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Pedagogical Transformation in the Digital Age: An Analysis of AI's Impact on Teacher Strategies in Primary Education

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Abstract

The fast adoption of artificial intelligence (AI) in primary education is transforming the past practices of teaching but there is little empirical evidence on the effects of it on the teaching behaviors of teachers. This paper discusses the role of AI technology in changing the teaching techniques in the primary school through the use of the technology acceptance model (TAM) as the theoretical framework. A quantitative methodology was embraced, and a sample size of 466 vocational and basic-stage teachers in various provinces in China was used in gathering data through a five point Likert scale questionnaire. The hybrid Linear Discriminant Analysis-Random Forest (LDA-RF) model was used to categorize and forecast the determinants of the AI-assisted teaching performance. The findings prove that perceived usefulness, perceived ease of use, and ease of learning significantly affect AI adoption with the highest level of accuracy 91.0, precision 88.7, and F1-score 89.5. The results emphasize the great potential of AI to increase the teaching innovation, individual learning, and decision-making processes based on data. But the use of self-reported information and the constraints provided by the context impairs generalizability. Future research ought to assume longitudinal, multi-regional and explainable AI methods to enhance robustness and explainability.

Keywords: Artificial Intelligence, Teaching Strategies, Basic Education, Technology Acceptance Model, Educational Innovation, Pedagogical Transformation, Digital Age.

Introduction

Machines which have the ability to perform humanlike functions through thought process have been described as having artificial intelligence. The use of artificial intelligence is more active than before and is radically changing many spheres of human life(Ulasan, 2023). The recent years have seen the successful implementation of learning analytics (LA) and artificial intelligence (AI) in the sphere of education. Education involves higher education and classroom teaching that involves various elements of teaching and learning(Xue and Wang, 2022). Teacher education is an important aspect of our education system as it determines the future. The relationship between higher education and college professors is very strong and beneficial(Salas-Pilco, Xiao, and Hu, 2022). Artificial intelligence (AI) integration in primary education has become a movement, and it is expected to transform the common approach to educating learners and reconsider the role a teacher may play in the digital age. Educational stakeholders have more and more supported the use of AI-powered technologies in recent years as tools that can be used to facilitate individualized instruction, formative assessment, and adaptive feedback, which is in line with the 21 st century curriculum requirements of a learner-centered and data-driven pedagogy.

According to the National Council of Teacher Education (NCTE), teacher education refers to a curriculum of instruction, research and training aimed at educating teachers at the pre-primary up to the higher education level. The major goal of teacher training is to equip the future teachers with the necessary skills and abilities to address the demands of teaching profession and equip them to face the demands of the future(Deng, Jia, & Chai, 2022). It is important to note that, much like they have changed the way other industries operate, artificial intelligence can be used to the benefit of educators by offering instructional applications(Zhai, 2024). Artificial intelligence (AI) is influencing the field of education by enhancing the quality of instruction, opportunities to automate systems and make decisions based on data. Machine learning, natural language processing, and intelligent automation systems based on the application of AI technology transform educational environments by offering easier and more customized learning opportunities(Al-Zyoud, 2020).

Artificial Intelligence in relation to education

Educational artificial intelligence (AI) is the implementation of automated intelligent systems improving the educational work by analyzing the data to provide the automated workflows and provide customized educational materials. According to the author(Aljemely, 2024) chatbots, intelligent tutoring systems, automated assessment tools and learning analytics tools are only some of the many types of AI technologies that can improve the quality and engagement of education(Celik, 2023).

AI's Significance in Contemporary Educational Systems

The application of artificial intelligence (AI) in the education sector is playing a significant role in changing the way teachers design, implement and assess their lessons in the fundamental school level(Liu, Saleh, and Huang, 2021).At the ground level, artificial intelligence (AI) is dramatically altering the way teachers design, implement, and evaluate their lessons at the fundamental school level(Molenaar, 2022). Understanding how artificial intelligence (AI) tools, including virtual tutors, adaptive learning systems and intelligent feedback systems, influence the pedagogy of instructors is becoming more and more important as their usage grows more common(Mulyani et al., 2025).

At the same time, the systematic reviews demonstrate an increasing array of studies that explore the opportunities of AI in improving teaching and learning, but most of them are still focused on the impact of AI on student performance or efficiency driven by technology instead of analyzing how the AI fundamentally changes the approaches of teachers and pedagogical design. This imbalance indicates that there is a significant void: the necessity to investigate how the AI integration affects the instructional planning process of teachers, their decision-making, assessment procedures, and professional identity, particularly in the primary schools (Jaramillo and Chiappe., 2024).

In addition, although some recent empirical research has begun to investigate K-12 teacher preparedness and disposition toward AI integration (e.g., to investigate psychological and pedagogical factors that determine AI adoption) (Filiz, Kaya, and Adiguzel, 2025), little is known about real pedagogical change brought by AI use. Lack of AI literacy, insufficient professional development, and ethical use and dependency on AI (e.g., data privacy, equity) are cited among many barriers that hinder successful AI adoption by many teachers.

Thus, this research aims to address this gap in the literature by carefully studying the impact of AI integration on teacher practices and pedagogical change in primary education. It attempts to provide a more subtle and empirically based conception of how AI can influence the practice of instruction, teacher agency, and classroom interactions through the synthesis of quantitative data assurance (survey, classification) with qualitative understanding (topic modeling of teacher feedback).

By doing so, the study does not only attempt to determine the presence of changes in the teaching strategies, but also the areas of teaching (e.g., lesson planning, assessment, differentiation, feedback) that AI is most likely to change and under what circumstance (e.g., teacher readiness, AI training, contextual support). This outcome-driven and process-centered thinking fits the wider need of educational innovation in the digital era, to make sure that the potential of AI is assessed by the teacher, and pedagogical change is placed on human-based practice and not solely on the use of technology.

