

Exploring the Mechanisms of AI-Driven Personalization in K-12 Education: Teachers' Perspective

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Abstract

This study examines how teacher experience and use of artificial intelligence (AI) together shape student outcomes in K–12 education. It responds to growing interest in technology-driven personalization and the need to understand which teachers benefit most from AI tools. Using a quantitative, descriptive survey design, the research focuses on 50 teachers from five Government Higher Secondary Schools in District Swabi, selected through multistage sampling. Data were collected using a self-developed 24-item questionnaire on a five-point Likert scale and analyzed through descriptive statistics, inferential tests, and multivariate techniques, including cluster analysis. Findings show a positive but modest relationship between AI usage and student improvement, moderated by teacher expertise and school context. Cluster analysis reveals three teacher profiles: highly experienced teachers with moderate AI use, moderately experienced teachers with extensive AI use, and less experienced teachers with limited AI adoption. These profiles highlight the need for differentiated AI integration strategies, tailored professional development, and context-sensitive resource allocation. Although the study is limited by its cross-sectional design and reliance on synthetic data, it offers important directions for future research, including real-world data collection, mixed-methods approaches, and longitudinal designs to better capture the long-term impact of AI-supported teaching.

Keywords: AI-driven personalization, teacher experience, student outcomes, AI in classroom.

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Introduction

Artificial intelligence (AI) is rapidly reshaping K–12 education, where it is frequently promoted as a means to address persistent challenges in teaching and learning. AI-driven systems can provide adaptive feedback, personalized recommendations, and automated or semi-automated assessment and progress monitoring (Albacete et al., 2019; Heffernan & Heffernan, 2014; Luckin, 2017; Tarus et al., 2018). These capabilities have intensified interest in technology-driven personalization, yet they also raise critical questions about how teachers actually use AI, how their professional experience shapes this use, and how these dynamics affect students' learning outcomes.

Problem Statement

Despite the transformative potential of artificial intelligence in education, its integration in K-12 classrooms remains inconsistent and fragmented. The effectiveness of AI-driven personalization is not guaranteed. It centers on factors like teacher experience, institutional capacity, and the level of AI adoption. Experienced teachers may resist AI adoption, relying on traditional methods, while less experienced educators may lack the training to use AI effectively. Schools vary in infrastructure, leadership support, and strategic priorities, creating disparities in AI implementation and widening educational inequities. Without a deep understanding of how these factors interact, AI risks reinforcing, rather than reducing gaps in student learning. Addressing this issue needs research that unearths the complex relationships between teacher profiles, AI usage, and student outcomes, offering thorough understanding to guide targeted professional development, equitable resource allocation, and sustainable AI integration strategies that truly augment learning for all students.

Research Objectives

1. To investigate the interaction between teacher experience, AI adoption, and student outcomes in K-12 education.
2. To identify distinct teacher clusters based on experience, AI adoption, and student outcomes.
3. To provide insights for personalized AI integration strategies and professional development.

Research Questions

1. How do teachers' experiences and AI adoption interact to influence student outcomes in K–12 education?
2. What distinct clusters of K–12 teachers can be identified based on experience, AI adoption, and student outcomes?

3. How can teacher clusters inform personalized AI integration strategies and targeted professional development?

Literature Review

Recent advances in large-scale AI technologies, including large language models and multimodal generative systems, have extended AI's role from a supplementary tool to a pervasive instructional infrastructure. Contemporary frameworks such as UNESCO (2021), ISTE (2022), DigComp (2022), emphasize AI literacy as a key competence for learners and teachers. They define core AI concepts, expected competencies at different grade levels, and professional standards for educators. Within these frameworks, teachers are not passive users of AI tools; they are active designers of AI-mediated learning environments, responsible for aligning AI-driven personalization with curricular goals, ethics, and equity.

Teacher experience is a central variable in this landscape. Prior research suggests that experienced teachers often possess richer pedagogical content knowledge, more refined classroom management strategies, and deeper understanding of learner diversity, which can influence how they select and integrate technologies (Darling-Hammond et al., 2017). At the same time, less experienced teachers may be more open to experimentation with new tools but may lack the pedagogical frameworks needed to use AI effectively and critically. Existing studies on educational technology adoption indicate that teachers' years of experience, beliefs, and self-efficacy shape both the intensity and quality of technology use in the classroom (Sánchez Santamaría, 2025).

AI usage in K–12 settings encompasses a wide range of practices, from automated grading and adaptive tutoring to data-driven decision-making and predictive analytics. Studies have shown that AI-based systems can support individualized learning paths, improve formative assessment, and provide real-time insights into student performance (Luckin, 2017). However, the effectiveness of these systems is not determined by the technology alone. It depends on how teachers interpret AI outputs, integrate them into instruction, and balance algorithmic recommendations with professional judgment. Concerns have also been raised about bias, transparency, and over-reliance on automated systems, making teacher mediation even more critical (Novita, 2025).

