International Journal of Pedagogy and Teacher Education

Journal Homepage: jurnal.uns.ac.id/ijpte

Preservice Chemistry Teachers' Views on the Use of Artificial Intelligence in the Classroom

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ARTICLE INFO

Article History

Received : September 2, 2024

1st Revision : March 29, 2025

Accepted : April 17, 2025

Available Online: April 30, 2025

Keywords:

Artificial Intelligence in Education, Preservice Chemistry Teachers, Teacher Perceptions, Educational Technology, Professional Development.

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ABSTRACT

As Artificial Intelligence (AI) becomes increasingly integrated into education, understanding how future educators perceive its use is essential. This study explores the perceptions of 150 preservice chemistry teachers in Indonesia regarding the integration of AI in chemistry education. Participants completed a validated 12-item Likert-scale survey covering four dimensions: Pedagogical Benefit, Technical Benefit, Risk to Student, and Risk to Teacher. The data were analyzed using descriptive statistics, correlation, regression, clustering, and Principal Component Analysis (PCA). Results indicate that participants perceived AI as highly beneficial, particularly for simplifying material preparation and supporting understanding of abstract concepts. However, concerns also emerged, especially around potential declines in student motivation, critical thinking, and the teachers' readiness to use AI effectively. Correlation analysis revealed that benefit and risk perceptions were evaluated independently. Regression models identified "real-life connection" and "AI knowledge gap" as significant benefit and risk perception predictors. Cluster analysis grouped respondents into three profiles: Cautious Adopters, Enthusiastic Supporters, and Selective Optimists, each reflecting different levels of acceptance and concern. These findings underscore the need for differentiated teacher training programs that address technical competence and pedagogical reflection. Limitations include the reliance on self-report data and a single-country sample. The study emphasizes the importance of preparing educators to critically and effectively integrate AI into science instruction.

How to cite: Ramadhani.D.G, Susilogati. S, Harjono, Kusumastuti. E (2025). Preservice Chemistry Teachers' Views on the Use of Artificial Intelligence in the Classroom. *International Journal of Pedagogy and Teacher Education, 9*(1), 153-169. https://doi.org/10.20961/ijpte.v9i1.89534

1. INTRODUCTION

Artificial Intelligence (AI) is significantly reshaping the educational landscape, particularly in science education, where it is increasingly integrated to enhance instructional effectiveness (Abbas et al., 2023; Pendy, 2023). In chemistry education, AI offers substantial support by personalizing learning experiences, allowing content to be adapted based on individual student progress, preferences, and cognitive needs (Hardaker & Glenn, 2025; Murtaza et al., 2022). Such personalized systems challenge the conventional one-size-fits-all teaching model and create dynamic pathways for learners. AI-powered platforms, for instance, can modify the sequence, depth, and type of content delivery to align with student profiles. This is particularly valuable in chemistry, where learners often struggle with abstract and submicroscopic concepts that require flexible instructional approaches. Additionally, using AI to generate simulations and interactive visualizations helps students better conceptualize molecular structures and chemical reactions, which are difficult to grasp through static explanations alone (Schwaller et al., 2021).

Moreover, in the Indonesian context, AI adoption in classrooms remains in its early stages, with uneven distribution across institutions and limited integration in teacher education curricula, highlighting the urgency of context-specific research. Beyond personalization and visualization, AI also contributes to chemistry learning by offering automated feedback powered by natural language processing and machine learning techniques (Bulut & Wongvorachan, 2022; Pijeira-Díaz et al., 2024). These systems can provide formative feedback in real time, allowing students to recognize misconceptions and make immediate improvements. Effective feedback improves academic performance and fosters deeper learning (Carless & Boud, 2018). Advanced AI models can analyze student responses and deliver feedback that is not only immediate but also targeted to specific learning gaps or errors (Liu et al., 2020). Furthermore, AI can support adaptive learning structures emphasizing key chemistry

p-ISSN: 2597-7792 / e-ISSN: 2549-8525
DOI: https://doi.org/10.20961/ijpte.v9i1.89534

competencies, such as connecting macro-level observations with submicroscopic reasoning (Bai et al., 2020; Murtaza et al., 2022). Collectively, these AI-driven innovations contribute to a more responsive, individualized, and cognitively engaging chemistry education experience for both learners and educators.