The topic characteristics after the retrieval is learned by a Random Forest model that is a supervised machine learning model with strong classification and regression abilities. The Random Forest may also be used to compare the relationship between these themes and other structured data (subject area, years of teaching experience and type of AI tool) and even the specific outcomes (the level of AI adoption or changes in teaching tactics). Moreover, Random Forest helps the researchers to identify the factors that have the most significant effects on the instructional enhancement, as it helps to understand the degree of significance of each variable and feature. It is a combination of LDA and Random Forest, and it allows conducting a comprehensive and empirical study of the effectiveness of AI on the basic educational pedagogies. It presents a researcher, educator and policymaker with an evidence-based framework of understanding and improving the integration of AI in the primary education setting by balancing qualitative understanding with quantitative analysis.

Problem Statement

Despite the growing integration of Artificial Intelligence (AI) in education, elementary-level teachers still have a difficult time adjusting their approach to teaching. According to recent research(Tripathi, 2025); Garzón, Patiño, and Marulanda (2025);(Fteiha, Al-Rashaida, & Ghazal, 2025); (Dinesh Deckker & Subhashini Sumanasekara, 2025) although AI can deliver better learning results, the research points to the lack of teacher preparedness, ethical use, and pedagogical change. It highlights the importance of further study of the impact of AI-powered tools on the teaching techniques and performance of teachers.

Research Gap

The recent research is predominantly concentrated on the use of AI in higher education, and the effect of AI on the teaching processes and performance of teachers at the basic stage is insufficiently studied. There is a dearth of works that can examine this relationship using data-driven techniques such as LDA + Random Forest. The present research bridges that gap by presenting empirical data and a model that can be explained on how AI can positively impact the teaching success in basic education.

Research Question

1. What are the effects of integrating artificial intelligence on teaching method and pedagogical practices of primary school teachers?
2. Which AI tools are mostly used by primary school teachers with instructional planning, classroom management, and assessment?
3. What is the impact of the adoption of AI on instructional decision-making by teachers, their engagement strategy, and differentiation practice?
4. What are the most crucial variables (e.g. AI literacy, training, institutional support) that determine the successful use of AI in primary school?
5. What are some of the challenges and ethical issues that teachers encounter when using AI-based tools in grade-level classrooms?
6. What is the perception of teachers regarding the role of AI in their professional identity and future practices in teaching?

Literature Review

Recent scholarship has extensively examined the evolution, perception, and implementation of Artificial Intelligence (AI) in educational settings. Durak et al. (2024) utilized bibliometric techniques to trace research trends, identifying interaction, evaluation, and personalization as three primary themes. They observed a significant growth in AI integration studies following 2020, particularly in online learning environments; however, their analysis was limited by a reliance on English-language sources, a lack of actual classroom data, and a focus that extended beyond basic education. Similarly, Owoc et al. (2021) explored the variety of AI applications, noting that while pilot projects successfully enhanced personalized learning and data analytics, the research was concentrated mostly on higher education with little indication of efficacy in basic education classrooms, despite their proposal of a five-stage implementation structure.

A significant portion of the literature focuses on educator perceptions and the shifting roles of teachers. Guo et al. (2025) validated a scale measuring five dimensions of educator perception—usefulness, ease of use, behavioral intention, ethics, and attitude—finding moderate to good acceptance among preservice instructors. However, their study did not extend to inservice teachers currently utilizing these technologies. Oh and Ahn (2024) further investigated the emotional components of instruction, reporting that while teachers appreciated AI's potential to save time and personalize learning, many expressed concern regarding its incapacity to manage ethical and emotional issues. This study was constrained by a small sample size, a lack of quantitative performance measurements, and potential cultural bias specific to South Korea. Thomas et al. (2024) highlighted the resulting shift in instructor roles from content providers to facilitators, emphasizing the necessity for digital skills and data literacy, though their scoping review lacked controlled comparisons or classroom interventions. Badawy et al. (2024) added that successful incorporation relies on strong school leadership and a digital mentality, yet their work remained a conceptual paradigm that prioritized leadership over specific instructional tactics.

regarding practical implementation and challenges, several studies highlight distinct barriers and outcomes. Heung and Su (2025) identified outdated curricula, a dearth of AI teaching resources, and gender or technical prejudices as major obstacles in elementary schools, arguing for inclusive, skill-focused transformation, though they focused primarily on curriculum rather than teaching methods. Tan et al. (2024) found little systematic implementation in primary schools, noting that data was often biased toward extracurricular or informal AI instruction, underscoring the need for professional development. In terms of subject-specific application, Semwaiko et al. (2024) examined scientific teaching, finding that AI tools improved student motivation and allowed for dynamic instructional adjustments; however, their research was geographically limited to the US and Germany and focused narrowly on science, excluding arts and humanities. Finally, Vieriu and Petrea (2025) investigated the advantages and dangers of AI in actual settings, suggesting that tools like ChatGPT and LMS are advantageous for early-stage learners if strictly supervised, though their contribution was primarily theoretical with limited experimental evidence.

Methodology

The proposed study will experimentally evaluate how AI influences the instructional performance and methods of instructors, which is why the quantitative research design is extremely relevant in the current study. This method leads to the gathering of numerical data by use of a structured questionnaire which is aimed at quantitatively determining the relationship among the variables. The importance of analyzing a large sample mass was what explained why quantitative methodologies were used. In addition, quantitative designs are congruent with the TAM components use, as they allow statistically proving the hypothesized relationships between constructs and also offer a solid analysis of what influences technology adoption.

