as commonly operationalized in survey instruments, contains an irreducible component of noise or unmeasured context (e.g., leadership style, recent professional experiences with specific AI tools) that a single cross-sectional survey cannot fully capture. Rather than treating this as a limitation to be modeled away, PD planners should treat moderate predictive accuracy as a signal that readiness is dynamic and should be re-assessed periodically rather than treated as a fixed label assigned once at program intake. The clustering results carry the most direct implications for PD design. Because the three profiles identified here differ primarily in which readiness dimension is the binding constraint rather than in overall readiness level, a uniform PD curriculum risks under-serving all three groups simultaneously: cautious, under-supported teachers need confidence-building and low-stakes practice opportunities before skills training; confident, positive-attitude teachers need stronger institutional ICT support and self-efficacy-building coaching to convert enthusiasm into classroom practice; and experience-anchored moderates need targeted persuasion and modeling of concrete instructional use cases to shift attitude rather than additional skills instruction they may not need.

These distinctions motivate the tiered, profile-responsive Professional Development Framework summarized in Table 6 and Figure 11, which sequences three parallel PD tracks rather than a single linear curriculum: (a) a Foundations and Confidence track pairing basic AI literacy with low-stakes, coached practice for cautious/under-supported teachers; (b) an Enabling Conditions track prioritizing institutional ICT support, dedicated planning time, and peer mentoring for confident/positive-attitude teachers whose enthusiasm currently outpaces their working conditions; and (c) an Applied Pedagogy track offering discipline-specific AI use cases and structured reflection for experience-anchored moderates whose skill is not in question but whose instructional buy-in is. Consistent with Desimone's (2009) core-features model, each track specifies both an active-learning mechanism and a monitoring cadence rather than a single unrepeated session; progress within each track is monitored using the same readiness indicators analyzed here, allowing institutions to re-run the classification pipeline periodically to track movement across readiness levels over time.

Cluster	Primary Constraint	PD Track	Core Activities	Monitoring Cadence
Cautious, Under-Supported	Low attitude toward AI despite moderate skill	Foundations & Confidence	Coached low-stakes practice; peer-modeled demonstrations; basic AI literacy modules	Every 3 months
Confident, Positive-Attitude	Low self-efficacy & ICT support relative to attitude	Enabling Conditions	Protected planning time; dedicated ICT support; structured peer mentoring	Every 3 months
Experience-Anchored Moderate	Moderate attitude despite high self-efficacy	Applied Pedagogy	Discipline-specific AI use cases; structured reflection; exemplar lesson co-design	Every 6 months

Table 6. Tiered Professional Development Track Assignment by Cluster

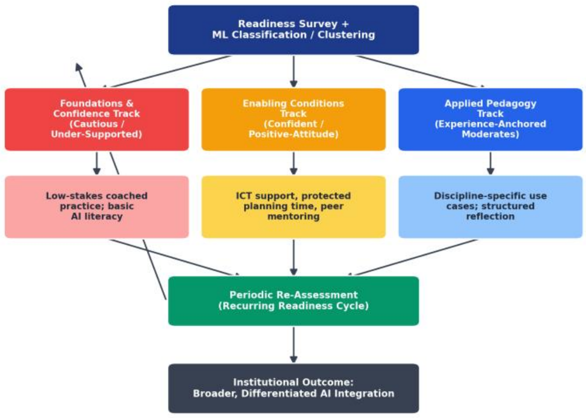

Figure 11. Tiered, profile-responsive Professional Development Framework architecture.