Integrating Artificial Intelligence into educational systems presents opportunities and substantial challenges, particularly ensuring educators can use these technologies effectively. One major obstacle is the lack of readiness among teachers, especially preservice educators, to understand and integrate AI in classroom practices. Many teacher education programs fail to embed AI-related content into their curricula, resulting in limited exposure and insufficient competencies (Chan, 2023; Ibrahim, 2024). This gap not only reduces teachers' confidence in adopting AI tools but also constrains the potential impact of such technologies on learning outcomes. Moreover, lacking formal training may lead educators to misuse or underutilize AI, undermining its intended pedagogical value. Addressing this gap through structured AI training is essential for preparing future teachers to navigate the evolving demands of technology-enhanced education.

Beyond preparedness issues, the widespread adoption of AI in classrooms introduces new concerns related to teacher identity, student autonomy, and academic integrity. As AI increasingly performs functions traditionally handled by educators, such as delivering content and providing feedback, there is growing apprehension that it may erode essential human elements of teaching, including mentorship and motivation (Storey & Wagner, 2024). Overreliance on AI could also hinder the development of students' critical thinking and self-directed learning skills. Additionally, the accessibility of AI tools raises the risk of academic misconduct, such as plagiarism or unauthorized content generation (Forgas et al., 2021; Fowler, 2023). Researchers and institutions have highlighted the urgent need for policies that balance innovation with ethical use, ensuring that academic honesty remains a core educational value (Barrientos et al., 2024; Fowler, 2023). Despite increasing discourse, empirical studies that quantitatively examine how preservice teachers perceive AI, particularly within specific instructional contexts like chemistry, remain scarce. A deeper understanding of these perceptions is critical to inform curriculum reform and professional development, ultimately fostering more responsible and effective AI integration in education.

This study aims to analyze prospective chemistry teachers' perceptions toward the use of Artificial Intelligence in chemistry education by examining four key dimensions: pedagogical benefit, technical benefit, risk to students, and risk to teachers. The study also seeks to investigate the relationships among these dimensions and assess the influence of individual indicators on overall perception scores. In addition, the research aims to classify respondents into distinct perception profiles using a data analytic approach that includes correlation analysis, regression modeling, and clustering techniques. This multidimensional framework is designed to generate actionable insights for improving teacher education curricula and informing AI integration strategies in science instruction.

2. MATERIAL AND METHOD

Research Design

This study adopted a quantitative research approach with a strong orientation toward data analytics to systematically examine the perceptions of prospective chemistry teachers regarding the use of Artificial Intelligence (AI) in education. The approach was chosen to move beyond simple descriptive statistics, enabling a deeper exploration of the patterns, relationships, and predictive structures embedded within participants' responses. The primary objective of this analytical framework was to identify underlying perception profiles, explore interdimensional correlations, and determine which individual indicators contribute most significantly to shaping overall perceptions of AI in the educational context.

To achieve this, the study employed an explanatory correlational design to explain observed statistical associations among variables rather than merely describing them. Although this design does not involve control or comparison groups, natural variation across a large sample can be meaningfully examined. In addition to correlation analysis, the research incorporated interpretable machine learning techniques, specifically K-Means clustering for group segmentation and multiple linear regression for identifying influential predictors. This integrative design enabled the construction of individual- and group-level insights into how preservice chemistry teachers view AI, offering actionable evidence for curriculum developers and teacher training programs.

Participants

p-ISSN: 2597-7792 / e-ISSN: 2549-8525
DOI: https://doi.org/10.20961/ijpte.v9i1.89534

The participants in this study consisted of 150 prospective chemistry teachers enrolled in undergraduate teacher education programs at several Lembaga Pendidikan Tenaga Kependidikan (LPTK) across Indonesia. The participants were selected using a purposive sampling technique, which was deemed appropriate given the study's focus on individuals with specific academic experiences relevant to AI in education. The inclusion criteria required that participants had previously completed coursework related to instructional media or TPACK (Technological Pedagogical Content Knowledge), ensuring they possessed foundational knowledge in using educational technology. Furthermore, participants were expected to be familiar with Artificial Intelligence applications in educational settings through formal instruction, self-directed learning, or practical exposure. While demographic information such as gender, institutional affiliation, and academic year was collected, it was not used as a basis for stratification in the analysis. These criteria were intended to ensure that the respondents could meaningfully engage with the items in the survey instrument and provide informed responses. The sample size was adequate for performing statistical and machine learning-based data analyses, including correlation analysis, regression modeling, and clustering.