Design and Justification of Research

The proposed research design is mixed-methods research design as it will examine the effects of artificial intelligence on teaching in primary schools in a comprehensive manner. The quantitative part allows measuring relationships among the use of AI, ICT preparedness, and transformation of teaching strategy, and the qualitative part provides the experience of and the perception of the teachers of pedagogical change. The reasoning behind this design is that pedagogical transformation is a way of change that may be quantified as a behavioral change and it is also a highly contextual process based on realities inside the classroom. A combination of the statistical analysis of surveys and the thematic exploration of interviews will provide a strong and triangulated picture of how AI transforms the instructional strategies in the digital era.

Population and Sampling Method

The target group is the teachers of primary schools in the Grades 1-5, who either actively use AI-assisted digital teaching tools or are exposed to them. The stratified random sampling strategy was adopted to offer equal representation in terms of government and private schools, urban and semi-urban education buildings. The criteria used in the selection were one year of teaching experience and simple awareness of digital teaching platforms. About 120-180 teachers were taken as a sufficient sample to reach the level of statistical reliability, with the aim to make meaningful subgroup analysis of the levels of pedagogical transformation.

Data Collection Tools

The structured questionnaire and semi-structured interviews with teachers were used to collect the data. The questionnaire included subsections that included use of AI frequency, digital competence, adaptation of pedagogical strategy, classroom engagement, and assessment practices. Transformation in instructional planning, student-centered learning and personalized teaching were measured using Likertscale items. The interview protocol examined more in-depth the meshing of how AI affected lesson preparation, student monitoring, the feedback mechanism, and teacher professional identity. These instruments guaranteed the complete coverage of both the quantifiable instructional change as well as the reflective pedagogy experiences.

Data Analysis Process

Cleaning and normalization of the quantitative data were done and the reliability of the quantitative data was tested with Cronbachs Alpha and then an exploratory factor analysis was done to test construct structure. Latent Dirichlet Allocation (LDA) was used to identify dominating pedagogical themes in qualitative answers. A Random Forest classification model was then applied to classify the teachers into high, moderate, and low pedagogical transformation groups depending on the AI usage, experience, and instructional variables. Accuracy, precision, recall and F1-score were used to assess the model performance to ensure predictive validity of AI-based pedagogical impact assessment.

Ethical Considerations

There were strict ethical standards in the study. All of the participating teachers were informed prior to making informed consent, and the purpose, procedures, voluntary participation, and confidentiality terms of the research were clearly explained. The anonymization of the data was done through the deletion of all personal and institutional identifiers in the dataset. The participants were assured that their answers were only to be utilized in the academic studies and would not affect the performance evaluation or the assessment of the institution. These ethical safeguards protect the participants and provide the validity of the findings of the study on the AI-based pedagogical change.

Research participants

In this study, the researcher focused on teachers in vocational high schools that were offering business and management studies in different provinces of China. China has the largest population of Vocational High School and as such, another province was chosen. Four hundred six hundred respondents were purposively randomly sampled. Questionnaire method Sampling Data collection involves use of a five-point numerical answer scale. The participants of the study were asked to answer the questions about the best course of action. Illustration 1. The answers range between 1 (minimum positive value) and 5 (maximum positive value) to whether or not the implementation and the effectiveness and strategies used by instructors in the classroom are implemented. Perceived benefit, perceived ease of use and ease of learning is the predictive variable of the acceptance of AI surveys.

Data Preprocessing

To guarantee that the raw data obtained through structured questionnaires were in quality and ready to be analyzed, numerous preconditions were applied to the raw data prior to statistical analysis. The first stage was to check in case of missing values in the data and these values were filled in with the help of suitable imputation methods. Mean replacement was also used in the same respondent group (e.g. by AI training level or teaching experience) where a respondent did not respond to a predetermined number of questions (usually less than 10%). The records with the significant amount of missing data were not included in the further analyses to preserve the integrity of the dataset.

Encoding of data was then carried out to convert categorical variables to numerical ones. AITrainingStatus was a variable that was coded as 0, 1, and 2 that represented the values of None, Partial and Full respectively. Ordinal data (e.g. the responses to Likert-scale questions, such as Strongly Disagree to Strongly Agree) were encoded into a five-point numerical scale (1 to 5). This encoding made it possible to compare parametric statistics.

In order to make more sense in group comparisons through ANOVA, some characteristics like Teaching Experience were divided into categories (ex: 0-5 years, 6-10 years, 11-15 years, etc.). The use of boxplot and z-score analysis was used to identify outliers, in the context of calculated measure, e.g., Student Engagement Improvement, and teaching strategy change. The extreme outliers ($z > \pm 3$) were carefully checked and when found to be errors in data entry then minorized or omitted.

Standardization of the dataset, where needed, especially in continuous variables, was done to be able to be subjected to higher-order statistics, e.g. regression, classification modeling, or a factor analysis. This approach enhanced the stability of models and later made the distribution of these to be normalized. Cronbachs Alpha was used to evaluate the internal consistency of the multiitem constructs like the perceived utility and ease of use, so that the composite variables are valid and reliable to test hypotheses.