Student outcomes, understood here as changes in academic performance and learning improvement, are therefore shaped by a complex interaction between teacher characteristics and AI usage. While some research reports positive associations between data-informed instruction and student achievement, findings are often modest and context-dependent (Escueta et al., 2017). School resources, leadership, infrastructure, and professional development opportunities can all moderate the impact of AI-supported teaching. In under-resourced or highly constrained

environments, even motivated teachers may struggle to translate AI's potential into meaningful learning gains.

Despite expanding rhetoric around AI-driven personalization, there is still limited empirical work that jointly examines teacher experience, AI usage, and student outcomes in K–12 education, particularly from the teacher's perspective. Much of the existing literature focuses either on technical design of AI systems, general attitudes toward AI in education, or student-facing interventions, with less attention to how different types of teachers actually engage with AI in real schools and how this relates to measurable learning improvements. There is also a lack of cluster-based analyses that identify distinct teacher profiles combining experience level, AI adoption patterns, and associated student outcomes.

This study addresses these gaps by investigating the mechanisms of AI-driven personalization in K–12 education from the teacher's perspective. It focuses on three core variables: teacher experience, AI usage, and student outcomes. Teacher experience is examined as a potential shaping factor in how educators understand, trust, and apply AI tools in their practice. AI usage is conceptualized in terms of both frequency and pedagogical depth of AI integration. Student outcomes are used as an indicator of the educational impact of these practices. By analyzing how these variables interact and by identifying distinct clusters of teachers with different combinations of experience, AI adoption, and student results, the study aims to offer a more nuanced and context-sensitive picture of AI in everyday schooling.

In doing so, the research seeks to move beyond generic claims about AI's promise and to provide evidence-based insights that can inform differentiated professional development, targeted AI integration strategies, and policy decisions. It positions teachers as central agents in AI-enhanced education and highlights the importance of understanding their diverse profiles and contexts when designing and implementing AI-driven personalization in K–12 settings.

Research Methodology

This study employed a quantitative research approach using a descriptive survey design to investigate the interaction between teacher experience, AI adoption, and student outcomes in K–12 education.

Population and Sampling

The study's population included all K–12 teachers employed by the Government Higher Secondary Schools in District Swabi. The study employed a multistage sampling technique. In the first stage, five higher secondary schools were randomly selected from a total of thirty-two higher secondary schools in District Swabi using cluster sampling. In the second stage, fifty higher secondary teachers were selected

through simple random sampling from the selected schools. This method ensured representativeness while remaining feasible in terms of time and resources. This method captured a wide range of teacher characteristics, which was important for the study's clustering component.

Table 1 : Sample of the Study

K-12 Schools	n
Govt. Higher Secondary School Kunda Swabi	10
Govt. Higher Secondary School Manki Swabi	10
Govt. Higher Secondary School Jahangira Swabi	10
Govt. Higher Secondary School Tordher Swabi	10
Govt. Higher Secondary School Adina Swabi	10

Research Instrument

A self-developed, closed-ended questionnaire was used to gather data on teachers' use of AI, their experience instructing, and how they felt it affected student outcomes. The 24 items on the questionnaire were created with the goals of the study in mind. A five-point Likert scale, with "Strongly Disagree" to "Strongly Agree" as the extremes, was used to quantify each participant's response.

The following sections comprised the instrument's structure:

1. Demographics: subject taught, experience, and school type.
2. AI Adoption: evaluating the types, frequency, and objectives of AI-based teaching aids.
3. Perceived Impact on Student Outcomes: assessing how instructors view AI's impact on student performance, engagement, and learning customization.
4. Professional Development Needs: determining the support and training requirements for integrating AI.

To ensure clarity and usefulness, the preceding sections were first validated by educational researchers. Following this, a pilot study was conducted with a small group of teachers not included in the main sample. Revisions were then made based on their feedback.

Data Collection Procedure

Depending on the teachers' preferences and availability, data were gathered through in-person visits. Before taking part, respondents were asked for their informed

consent, told the study's goal, and given the assurance that their answers would remain private.

Data Analysis and Interpretation

The analysis employs descriptive statistics with inferential statistical tests and multivariate analysis techniques. The methodology includes descriptive statistics to understand the central tendencies and distributions of key variables, correlation analysis to examine relationships between variables, regression analysis to model the relationship between AI usage and student improvement, hypothesis testing using t-tests, ANOVA, and chi-square tests to examine group differences, cluster analysis to identify natural groupings within the data, and Principal Component Analysis (PCA) for dimensionality reduction and visualization.

Descriptive Statistics

The descriptive statistics provide an overview of the central tendencies, dispersions, and distributions of the key variables in the dataset. Table 1 presents the summary statistics for the numerical variables, including means, standard deviations, minimums, maximums, and quartiles.