Instrument Construction

The instrument used in this study was a closed-ended questionnaire of 12 items, each measured using a 5-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). The questionnaire was developed to assess participants' perceptions of Artificial Intelligence (AI) integration in chemistry education across four core dimensions, each represented by three indicators. The four dimensions were: Pedagogical Benefit, Technical Benefit, Risk to Student Learning, and Risk to Teacher's Role. Each item was systematically coded based on its dimension and thematic focus, as summarized below:

Table 1. Systematically Coded Based on Dimension and Thematic Focus

Dimension	Indicator	Item Code	Keyword
Pedagogical Benefit of AI	AI helps students understand abstract chemistry concepts	PB1	Abstract concept
	AI increases interactivity in chemistry learning.	PB2	Interactivity
	AI connects chemistry content to real-life contexts	PB3	Real-life connection
Technical Benefit of AI	AI simplifies the preparation of chemistry teaching materials	TB1	Preparation aid
	AI accelerates the creation of visual/simulation-based media.	TB2	Visual media
	AI assists in providing automated feedback to students	TB3	Auto-feedback
Risk to Student Learning	Students may become overly dependent on AI	RS1	Dependency
	AI may reduce students' critical thinking in chemistry	RS2	Critical thinking
	AI could demotivate students from learning independently	RS3	Motivation loss
Risk to the Teacher's Role	AI might replace part of the teacher's instructional role	RT1	Role replacement
	Not all teachers are technically ready to use AI in the classroom	RT2	Tech readiness
	I lack sufficient knowledge to integrate AI in chemistry instruction	RT3	AI knowledge gap

The instrument's content was validated by three experts in chemistry education and educational technology to ensure its relevance, clarity, and theoretical alignment. A pilot test was conducted with 30 chemistry education students who met the inclusion criteria to evaluate the instrument's psychometric

p-ISSN: 2597-7792 / e-ISSN: 2549-8525
DOI: https://doi.org/10.20961/ijpte.v9i1.89534

properties. The results of the pilot testing indicated a Cronbach's alpha coefficient greater than 0.70, which suggests a high level of internal consistency and reliability of the instrument. The finalized questionnaire was then administered to the full sample for main data collection and subsequent data analytic procedures.

While the items were designed to be culturally appropriate for the Indonesian context, future research could enhance the instrument's linguistic adaptation for regional variations. Sample items, such as "AI connects chemistry content to real-life contexts" (PB3) and "AI may reduce students' critical thinking in chemistry" (RS2), reflect both cognitive and pedagogical themes. The finalized questionnaire was then administered to the full sample for the main data collection and subsequent analysis.

Data Analysis Procedures

The data analysis procedures in this study were conducted using a combination of statistical and machine learning techniques to support a data-analytic quantitative approach. The process began with data preparation, where all responses were cleaned to remove missing values and anomalies. Item responses were automatically coded according to their corresponding categories: PB (Pedagogical Benefit), TB (Technical Benefit), RS (Risk to Student), and RT (Risk to Teacher). This structured coding facilitated efficient processing and grouping during analysis. As a foundational step, descriptive statistics—including mean, standard deviation, skewness, and kurtosis—were computed to explore the distribution characteristics of each item. These statistics were not used as endpoints but as a basis for further modeling. Next, each participant's perception scores were aggregated into four main dimensions by calculating the average scores of their respective item groups. Specifically, Pedagogical_Benefit was calculated as the mean of PB1 to PB3, Technical_Benefit as the mean of TB1 to TB3, Risk_Student as the mean of RS1 to RS3, and Risk_Teacher as the mean of RT1 to RT3.