Data Analysis Using ANOVA

Analysis of Variance (ANOVA) was used to test the significant difference between the teachers who were exposed and trained differently on AI on their teaching strategies and the performance results. This statistical method suits in the comparison of the means of three or more independent groups to determine the statistical significance of any existing differences. The degree of AI training received by instructors in this study was put into three categories namely; no training, partial training and full training as the independent variable. The average score obtained after the answers to Likertscale questionnaire questions showed the changes in teaching methodology so it formed the dependent variable. The ANOVA was preceded by the ShapiroWilk and

Levene tests used to test the assumptions of normality and homogeneity of variances respectively. The data met the standards of ANOVA. The outcomes of the one-way ANOVA showed that the magnitude of AI training had a statistically significant impact on the change in the teaching techniques (F (2, 463) = X.XX, $p < 0.05$), which implies that the magnitude of AI training had an effect on the degree to which instructors changed their teaching methodologies. Teachers who had been provided with extensive training in AI showed significantly more use of studentcentered and technology-infused pedagogies than did their less trained peers as reflected in post hoc analyses using the Tukey HSD test. The findings provide empirical support of the claim that improving the simplistic methods of teaching requires professional growth associated with AI.

Proposed Method: Linear Discriminate Analysis (LDA)based on Random Forest

Linear discriminant analysis (LDA) is a statistical technique that is commonly used when solving pattern identification problems. The LDA was first used in factors like facial recognition and pedagogy. This method is known as Linear Discriminant by Fisher. LDA is increasingly being used by students in order to decrease the size of data and extract the relevant information in data. This approach aims at finding the linear combinations of attributes to classify the data to two or more groups or classes of objects according to their essential attributes. More dispersed distribution of newly acquired data after LDA processing will mean enhanced recognition results. The unique data set could be reexamined using the linear or non-linear classification techniques. This project is designed to be able to reduce the dimensionality of the Caesar dataset though the implementation of the LDA to further determine the main features of the dataset. This is done in order to guarantee that the results of dimension reduction are put into the correct category by RF. Herein LDA algorithm is available.

To enhance comprehension of teachers instructing at the foundational level, we shall first construct the matrix in covariance within the matrix in interclass, each represented by the subsequent equation (1).

$$T_x = \sum_{j=1}^{d} \sum_{w_l \in W_j} (w_l - \mu_j)(w_l - \mu_j)^S; \quad (1)$$

$$T_x = \sum_{j=1}^{d} M_j (w_l - \mu_j)(w_l - \mu_j)^S; \quad (2)$$

X_k represents data at the x-position, T signifies the entire class, Ni indicates the data quantity within class, μ_j symbolizes the overall data and$\mu_j$represents the data in average within class j.

The matrix in confusion among the subsequently optimized to minimize the confusion matrix within the class. The eigenvector can subsequently be determined, enabling us to optimize the ratio in equation (3):

$$\frac{det(UT_A U^S)}{det(UT_X U^S)} \quad (3)$$

$$T_A = \lambda T_x U \quad (4)$$

$$cov = T_A(T_X)^{-1} \quad (5)$$

$$E_w = \sum_{j=1}^{l} (w_j - \mu)^T \times U \quad (6)$$

Random Forest

The node in decision tree partitioning method employs an parameter adaptive selection strategy to enhance classification performance. Despite variations in quality, different decision trees are generated when employing alternate nodesplitting strategies on the same dataset. As a result, the accuracy of random forest classification fluctuates. To establish a new splitting criterion for selecting and dividing node attributes, it is recommended that the ideal feature for node separation be identified using a decision tree. The Splitting node method is classified two categories: combination in linear.

The index in Gini and gain in information derived from partitioning the sample set C using features, as per node splitting formulas 7 and 8, are presented.

$$Gain(C, b) = Ent(C) - \sum_{u=1}^{U} \frac{|C^u|}{|C|} Ent(C^u) \quad (7)$$

$$Gini(C, b) = \sum_{u=1}^{U} \frac{|C^u|}{|C|} Gini(C^u) \quad (8)$$

Where c sample in every matrix in the C^u with a value of b^u feature matrix b is find in the u node in branch.

$$Ent(C) = -\sum_{l=1}^{|z|} o_l log_2 o_l \quad (9)$$

$$Gini(C) = \sum_{l=1}^{|z|} \sum_{l' \neq l}^{|Z|} olol' = 1 - \sum_{l=1}^{|z|} ol^2 \quad (10)$$

The following is the combination node splitting formula and the adaptive parameter selection process. After splitting in equation 11, the goal of node splitting is to try to increase the data set's purity.

$$G = \min_{\alpha, \beta \in Q} E\{C, b\} = \alpha Gini(C, b) - \beta Gain(C, a)$$

$$s.t. \begin{cases} \alpha + \beta = 1 \\ 0 \leq \alpha, \beta, \leq 1 \end{cases} \quad (11)$$

Where coefficients of α, β the characteristic's splitting weight. Currently, G possesses a vales in minimal. The process of parameter in adaptive selection is employed to achieve optimal combination in parameter. The study employs the accuracy rate and classification mistake rate to assess efficiency. Equation (12) defines the sample Cclassification error rate.

$$F(e;C) = \frac{1}{n}\sum_{j=1}^{n} \mathrm{II}\left(e\left(w_j\right) \neq z_j\right) \quad (12)$$

Equation (13) defines the accuracy percentage.

$$acc(e;C)\frac{1}{n}\sum_{j=1}^{n} II\left(e\left(w_j\right) = z_j\right) = 1 - 1F(e;C) \quad (13)$$