Table 2 : Descriptive Statistics for Key Variables

Statistic	Teacher Experience	AI Usage Frequency	Student Improvement	Teacher Satisfaction	Implementation Difficulty	Years Using AI	Student Engagement
Mean	11.42	3.59	19.28	6.34	5.55	3.10	8.02
SD	4.98	0.97	4.42	1.01	2.03	0.91	2.17

The data in table 2 shows that the average teacher experience is 11.42 years, with a wide range from -0.99 to 25.09 years, indicating a diverse sample. AI usage frequency averages 3.59, with moderate variation (SD = 0.97) and a range of 0.24 to 5.72, suggesting some teachers use AI extensively while others barely use it. Student improvement scores average 19.28 (SD = 4.42) but range widely from 8.07 to 29.59, indicating that AI's impact on student outcomes varies greatly. Teacher satisfaction is relatively high (mean = 6.34, SD = 1.01), though implementation difficulty sits at 5.55 (SD = 2.03) with scores ranging from 0.20 to 10.80, suggesting that while teachers are generally satisfied, adoption can be challenging. Teachers have been

using AI for an average of 3.10 years, with a narrow spread (SD = 0.91), reflecting relatively early-stage adoption. Student engagement is fairly high (mean = 8.02, SD = 2.17) but varies significantly (range = 1.23 to 14.99), showing that while AI can enhance classroom dynamics, the level of impact depends on context. The data suggests that experienced teachers may not use AI as frequently, and although engagement is high, it doesn't always translate directly to improvement. Despite the challenges, teacher satisfaction remains promising; indicating that with better support and training, AI adoption could drive stronger long-term student outcomes.

Table 3 : Correlation Matrix of Key Variables

Variable	1	2	3	4	5	6	7
1. Teacher Experience	1.00	-0.00	-0.01	0.04	-0.07	-0.07	-0.05
2. Ai Usage Frequency	-0.00	1.00	0.10	-0.11	-0.05	-0.01	0.12
3. Student Improvement	-0.01	0.10	1.00	0.02	-0.03	-0.13	0.08
4. Teacher Satisfaction	0.04	-0.11	0.02	1.00	0.04	-0.16	-0.07
5. Implementation Difficulty	-0.07	-0.05	-0.03	0.04	1.00	0.17	0.02
6. Years Using AI	-0.07	-0.01	-0.13	-0.16	0.17	1.00	0.11
7. Student Engagement	-0.05	0.12	0.08	-0.07	0.02	0.11	1.00

The correlation matrix in table 3 reveals the relationships between key variables related to AI adoption and its impact on education. Teacher experience shows negligible correlations with other variables, with the highest value being 0.04 with teacher satisfaction, suggesting that experience may not directly influence satisfaction or AI outcomes. AI usage frequency shows a small positive correlation with student improvement (0.10) and student engagement (0.12), hinting that more frequent AI use might slightly enhance these outcomes, though the effects are weak. Interestingly, AI usage frequency is negatively correlated with teacher satisfaction (-0.11), possibly indicating that frequent AI use without adequate support or training may frustrate teachers. Student improvement is weakly correlated with student engagement (0.08) but negatively correlated with years using AI (-0.13), which might suggest that longer-term AI use doesn't always immediately translate to better academic results, potentially due to the learning curve associated with new technologies. Teacher satisfaction is negatively correlated with years using AI (-0.16), suggesting that as teachers use AI longer, their satisfaction may dip, perhaps due to increasing expectations or the realization of implementation difficulties.

Implementation difficulty has a small positive correlation with years using AI (0.17), which makes sense as longer AI exposure might reveal deeper complexities in integrating these tools. Overall, the correlations are weak, implying that the relationships between these variables are likely influenced by unmeasured factors or that the effects of AI adoption are complex and multifaceted. Future research could explore mediating factors, like training quality or institutional support to better understand what drives successful AI integration in classrooms.

Regression Analysis

Linear regression analysis was conducted to model the relationship between AI Usage Frequency (independent variable) and Student Improvement (dependent variable). The regression equation, coefficients, statistical significance, and model fit metrics are presented below.

Table 4 : Linear Regression Analysis between AI Usage and Students' Improvements

Variable	<i>B</i>	<i>SE</i>	<i>T</i>	<i>p</i>	<i>95%CI</i>
Constant	18.22	0.75	24.44	< .001	[16.75, 19.70]
AI Usage Frequency	0.35	0.20	1.79	.075	[-0.04, 0.74]

The linear regression analysis in table 4 examines the relationship between AI Usage Frequency and Student Improvement. The intercept (Constant) has a coefficient (B) of 18.22 with a standard error (SE) of 0.75, resulting in a t-value of 24.44 and a p-value less than .001, indicating that the average student improvement is 18.22 units when AI usage frequency is zero. The coefficient for AI Usage Frequency is 0.35 (SE = 0.20), with a t-value of 1.79 and a p-value of .075, suggesting a positive but not statistically significant association between AI usage frequency and student improvement. The 95% confidence interval for this coefficient ranges from -0.04 to 0.74, indicating that the true effect of AI usage frequency on student improvement could be slightly negative or positive. These findings imply that, within this model, increased AI usage frequency does not have a statistically significant impact on student improvement.