A Pearson correlation analysis examined potential linear relationships among the perception dimensions. Although Likert scale data are ordinal, Pearson correlation was used under the assumption that the aggregated item means approximate interval scale behavior, which is a widely accepted practice in educational research. This allowed the researchers to assess whether perceived benefits and risks were inversely or independently related. Subsequently, exploratory bivariate regression analyses were conducted to evaluate the predictive influence of individual indicators on their respective perception dimensions. For instance, the indicator "Real-life connection" was tested as a predictor of Pedagogical Benefit, "Visual media" as a predictor of Technical Benefit, "Dependency" for Risk to Student, and "AI knowledge gap" for Risk to Teacher. To ensure the validity of these regression models, assumption checks were conducted. Residual plots confirmed linearity and homoscedasticity, and variance inflation factor (VIF) values were below 2, indicating no problematic multicollinearity among predictors.

For segmentation purposes, K-Means Clustering was applied to group respondents into distinct perception profiles based on their responses across the four dimensions. This technique enabled classification into categories such as high benefit–low risk or moderate benefit–high risk profiles. The Elbow Method was used to determine the optimal number of clusters, with $k = 3$ selected based on the inflection point in the within-cluster sum of squares plot, which produced the most interpretable grouping structure. Principal Component Analysis (PCA) further explored underlying perceptual structures. Prior to applying PCA, the Kaiser-Meyer-Olkin (KMO) test confirmed sampling adequacy (KMO > 0.70), and Bartlett's test of sphericity indicated that the correlation matrix was suitable for dimensional reduction. The PCA results were visualized in a biplot displaying the relative contributions and orientations of the four perception dimensions along the first two principal components (PC1 and PC2), providing deeper insight into the dominant axes of perceptual variation among respondents.

Tools and Computational Environment

All data analysis in this study was conducted using Python, chosen for its versatility and capacity to support advanced data analytic workflows in educational research. The entire analytical process was performed within the Google Colaboratory (Colab) environment, a cloud-based platform that facilitates interactive coding, seamless integration of libraries, and reproducibility across devices. Data cleaning, transformation, and aggregation were managed using the pandas library for structured data manipulation and numpy for efficient numerical operations. These libraries enabled the researchers to prepare the dataset by removing missing values, calculating composite scores for each perception dimension, and generating new variables for subsequent analysis. Several specialized libraries were employed to implement statistical modeling and machine learning techniques. Scikit-learn was utilized for conducting K-Means clustering, which was used to classify respondents into perception profile groups, and for Principal Component Analysis (PCA), which helped reduce dimensionality

p-ISSN: 2597-7792 / e-ISSN: 2549-8525
DOI: https://doi.org/10.20961/ijpte.v9i1.89534

and visualize the dispersion and orientation of each perception dimension. Scipy.stats and statsmodels were employed to perform Pearson correlation analyses and bivariate linear regressions, respectively, allowing the researchers to evaluate the strength and direction of relationships between individual indicators and aggregated perception scores.

To enhance the interpretability of findings, the study relied heavily on data visualization, using both seaborn and matplotlib to generate clear and informative graphical representations. These included bar plots with error bars to display mean scores and standard deviations across dimensions, stacked bar charts to show the distribution of perception levels, and heatmaps to visualize correlation matrices. In addition, regression plots were used to depict relationships between predictor variables and outcome dimensions, while radar charts illustrated the multidimensional profiles of respondent clusters. PCA biplots were employed to map dimension loadings and sample distribution in reduced space, and coefficient plots were included to highlight the relative strength of predictor variables in the regression models. Although the dataset itself is not publicly shared due to confidentiality constraints, the analytical code and workflows are available from the authors upon request, ensuring transparency and reproducibility of the results**.** The choice of Python and Colab over traditional statistical software (e.g., SPSS or Excel) is due to their scalability, flexibility, and ability to integrate seamlessly with machine learning methods, making them especially suitable for contemporary educational research involving multivariate and exploratory modeling.