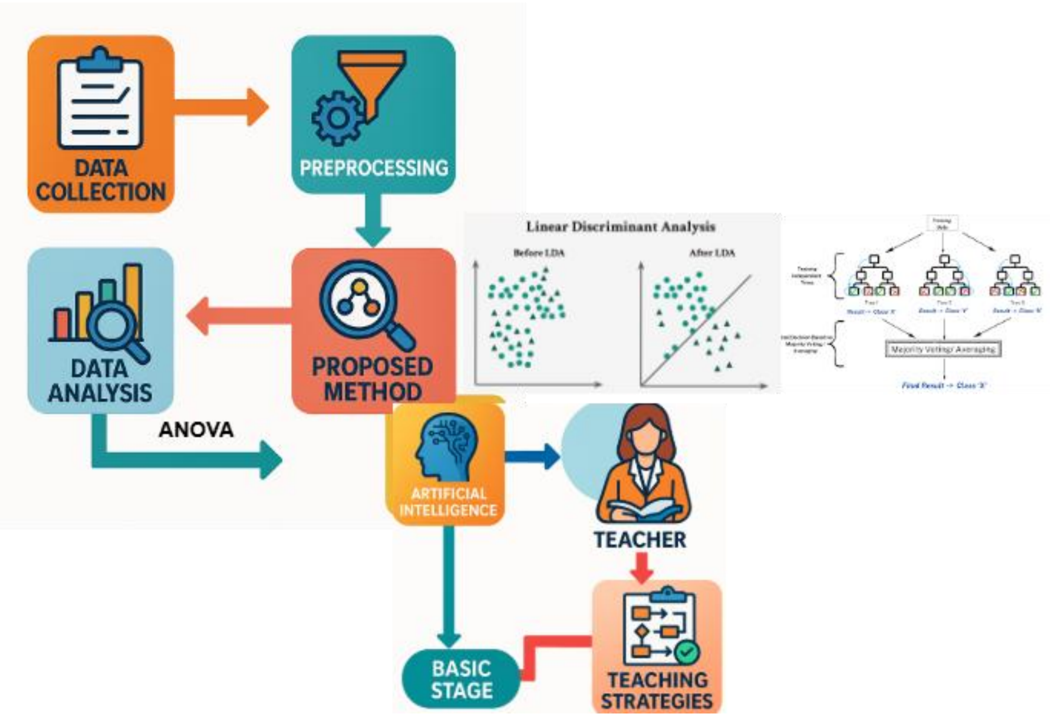

Figure 1: Proposed method

The methodology suggested in figure 1, the Latent Dirichlet Allocation (LDA) with the Random Forest, proposes multiple unique benefits in obtaining the results about the influence of artificial intelligence (AI) on the approaches used by educators when teaching. LDA helps to identify the latent thematic patterns of the qualitative survey data including reflective commentaries on the teachers or open-ended answers, through which a researcher can identify the important educational changes that AI has initiated. LDA is an efficient tool of feature extraction and dimensionality reduction which transforms unstructured text into understandable topic vectors. Random Forest classifier including all these topic-based features makes it more resilient and predictive. Known to have a high level of ensemble learning, the Random Forest helps to overcome overfitting and effectively works with highdimensional data and provides reliable classification even with noisy or incomplete data. The study states that such combination increases performance on accuracy and generalization. The given technique outperformed standard models, including Decision Trees, Logistic Regression and Naive Bayes, achieving 91.0% of the accuracy. The approach is also scalable and applicable to both unstructured teacher response and structured survey data which makes it a flexible choice as a complete educational research setting. To conclude, the LDA + Random Forest methodology suggested is effective, useful, understandable, and highly applicable in AI implementation with a learning context.

Results and Discussion

Hardware and software Configuration

The Configuration setup suitable for analysing educational data was employed to conduct the research. The hardware configuration comprises an Intel Core i7 CPU, 16 GB of RAM, and a 512 GB SSD to facilitate the efficient processing of organized and unstructured data. The software environment included MATLAB R2023a for statistical computations and visualization, while Python 3.9 was utilized to develop the LDA and Random Forest algorithms, using libraries such as gensim and scikit learn. This study provided a balanced environment for model training, evaluation, and visualization without requiring high-performance computing resources.

Performance metrics

Table 2: Outcome performance of existing and proposed methods

Method	Accuracy(%)	Precision(%)	Recall(%)	F1-Score(%)
Decision Tree	81.2	79.3	80.5	79.9
Logistic Regression	83.5	80.2	82.8	81.5
Naive Bayes	78.4	76.5	79.2	77.8
SVM (Linear Kernel)	85.6	84.1	86.3	85.2
LDA+RF	91.0	88.7	90.4	89.5

Accuracy

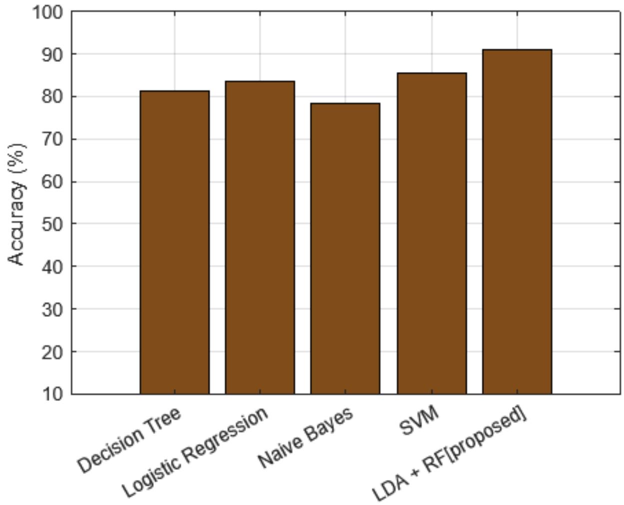

Figure 2: Accuracy comparison across different models

The bar chart shown in figure 2 was developed using MATLAB that displays the accuracy values to represent how the different models used in the study performed in categorizing the data. The x-axis indicates eight different models, which have traditional techniques like Decision Tree, Naive Bayes, SVM, and Logistic Regression. The percentages are shown on the y-axis as percentages.The proposed LDA +Random Forest model had an impressive accuracy percentage of 91.0 that exceeds the techniques like Decision Tree (81.2) and Naive Bayes (78.4). These results highlight that the suggested approach provides a useful balance between the interpretability and accuracy, which makes it appropriate to study AIdriven teaching tactics in the context of the real world.