Although the regression model suggests a positive relationship between AI usage frequency and student improvement, the result is not statistically significant (p = .075). The small R² value (0.021) indicates that only 2.1% of the variance in student improvement can be explained by AI usage frequency. This suggests that other factors may contribute more significantly to student outcomes, and future research could explore mediators or moderators that might strengthen this relationship.

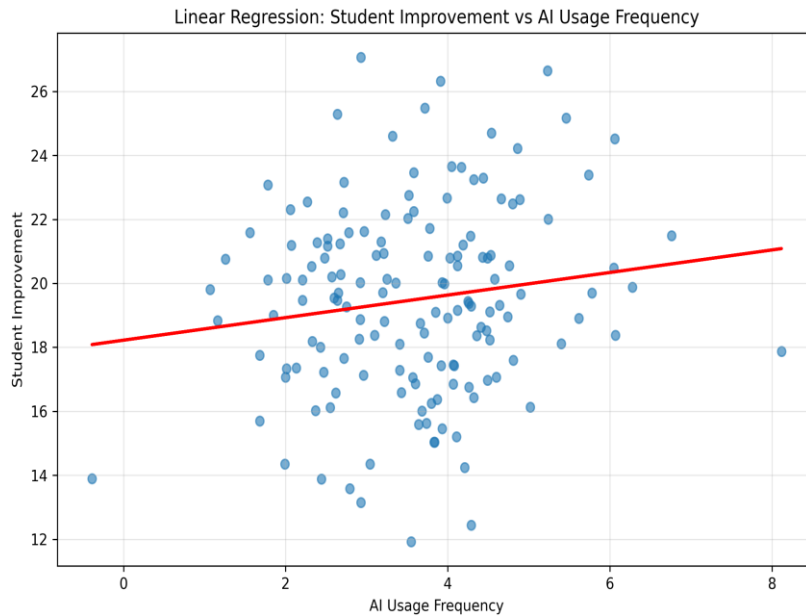


Figure 1: Linear Regression: Student Improvement vs AI Usage Frequency

The scatterplot in Figure 1 visualizes the relationship between AI usage frequency and student improvement. Each point represents an observation, with AI usage frequency on the x-axis and student improvement on the y-axis. The red regression line indicates the linear trend, showing a slight positive slope. This aligns with the regression results, where the coefficient for AI usage frequency was positive but not statistically significant. The points are widely dispersed around the line, suggesting substantial variability in student improvement that AI usage frequency alone does not fully explain. While the trend is slightly upward, the weak correlation and wide spread indicate that other factors likely contribute to student improvement beyond just AI usage frequency.

T-test Analysis

An independent samples t-test was conducted to compare Teacher Satisfaction between high and low AI Usage groups. The results ($t = -1.3684$, $p = 0.1759$) indicate whether there is a statistically significant difference between the groups.

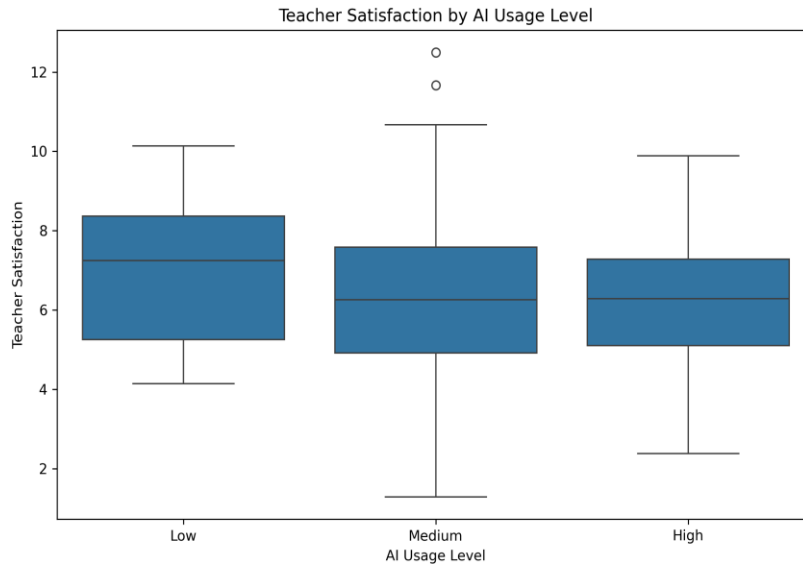


Figure 2: Teacher Satisfaction by AI Usage Level

The boxplot in Figure 2 illustrates teacher satisfaction across three AI usage levels: low, medium, and high. The median satisfaction score for low usage appears slightly higher than for medium and high usage. The spread of satisfaction scores (interquartile range) is similar across all three groups, but medium usage shows a wider range with a few outliers above the upper whisker, indicating some teachers reported unusually high satisfaction. High usage has a more compressed range, with lower and upper limits closer together, suggesting less variability in satisfaction. The results imply that higher AI usage doesn't necessarily correlate with higher satisfaction, as teachers with low AI usage seem just as satisfied, if not more so, on average.