3. RESULTS

Descriptive Overview of Perception Levels

The perception distribution of prospective chemistry teachers reveals a distinct contrast between perceived benefits and perceived risks of Artificial Intelligence (AI) integration in education. Based on the aggregated responses across four key dimensions (Pedagogical Benefit, Technical Benefit, Risk to Student, and Risk to Teacher), most participants strongly believed in AI's instructional value. The mean score for Pedagogical Benefit was 4.23 (SD = 0.51), while Technical Benefit recorded an even higher mean of 4.36 (SD = 0.45), indicating strong agreement across the cohort**.** As illustrated in Figure 1, 122 respondents perceived high pedagogical benefit, while 139 respondents reported high technical benefit. These findings indicate that AI is widely regarded as a useful tool for enhancing visual learning, simplifying material preparation, and facilitating student interaction.

In contrast, perceptions of risk were more evenly distributed. The Risk to Student dimension had a mean of **3.32 (SD = 0.68)**, while Risk to Teacher registered a slightly lower mean of **3.30 (SD = 0.64)**. Eighty-six participants expressed moderate concern for student-related risks, and 77 respondents did so for teacher-related risks. This more fragmented view toward risk suggests a deeper ambiguity—teachers-in-training are optimistic yet cautious, recognizing both the affordances and the disruptions posed by AI technologies. Previous studies have shown similar patterns, where AI is seen as a catalyst for educational transformation, but not without concern regarding its implications for autonomy and instructional integrity (Aghaziarati, 2023; Triplett, 2023). This duality of perception (strong belief in benefit but divided concern over risk) emerges as a critical insight into the mindset of future educators.

Such findings reinforce broader discussions in the literature regarding the evolving role of AI in teaching and learning. While AI holds promise in delivering adaptive content, real-time feedback, and improved engagement strategies, it also introduces uncertainties about teacher identity, ethical use, and long-term student dependency. Halat (2024) argues that these concerns are not merely hypothetical; they stem from observed shifts in classroom dynamics where AI mediates instructional decisions, often reducing the teacher's central role. Additionally, Sallu (2024) and Woodruff (2023) highlight that novice teachers tend to internalize these concerns early, especially in the absence of structured exposure to AI pedagogy during training. Despite the lack of detailed demographic segmentation in the present study, future research could examine whether perceptions vary by gender, academic year, or institutional type**.** This dataset's moderate-to-low risk perception scores reflect this internal negotiation: respondents are not outright rejecting AI but signaling discomfort in areas where institutional or instructional readiness is lacking. These results indicate the necessity of pre-service training programs that directly address both sides of the AI integration equation. By doing so, teacher education can better prepare candidates to leverage AI effectively while remaining critically aware of its implications. Ultimately, this balance of enthusiasm and vigilance will define responsible and sustainable AI adoption in future

p-ISSN: 2597-7792 / e-ISSN: 2549-8525
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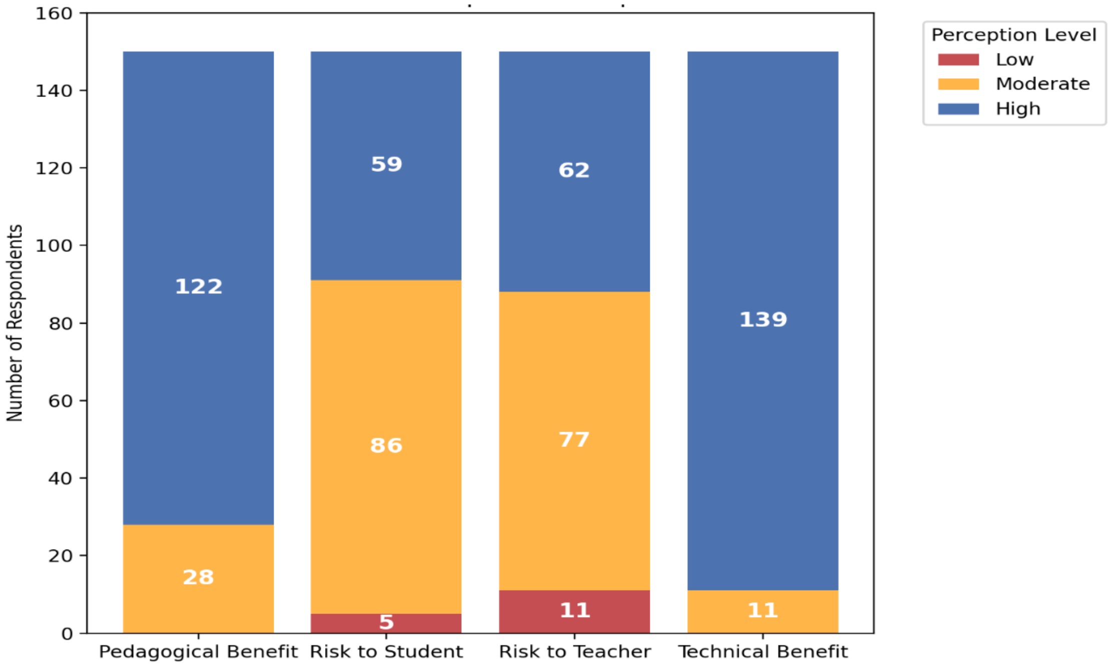