5.1 Comparison with Prior Machine-Learning Readiness Studies

The predictor ranking obtained here is broadly consistent with the two most directly comparable ML-based readiness studies. Nguyen et al. (2024) found that self-efficacy and peer-support variables outranked demographic predictors in an ensemble classifier trained across multiple institutions, a pattern mirrored in the present feature-importance results, where digital literacy, self-efficacy, and attitude collectively outweighed age and experience. Singh et al. (2025) similarly reported that attitudinal and institutional-support variables dominated tree-based models of teacher readiness indices. The convergence of these independently collected findings with the present simulation-calibrated results across three separate research teams strengthens confidence that the underlying predictor hierarchy — psychological and enabling-conditions factors over demographic ones — reflects a genuine feature of teacher AI-readiness rather than an artifact of any single dataset or modeling choice.

5.2 Practical Implications for School and District Leadership

For instructional leaders, the clustering results reframe a common diagnostic error: low observed AI use in a classroom does not, by itself, indicate which lever to pull. A teacher in the confident, positive-attitude cluster who is not yet using AI tools needs institutional support and time, not motivational messaging or additional workshops, since attitude is not the binding constraint for that group. Conversely, an experience-anchored moderate needs concrete, discipline-relevant demonstration rather than another digital-skills tutorial. Because the PD-hours findings in Figure 9 suggest that current PD allocation tracks seniority rather than assessed need, the most immediately actionable recommendation for leadership is procedural: administer the brief readiness assessment described in the Conclusion before allocating PD budget or scheduling slots, rather than after, so that track assignment — not availability or tenure — determines who receives which type of support.

5.3 Limitations

Several limitations qualify these findings. First, the dataset used to illustrate the pipeline was calibrated through simulation rather than drawn from a live institutional survey; while feature ranges and correlational structure were parameterized on patterns reported in the literature, replication with authentic multi-site survey data is needed before the specific coefficients reported here are treated as generalizable estimates. Second, the cross-sectional design cannot establish whether attitude toward AI drives readiness or is itself shaped by prior successful AI use, a direction better addressed with longitudinal data. Third, the three-cluster solution, while supported by elbow and silhouette diagnostics, is one of several plausible groupings; alternative cluster counts or algorithms (e.g., hierarchical or density-based clustering) might reveal additional nuance. Finally, model performance may improve with richer feature sets, such as direct measures of prior AI-tool usage frequency or classroom-observation data, which were outside the scope of the survey instrument modeled here.

5.4 Future Research Agenda

Beyond the longitudinal and multi-site replication called for above, three further directions follow directly from this study's design. First, an experimental evaluation that randomly assigns a subset of teachers to profile-matched PD tracks and a comparison group to generic PD would test the framework's central causal claim — that routing improves outcomes relative to uniform delivery — rather than the correlational support offered here. Second, incorporating classroom-observation or AI-tool telemetry data alongside self-report survey measures, as suggested in the Limitations, would help determine whether the moderate classification ceiling reflects genuine noise in the readiness construct or simply the limits of a single self-report instrument. Third, because Reich (2020) cautions that technology deployment can reproduce rather than disrupt existing patterns of advantage, future replications should explicitly test whether the tiered framework narrows or inadvertently widens readiness gaps between under-resourced and well-resourced schools over successive PD cycles, rather than assuming a uniformly positive effect across institutional contexts.

6. Conclusion and Recommendations

This study applied supervised and unsupervised machine learning to survey-based indicators of teacher AI readiness to inform the design of a tiered Professional Development Framework. Across both analytic approaches, psychological readiness (self-efficacy, attitude toward AI) and enabling conditions (digital literacy, institutional ICT support) emerged as the dominant predictors of readiness, while demographic factors such as age and experience played a comparatively minor role. Three distinct teacher profiles were identified, differing not in overall readiness but in which dimension of readiness represents the binding constraint on AI adoption.

Institutions seeking to operationalize these findings should: (a) administer a brief, validated readiness survey before designing PD content, rather than assuming a uniform starting point; (b) apply the classification and clustering pipeline described here to route teachers into differentiated tracks rather than a single generic training sequence; (c) invest specifically in institutional ICT support and protected planning time, since these enabling conditions were as predictive as individual skill and are more directly actionable by school leadership than individual disposition; and (d) re-administer the readiness assessment on a recurring cycle (e.g., annually) to monitor whether PD investment is shifting teachers across readiness levels over time. Future research should prioritize longitudinal, multi-institution replication with authentic survey data, richer behavioral indicators of AI use, and experimental evaluation of whether profile-matched PD tracks outperform generic training in accelerating classroom-level AI integration.