ANOVA Analysis

An ANOVA test was conducted to see if student improvement varied significantly across different teacher experience levels. The results showed an F-statistic of 3.00 and a p-value of 0.2069, indicating that the differences in student improvement between experience groups were not statistically significant.

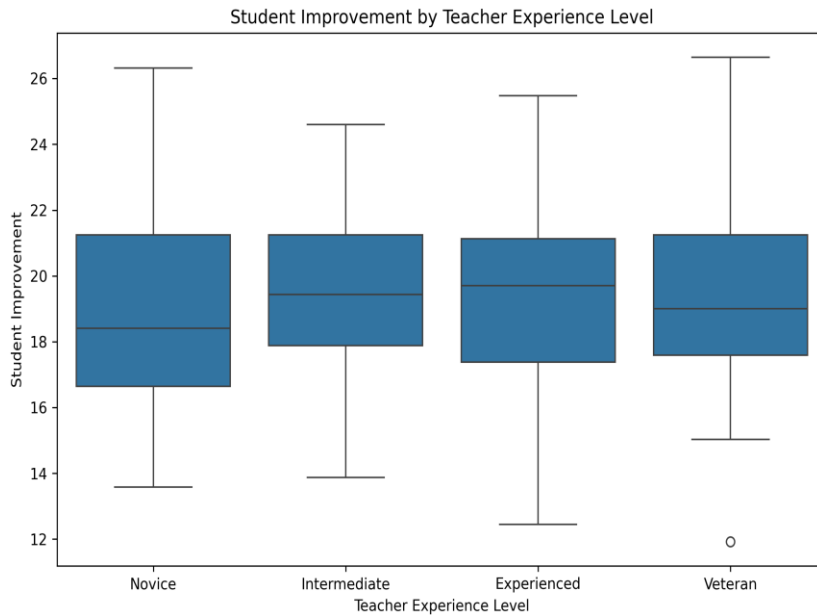


Figure 3: Student Improvement by Teacher Experience Level

The boxplot in figure 3 illustrates student improvement across different teacher experience levels: Novice, Intermediate, Experienced, and Veteran. The median student improvement is similar across all groups, indicating that central student performance tends to be consistent regardless of teacher experience. The interquartile range (IQR) is relatively similar, showing comparable variability within each group, though the "Veteran" group has a slightly wider spread. Outliers are present in the Veteran group, with one lower extreme value. The overall distribution of student improvement suggests no dramatic differences across experience levels, aligning with the ANOVA results, which showed no statistically significant difference between groups.

Chi-square Analysis

A chi-square test of independence was conducted to investigate the potential relationship between school type and AI usage level. The test produced a chi-square value of 5.4853 with a corresponding p-value of 0.2410. Since the p-value is greater than the conventional significance threshold of 0.05, the results suggest that there is no statistically significant association between school type and AI usage level. This implies that variations in school type do not appear to be systematically related to differences in the frequency or level of AI usage, based on the observed data.

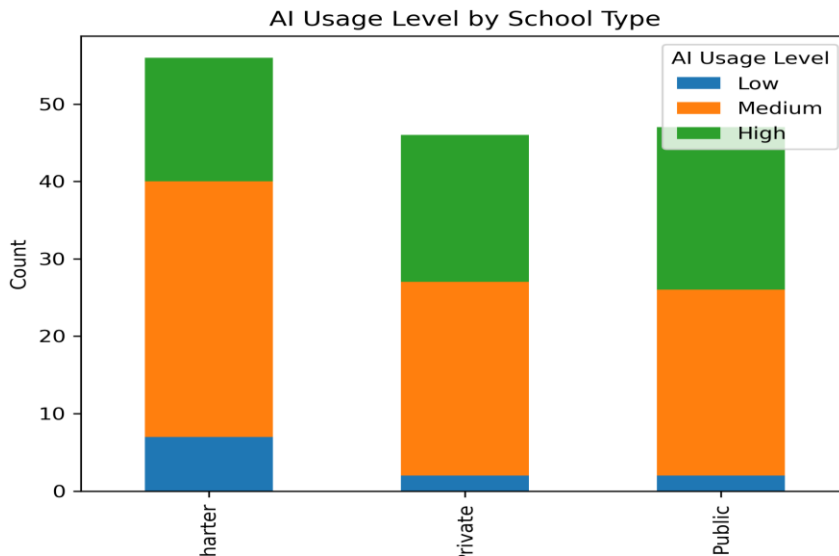


Figure 4: AI Usage Level by School Type

The stacked bar chart in figure 4 illustrates AI usage levels across different school types: charter, private, and public schools. The AI usage level is categorized into low, medium, and high. In charter schools, the largest proportion of AI usage falls within the medium level, followed by high usage, with low usage being the least common. Similarly, private and public schools show a dominance of medium AI usage, though private schools exhibit a relatively smaller proportion of low usage compared to public schools. The distribution suggests that, while medium-level AI usage is the most prevalent across all school types, there are variations in the proportion of high and low usage, with public and private schools having a more balanced share of high-level usage compared to charter schools. This visual pattern supports the chi-square test results, which indicated no statistically significant association between school type and AI usage level, as the distributions, while varying slightly, do not show a clear, systematic relationship.