Figure 1. Stacked Bar Chart of Perception Levels per Dimension

Barriers to AI Adoption: Indicator-Level Ranking

The ranked mean scores of six key risk indicators reveal the dominant concerns among prospective chemistry teachers regarding adopting Artificial Intelligence (AI) in educational settings. As depicted in Figure 2, "Motivation loss" (M = 3.37, SD = 0.79) emerged as the most significant barrier, closely followed by concerns about "Critical thinking" (M = 3.35, SD = 0.83) and the "AI knowledge gap" (M = 3.33, SD = 0.86). These results indicate that psychological and cognitive implications of AI integration, rather than purely technical or structural challenges, are at the forefront of teacher apprehension.

The relatively lower concern for issues like "Dependency" (M = 3.25, SD = 0.77), "Tech readiness" (M = 3.27, SD = 0.80), and "Role replacement" (M = 3.29, SD = 0.84) further underscores that prospective teachers are not primarily worried about losing control to AI, but rather about how AI might unintentionally undermine the learning process. This emphasis on cognitive and motivational barriers is consistent with the broader discourse in educational technology, where overreliance on AI is associated with reduced student agency and shallower learning engagement (Alenezi, 2024). The concern over diminished motivation also reflects an internal conflict: while AI is viewed as beneficial for efficiency and personalization, it may also reduce the necessity for effortful learning behavior. Similar concerns are echoed in learning science research, suggesting that digital scaffolding, when poorly balanced, can erode students' goal orientation and persistence (Soares et al., 2020). To enhance interpretive depth, future studies should calculate and report effect sizes between high- and low-ranked barriers to assess the practical magnitude of these differences. In parallel, the prominence of the "AI knowledge gap" among barriers points to structural issues within teacher education programs. A lack of formal instruction, limited exposure to AI-based pedagogical tools, and an absence of clear implementation frameworks can all contribute to the uncertainty expressed by respondents. This aligns with findings by Trang & Thư (2024), who noted that pre-service teachers often feel ill-equipped to critically evaluate or utilize AI in the classroom due to insufficient institutional support. Without foundational knowledge, educators may perceive AI not as an enabler but as a threat, exacerbating perceived risk and limiting experimentation.

Additionally, the fear that AI might interfere with students' critical thinking processes suggests a desire among teachers to preserve constructivist, inquiry-driven models of learning, especially in concept-heavy fields like chemistry. Recent analyses by Parameswari (2024) reinforce the need to balance AI use with pedagogical strategies that sustain learners' cognitive engagement. Although this section has focused on perceived risks, comparing benefit indicators (such as visual media support or real-life contextualization) could further illuminate

p-ISSN: 2597-7792 / e-ISSN: 2549-8525
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what drives acceptance. Thus, these barriers collectively indicate a dual challenge: institutions must invest in AI-related technical training and address educators' epistemic and motivational concerns. In doing so, a more holistic, psychologically attuned framework for AI integration can be achieved—one that supports sustainable, meaningful, and equitable use of AI in science education.