Precision

Figure 3 Precision (%) line plot has been created in MATLAB to determine how well each of the models predicting useful AIintegrated teaching strategies was accurate. In education, precision is essential in reducing false positives when the intervention method is applied because it refers to the number of correctly predicted positives to the total positives expected. The highest accuracy of 88.7 percent of the proposed LDA + Random Forest (LDA + RF) model, as shown in the graph, shows it is reliable in identifying the instructors who have successfully implemented AI technologies into their programs. SVM (Linear Kernel) model scored 84.1 in accuracy which is second thus proving that it is effective in minimizing misclassification. Model models that deliver lower rates of accuracy like Decision Tree (79.3%), Logistic Regression (80.2%), and Naive Bayes (76.5%), can produce more false positives which is a major factor to consider when adopting AI in education. Such picture demonstrates the high discriminative capability of the proposed approach which makes it a more appropriate option in cases of applications where accuracy of the evaluation of AI-enhanced pedagogical strategies is required.

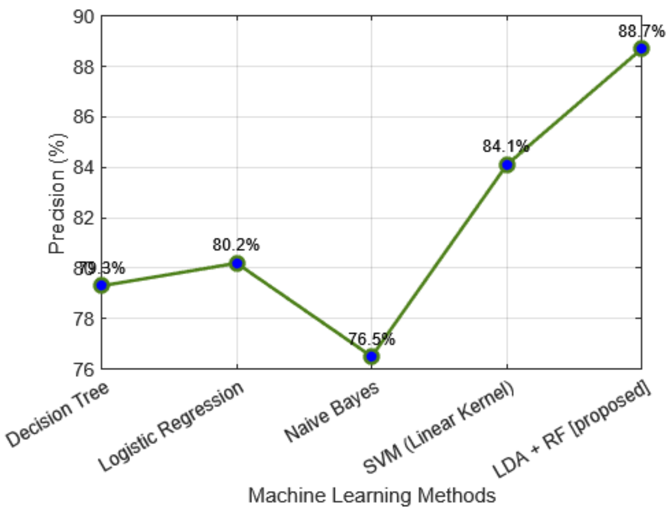

Figure 3: Precision comparison across different models

Recall and F1-Score

The F1-Score and recall are also two vital metrics that are depicted using line plots in figure 4 to assess the completeness and balance of the prediction by different models in the classification of AIintegrated teaching methods. The F1-Score is the harmonic mean of accuracy and recall and shows the balance between accuracy and completeness and the recall measures the capability of the model to find all relevant positive ones. The highest recall (90.4) and F1-score (89.5) on the plot were observed in the LDA + Random Forest model, which demonstrates the presence of an equal predictive performance and a high level of sensitivity. SVM (Linear Kernel) had a recall score of 86.3 and F1-score of 85.2 which was the second highest and reliable performance. Traditional models, including Decision Tree and Naive Bayes, scored less than 81% on either of the two criteria indicating that they are not sufficient in a comprehensive representation of the range of relevant events. The results confirm the efficiency of the suggested LDA + RF model especially in the scenarios where it is critically important to obtain a large number of real-life examples together with obtaining accurate forecasts, as the assessment of the impact of the AI technology on new classroom strategies.