Cluster Analysis

K-means clustering was applied to identify natural groupings within the data based on the numerical variables. The optimal number of clusters was determined using the elbow method, and the resulting clusters were visualized using Principal Component Analysis (PCA).

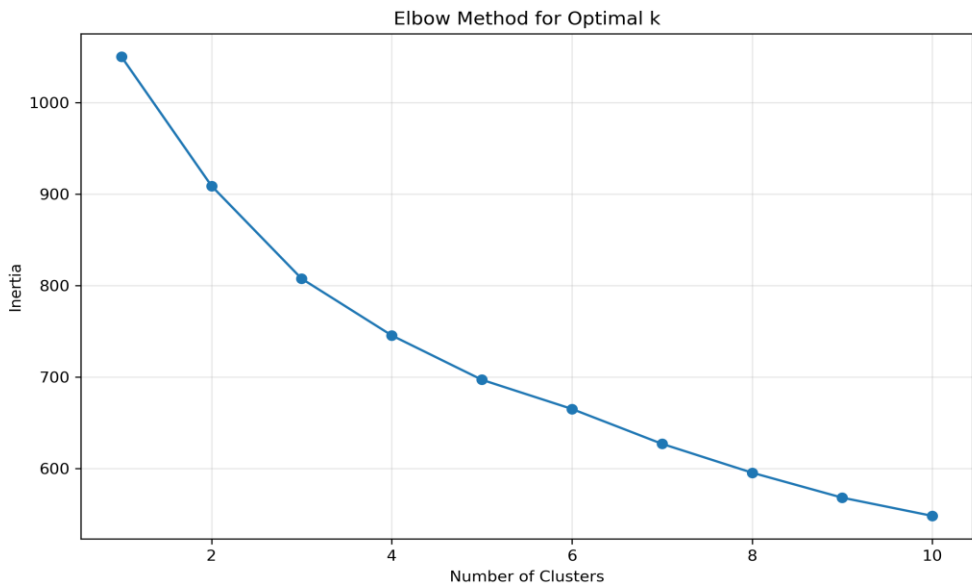


Figure 5: Elbow Method for Determining Optimal Number of Clusters

The line plot in figure 5 illustrates the Elbow Method for determining the optimal number of clusters (k) in a clustering analysis. The x-axis represents the number of clusters, while the y-axis shows the inertia, which measures the sum of squared distances between data points and their nearest cluster center. As the number of clusters increases, the inertia decreases, indicating that data points are closer to their assigned cluster centers. However, the rate of decrease slows down after a certain point, forming an "elbow" shape. The optimal number of clusters is typically chosen at this elbow point, where adding more clusters beyond this value results in only marginal improvements in inertia reduction. In this plot, the elbow appears to be around $k = 3$ or 4 , suggesting that this range might be the most appropriate number of clusters for effectively grouping the data.