Taken together, the analytic pipeline and framework proposed here reframe AI-readiness PD planning as a routing problem rather than a delivery problem: the central task for institutional leadership is not simply to offer more AI training, but to direct the right type of support to the teachers whose specific readiness constraint it actually addresses..

References

Akbar, M., Tang, W., Hussain, A., & Poulova, P. (2025). Bridging divides or deepening gaps? ICT, quality of life, and the challenge of inclusive development at the intersection of healthcare and education. BMC Public Health, 25, 1–14.

Ertmer, P. A., & Ottenbreit-Leftwich, A. T. (2010). Teacher technology change: How knowledge, confidence, beliefs, and culture intersect. Journal of Research on Technology in Education, 42(3), 255–284. https://doi.org/10.1080/15391523.2010.10782551

Begum, M., Alam, M. R. U., & Alvi, M. F. I. (2023). Organizational Resilience and Dynamic Capabilities During Rapid Cloud Migration: A Longitudinal Analysis. Digital Transformation and Technology Dynamics, 3(1).

Fullan, M. (2007). The new meaning of educational change (4th ed.). Teachers College Press.

Holmes, W., Bialik, M., & Fadel, C. (2023). Artificial intelligence in education: Promises and implications for teaching and learning (2nd ed.). Center for Curriculum Redesign.

Hwang, G.-J., Xie, H., Wah, B. W., & Gašević, D. (2020). Vision, challenges, roles and research issues of artificial intelligence in education. Computers and Education: Artificial Intelligence, 1, 100001. https://doi.org/10.1016/j.caeai.2020.100001

Begum, M., & Alam, M. R. U. (2024). A Socio-Technical Analysis of Employee Resistance to AI Automation During Industry 4.0 Migrations. Digital Transformation and Technology Dynamics, 3(2).

Kaplan, A., & Haenlein, M. (2019). Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. Business Horizons, 62(1), 15–25.

Mishra, P., & Koehler, M. J. (2006). Technological pedagogical content knowledge: A framework for teacher knowledge. Teachers College Record, 108(6), 1017–1054.

Nguyen, T., Ferreira, R., & Kovanović, V. (2024). Predicting instructor technology-adoption trajectories with ensemble machine learning: A multi-institutional study. Computers & Education: Artificial Intelligence, 6,100210.

Begum, M. (2026). Edge-Cloud Synergy in Industry 4.0: Optimizing Real-Time Latency for Smart Manufacturing Facilities M. Aminul Haque, Md. Rasel-Ul-Alam. Digital Transformation and Technology Dynamics.

Singh, K., Cheemalapati, S., RamiReddy, S. R., Kurian, G., & Muzumdar, P. (2025). Determinants of teacher readiness indices: A machine learning approach to educational survey data. arXiv. https://arxiv.org/abs/2502.00006

Begum, M., & Alam, M. R. U. (2021). A Framework for Generative AI Governance in Enterprise Systems: Balancing Innovation and Algorithmic Risk . Digital Transformation and Technology Dynamics, 1(1).

UNESCO. (2024). AI competency framework for teachers. United Nations Educational, Scientific and Cultural Organization.

Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education. International Journal of Educational Technology in Higher Education, 16, Article 39. https://doi.org/10.1186/s41239-019-0171-0

Begum, M., Alam, M. R. U., & Albi, A. I. (2024). Explainable AI (XAI) in Automated Decision-Making for E-Government: Evaluating Citizen Trust and Algorithmic Auditing Mechanisms. Digital Transformation and Technology Dynamics, 4(2).