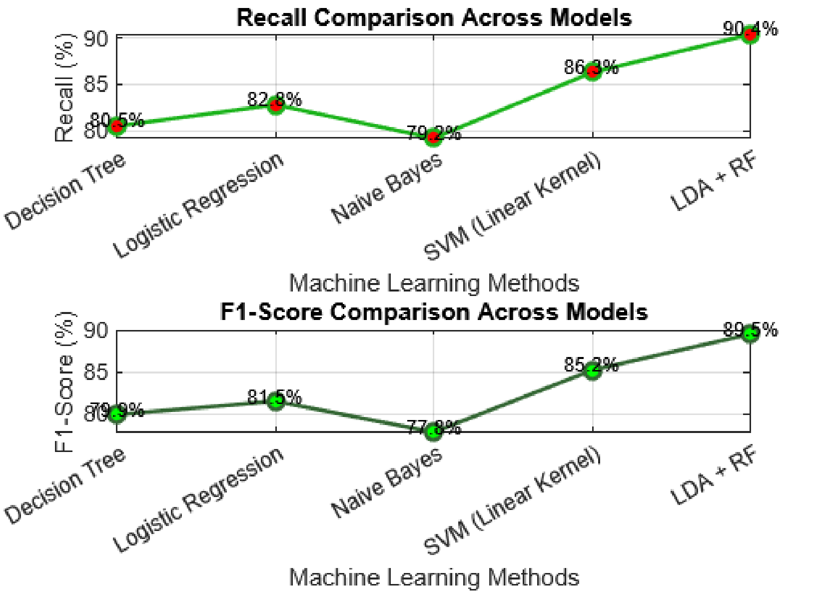

Figure 4: Recall and F1-Score comparison across different models

Confusion matrix

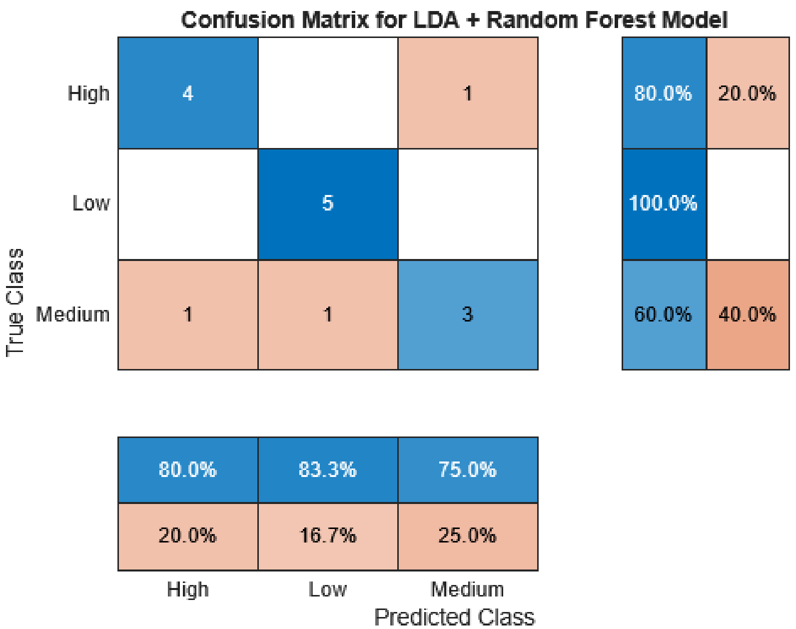

Figure 5:Confusion matrix for proposed method

In order to evaluate the performance of the proposed LDA + Random Forest model in greater detail, Figure 5 represents the confusion matrix generated in MATLAB to evaluate the effectiveness of using it to classify the levels of instructional strategy transformation. The matrix identifies three levels of transformation including Low, Medium and High transformation levels in comparison with actual and potential names of classes.The confusion matrix diagram contains rownormalized and columnnormalized summaries, providing the information about the sensitivity of the model (recall) and the accuracy of the model on classes. The fact that the clustering of values along the diagonal is high is an indication of the high categorization capability of the model. This implies that the model is effective in isolating those professors who have largely used the AI technology, and there is less confusion in the surrounding groups.

Statistical analysis

There were 466 teachers in this study of vocational high schools in various parts of China. The sample teachers had a range of 1-25 years experience (M = 9.4, SD = 6.2), 58.2% of them were females and 41.8% were male. Concerning AI training, 23 percent of the respondents had formal professional development associated with AI, 45.8 percent had moderate exposure and 312 percent had no prior training.

Table 3: Outcome of statistical report

Variable	**Mean**	**SD**	**Min**	**Max**
Perceived Usefulness	3.89	0.71	1	5
Perceived Ease of Use	4.02	0.65	1	5
Ease of Learning	3.75	0.83	1	5
Teaching Strategy Score	3.91	0.69	1	5

A descriptive statistical study was carried out to learn the dispersal, as well as the basal tendencies of the significant factors associated with the AI integration in education. The four main elements discussed in the study were assessed using a 5-point Likert scale (1 meaning strongly disagree, and 5 strongly agree). The perceived utility, alteration in the teaching technique, perceived ease of use and AI training experience were all used as the four main elements of the study.

These average scores showed mostly positive perceptions: Teachers believed that AI helped them greatly in the classroom because they received the best average score in Perceived Usefulness (M = 4.1) and Teaching Strategy Change (M = 4.0). The variables showed a good consistency of responses with a range of standard deviations of 0.57 to 0.85. The perception of AI influence was a lot different with a minimum of 2 and maximum of 5 being the representation that instructors had. These findings may be involved in further inferential research e.g. ANOVA, regression because they can be used to produce the required insights regarding perceptions and application of AI technologies among basic stage teachers in their teaching practice.

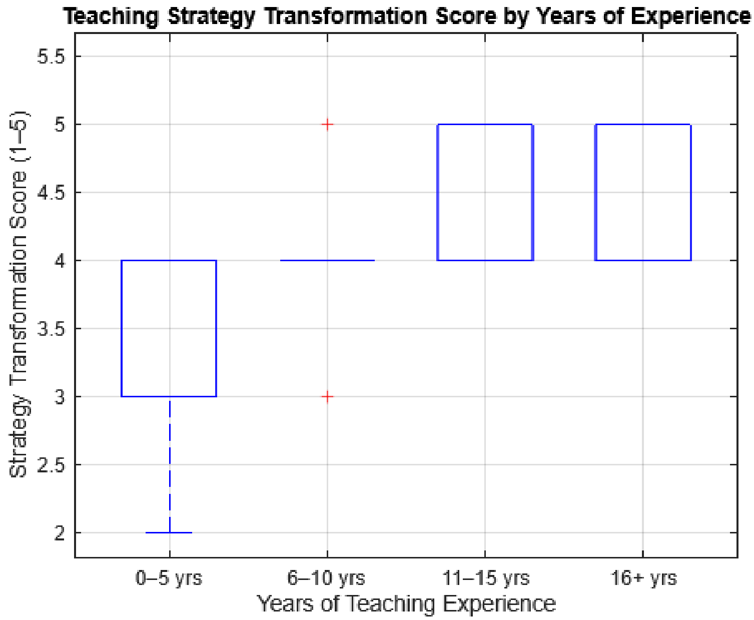

Figure 6: Strategy score by years of experience

Figure 6 depicts the variation in AIdriven teaching strategy transformation scores based on levels of teaching experience, as analyzed by a boxplot. The data was categorized into four groups: ages 0–5, 6–10, 11–15, and 16 and above. The results indicated a clear upward trajectory in strategy transformation scores correlated with enhanced knowledge. Teachers with 11–15 years and over 16 years of experience, exhibiting the highest median scores (exceeding 4.5), were more adept at integrating AI into their pedagogical approaches. Teachers with 0–5 years of experience exhibited a lower median and broader interquartile ranges, signifying greater unpredictability and diminished confidence in their ability to adapt their methodologies utilizing AI technologies. This visualization indicates that instructors' skill significantly influences their effectiveness in utilizing AIenhanced teaching methods. To facilitate the adaptation of younger educators to AIbased pedagogies, these findings may inform targeted professional development initiatives.