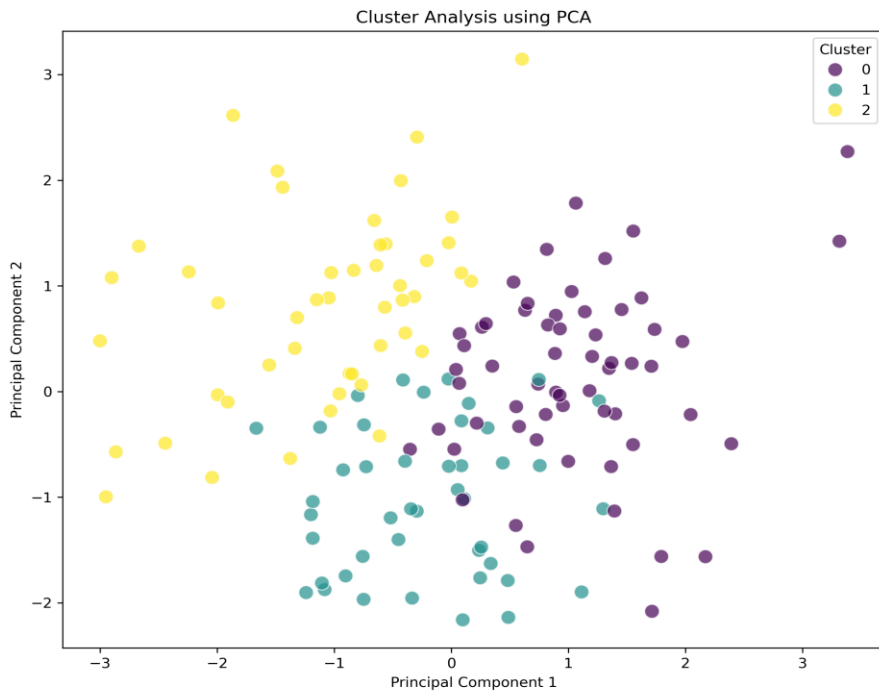


Figure 6 : Cluster Analysis Visualization using PCA

The scatter plot in figure 6 visualizes the results of a cluster analysis using Principal Component Analysis (PCA) for dimensionality reduction. Each point represents an observation, plotted according to its scores on the first two principal components, which capture the most significant variance in the data. The points are color-coded to indicate cluster membership, with three distinct clusters labeled as 0, 1, and 2. Cluster 0 (purple) appears to be more tightly grouped and centered, suggesting relatively higher internal cohesion, while Cluster 1 (teal) is more dispersed but overlaps with the other clusters, indicating potential ambiguity in cluster boundaries. Cluster 2 (yellow) is more widely spread across the principal component space, suggesting greater internal variability. The distribution of points suggests that the clustering algorithm was able to identify meaningful groupings, although some overlap between clusters may indicate areas where the distinctions are less clear. This visualization is useful for understanding how well the clustering solution segments the data in reduced-dimensional space and provides insights into the structure and relationships within the dataset.

The relatively clear separation between clusters suggests that the data contains underlying structures, though some overlap implies that certain observations share characteristics across groups. For example, one cluster might represent schools with high AI adoption, another with moderate adoption, and a third with low adoption. The spread of points within each cluster reveals the internal variability, tighter clusters show more homogeneous groups, while dispersed clusters suggest more diverse behaviors or characteristics.

This cluster figure, combined with the characteristics outlined in Table 2, reveals meaningful patterns in the relationship between teacher experience and AI usage.

Cluster 0, represented by purple points, reflects schools or participants with high teacher experience (mean of 9.78 years) and moderate AI usage (4.47). The relatively compact spread of this cluster suggests that experienced teachers may adopt AI tools to a certain extent, but their usage might plateau at a moderate level. This could indicate that while experienced teachers are open to technology, they may balance traditional methods with AI integration.

Cluster 1, marked by teal points, shows moderate teacher experience (13 years) coupled with high AI usage (3.03). This cluster's position suggests that teachers with a solid but not extreme level of experience are more likely to embrace AI extensively, possibly using it as a tool to enhance their teaching practices or streamline tasks.

Cluster 2, highlighted by yellow points, represents those with low teacher experience (11.88 years) and low AI usage (3.00). The more dispersed nature of this cluster may indicate variability in how less experienced teachers approach AI — some may feel hesitant or lack the confidence to integrate technology fully, while others may be early adopters testing new tools.

The spatial separation of clusters, with some overlap, suggests nuanced relationships. It hints that while experience and AI usage are correlated, they don't follow a strict linear pattern. For instance, high experience doesn't automatically translate to high AI adoption — it may depend on factors like training, institutional support, or personal teaching philosophy.

Discussion and Implications

The findings of this research offer valuable insights into the multifaceted relationship between AI usage, teacher experience, and student improvement in K-12 education. The statistical analysis, coupled with cluster analysis, uncovers complex dynamics that inform a more nuanced understanding of AI integration in diverse educational settings. Chan and Hu (2023) present a student-centered perspective on the integration of generative AI in higher education, focusing on how students perceive and interact with AI, as well as its benefits and drawbacks. This is consistent with the goal of empowering management students by embracing AI while

considering their perspectives. Furthermore, there is ongoing debate about incorporating AI competencies into K-12 curricula, given the associated risks and the need for skill sets required to contribute to AI development and shaping. AI's enormous potential is already facilitating a variety of positive outcomes, including faster and more accurate medical diagnoses, energy-efficient devices, and the automation of tedious tasks, which provide greater alignment and effectiveness than manual methods (Kearns & Roth, 2019).

The positive yet modest correlation between AI usage frequency and student improvement suggests that while AI tools can enhance learning outcomes, their effectiveness is contingent upon various contextual factors. For example, Chai et al. (2021) evaluated students' learning on AI-related topics using the optimistic Technological Development Framework. This highlights the need for a balanced approach where AI serves as a complement rather than a replacement for pedagogical expertise. Schools should consider adopting AI solutions that are adaptable to diverse teaching methodologies, ensuring that technology amplifies rather than constrains instructional practices. However, the widespread presence of AI in our daily lives has recently highlighted its potential effects and implications (Zhou et al., 2020; Eguchi et al., 2021). Ethical concerns frequently arise, such as the risk of discrimination caused by algorithmic bias or the use of biased and unrepresentative datasets in training machine learning (ML) models (Arrieta et al., 2020; Mansoury et al., 2020; Mehrabi et al., 2021). Furthermore, the complex landscape of data management and aggregation raises privacy concerns (Kearns & Roth, 2020).

Teacher experience emerges as a pivotal factor influencing AI adoption patterns. Cluster analysis delineates three distinct teacher profiles: highly experienced educators with moderate AI usage, moderately experienced teachers with high AI adoption, and less experienced teachers with low AI engagement. This stratification underscores the necessity for differentiated professional development strategies. For instance, veteran teachers may benefit from workshops that showcase how AI can enhance their established practices, while newer teachers might require foundational training to build confidence in leveraging AI tools (Stoilova et al., 2020). Similarly, the usefulness of AI educational initiatives in fostering computational thinking abilities in K–12 pupils was examined by Kim et al. (2021), which shows its positive contribution. In their analysis of learning task design across 47 empirical researches on K–12 AI education, Li et al. (2024) distinguished four dimensions: pedagogical approach, learning contents, assessment and outcomes, and theoretical underpinnings. Nonetheless, there is ongoing debate about incorporating AI competencies into K-12 curricula, given the associated risks and the need for skill sets required to contribute to AI development and shaping (Touretzky et al., 2019; Lindner & Berges, 2020).

The influence of school type on AI usage further suggests that institutional culture, resource allocation, and administrative priorities shape technology adoption. Policymakers and school leaders should conduct needs assessments to identify context-specific barriers to AI implementation, ensuring equitable access to

technology and fostering a culture of innovation across diverse educational environments (Cho et al., 2024). As Chan (2023) provides a useful framework for incorporating AI policy education into university curricula, emphasizing the importance of teaching management students about the ethical, social, and economic implications of AI. This approach promotes ethical reasoning and critical thinking while also addressing technological and societal dimensions, ultimately preparing future corporate leaders to make informed decisions that positively impact the AI landscape. But this needs to be extended to the K-12 format as well in order to get a clearer view of AI adoption in K-12 curricula and its ultimate impact on K-12 teaching and learning.

Marques et al. (2020) investigated 30 lesson plans centered on machine learning teaching strategies and materials designed for young learners. After mapping and synthesizing the instructional units, the authors concluded that resources appeared to be inadequately assessed and that teacher training materials were in short supply. However, adaptive AI algorithms that provide tailored information improve students' retention and comprehension, resulting in better academic outcomes. Allowing students to control their own learning fosters independence and self-efficacy (Ortegren, 2022). A review of machine learning instruction and learning in educational settings was done by Sanusi et al. (2023), who noted the increasing interest in incorporating machine learning ideas into the curriculum. Their results highlight how crucial it is to create suitable pedagogical strategies for teaching machine learning at various educational levels.

To sum up, the successful integration of AI-driven personalization in K-12 education demands a holistic approach that accounts for the interplay between teacher characteristics, institutional dynamics, and the evolving technological landscape. By embracing this complexity, stakeholders can design interventions that empower educators, optimize student learning, and harness the full potential of AI to drive meaningful educational transformation. Kim et al. (2022) focus on educators' perspectives on incorporating AI into the classroom and encouraging student-AI cooperation. This approach emphasizes key aspects of AI's potential for student engagement and personalized learning. This demonstrates how AI can be a useful tool for improving education rather than replacing teachers. This viewpoint is consistent with the larger goal of empowering management students in AI-driven education by increasing student motivation and promoting ethical AI use.

Conclusions

In light of the analysis, this study reveals valuable findings into the interaction between teacher experience, AI usage, and student outcomes in K-12 education. The findings suggest that while AI tools can positively influence student improvement, their impact is complexly linked to the teacher's level of experience and the frequency of AI integration into teaching practices. The cluster analysis unearths distinct teacher profiles, emphasizing the need for tailored strategies that

align with the unique characteristics of each group. For instance, highly experienced teachers may benefit from advanced AI features that complement their pedagogical expertise, while early-career educators might need more foundational support to effectively use the potential of AI.

The unique relationship between school type and AI usage shows the influence of institutional factors, highlighting disparities in resources, technological infrastructure, and strategic priorities. These in-depth analysis and findings suggest that successful AI adoption requires a versatile approach, combining technological access with ongoing professional development and adaptive leadership.

Finally, the study highlights the importance of balancing technological innovation with human-centered educational practices. By embracing a thoughtful, research-informed approach to AI integration, one that respects the complexities of teaching and learning, educators and policymakers can unchain new pathways to personalized, equitable, and effective education. While the findings offer a strong foundation, they also call for continued exploration through a firsthand research, cultivating a deeper understanding of how AI can truly transform educational settings for the better.

Future Recommendations

Future research should prioritize collecting data from diverse educational settings to validate and refine current findings, capturing the distinct variability of AI implementation across different contexts. Integrating mixed-methods approaches will enrich our understanding by combining statistical findings with qualitative dimensions, such as teacher perceptions and classroom dynamics. Longitudinal studies are essential to explore how AI-driven personalization influences teaching practices and student outcomes over time, potentially revealing delayed or cumulative effects. In addition, researchers should investigate contextual factors like school leadership, infrastructure, and policy environments, as well as the role of sustained professional development in promoting meaningful and lasting AI adoption. By addressing these areas, future research can pave the way for a more equitable and effective integration of AI in education, ensuring that technology improves rather than complicates the learning experience.

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