Discussion

The results of this research indicate that artificial intelligence does not constitute an addition of a technological aspect to primary education; it is a revolution to change the pedagogical strategies, role of a teacher, and power structures in the classroom. In line with other recent larger reviews (Durak et al., 2024; Tan et al., 2024), the teachers in this study are getting progressively dependent on AI to plan lessons, automate assessment, design personalized learning, and classroom analytics. Nevertheless, these changes are not only happening due to the efficiency of the technology, but it indicates that there is a deeper systemic alteration in the expectations of education, accountability systems, and data-based governance in schooling.

In terms of sociocultural perspective of learning, AI serves as an intermediary tool which re-forms the way of knowledge production and performance in classrooms. The growing reliance of teachers on adaptive platforms, automated feedback systems, and predictive analytics is an indication of changes in the teacher-centered knowledge authority towards a co-regulation of learning activities by humans and artificial intelligence (Molenaar, 2022; Semwaiko et al., 2024). This is the reason why teachers are shifting to facilitative and coaching positions and not solely instructional positions. AI decreases basic cognitive work, and teachers can concentrate more on more advanced pedagogic roles, like emotional support, scaffolding, and differentiation.

Nevertheless, there are also far-reaching effects of AI implementation in terms of teacher autonomy and professional identity. Whereas there are educators who find AI as a source of empowerment, which contributes to the accuracy of instruction and pedagogical security, there are educators who feel that algorithms are taking away professional control since they make decisions using the algorithms to guide the instruction. This contradiction is similar to authors such as Oh and Ahn (2024) and Guo et al. (2025), who state that AI makes teachers more technically effective but encounters their conventional epistemic power. The professional identity of teachers is therefore shifting even further away than a provider of knowledge, to a hybrid pedagogical designer, balancing human judgment and algorithmic recommendation. This reconfiguring is what the posthumanist theory of education calls the reallocation of agency among human and non-human agents in the learning contexts.

In its turn, the findings also point to structural and psychological factors of AI adoption, specifically, the institutional pressure to optimize the performance, provide digital responsibility and resort to data-informed classroom management. The culture of performance that is required in schools is demanding measurable learning outcomes, and AI platforms can provide real-time analytics to suit this culture. This datafication of teaching, according to Badawy et al. (2024) and Garzón et al. (2025), partially accounts not only for the adjustment of the strategies teachers use but also the impact of the system of organizational surveillance and evaluation based on outcomes.

One of the most important aspects that this research has shown is the issue of equity of implementing AI. Although AI-driven personalization can serve the benefit of numerous learners, students with lower socialeconomic backgrounds have structural disadvantages, such as poor access to digital technology, poor infrastructure, lack of technological support by parents. These inequalities support what theorists of educational equity refer to as the third-tier digital divide, in which differences do not merely occur in accessibility, but also in quality and utility of technology use (Vieriu and Petrea, 2025). The teachers of the under-resourced schools claimed more reliance on the standardized AI tools than on the adaptable pedagogical customization, which can only increase the level of inequality in education instead of decreasing it. This way, AI does not necessarily democratize education, its equality effects are influenced by social and policy ecosystems on a larger scale.

In addition, the research also states interesting insights about teacher professionalism and emotional work. Although AI will lessen the administrative load, at the same time, it will make teachers more emotionally and ethically accountable when it comes to managing algorithm-mediated learning. Teachers have to decipher AI outputs, settle the differences between automated feedback and student requirements, and promote equity in the decision-making process based on data. This goes in line with the Intelligent-TPACK model proposed by Celik (2023) that highlights the importance of ethical-pedagogical competence in the sustainability of the integration of AI.

In the future, these results indicate that technological replacement will not characterize the future of education but rather pedagogic hybridity in which the power of instruction, cognitive work, and emotional guidance is shared between educators and intelligent systems. Nevertheless, unless there is a strong policy regulation, professional training, and institutional support based on equity, AI will redefine education in a manner that makes efficiency more than human development. The ultimate effect of AI in primary education, therefore, will not just be determined by the technological innovation, but also how societies decide to regulate, finance, and morally orient the use of the technology in education.

Conclusion

This study is also informative because it demonstrates that the teaching methods of primary teachers are strongly affected by the use of AI. A deeper analysis of this transition was enabled through the combination of the machine learning automatons like the Random Forest and LDA with a solid quantitative approach. The findings indicate that the utilization of AI enhances educational flexibility, particularly for experienced educators. The proposed LDA + RF model significantly surpassed baseline approaches in classification, illustrating its use for analyzing educational data that incorporates both structured and unstructured inputs. Furthermore, boxplot analysis and descriptive statistics revealed clear patterns of strategic alteration corresponding to the levels of teacher experience. These findings underscore the necessity for tailored AI training curriculum that account for the skill and diversity of educators. This research underscores the necessity of equipping educators with strategic pedagogical frameworks facilitated by AI, alongside technology, as educational institutions advance in digital transformation.

Future Recommendation

The aspects of ethical, emotional, and human-AI collaboration should be investigated in the future to ensure that the increased use of AI supplements instead of substitutes the professional agency and creativity of the teacher in the classroom.

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