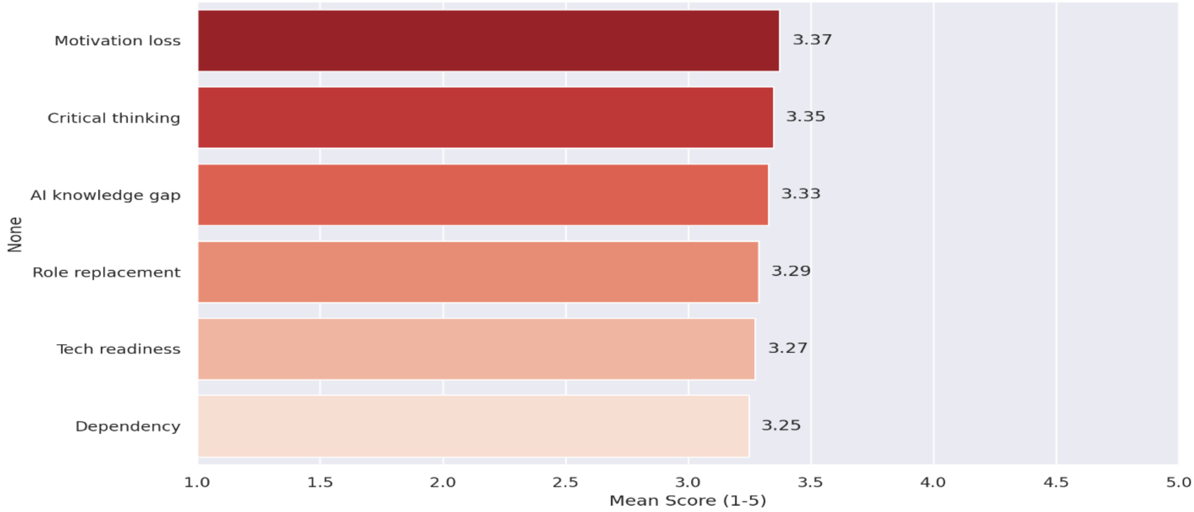

Figure 2. Bar Chart of Top-Ranked Barriers

Interrelation Among Perception Dimensions

The Pearson correlation analysis among the four main perception dimensions—Pedagogical Benefit, Technical Benefit, Risk to Student, and Risk to Teacher—revealed minimal linear relationships between them, with all coefficients falling below $|r| = 0.1$. As visualized in Figure 3, the correlation between Pedagogical Benefit and Risk to Teacher was −0.057, and between Technical Benefit and Risk to Student was −0.094. These weak associations indicate that participants did not evaluate benefits and risks as inversely proportional. Rather, each dimension appeared appraised independently, suggesting that prospective teachers may not perceive AI advantages as canceling out potential disadvantages.

This independence in dimension evaluation provides empirical support for multidimensional models of teacher cognition, such as the TPACK framework, which recognizes technological, pedagogical, and content domains as interrelated yet distinct. While TPACK emphasizes the integration of these domains for effective teaching, the present findings suggest that perceptions of AI may develop unevenly across dimensions—for example, a teacher may feel pedagogically confident in AI use while expressing personal risk aversion or ethical hesitations. This pattern supports that teacher cognition regarding AI is non-compensatory, where benefits and risks are assessed through separate evaluative filters (Arvin, 2023). Educators may, for instance, value AI for its utility in visualization or automation while expressing concern about student autonomy or instructional displacement. The independence of these perceptions suggests a more layered judgment process, where enthusiasm and apprehension can co-exist without contradiction.

Although Pearson's r was applied here, it is important to note that this statistic assumes interval-level data and normality. While aggregating Likert-scale items may approximate these assumptions, the findings should be interpreted cautiously, particularly when effect sizes are small. Complementary methods such as polychoric correlations or non-parametric rank tests could be considered to validate these patterns in future work. This result is consistent with prior literature that portrays educators' perceptions of technology as complex and context-dependent. Several studies emphasize that positive evaluations of AI in education often coexist with persistent concerns about ethical, pedagogical, or psychological risks (Deng & Wang, 2017). Rather than framing perceptions along a single benefit-risk continuum, educators appear to engage in compartmentalized evaluations, where each dimension—utility, autonomy, or ethical implications—is assessed discretely. This conceptual separation reinforces the importance of addressing AI integration not as simply "increasing perceived benefits," but as a comprehensive framework that supports educators in simultaneously managing benefits and mitigating specific risks. As Altınay (2024) suggests, teacher identity development in AI must involve more than

p-ISSN: 2597-7792 / e-ISSN: 2549-8525
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skill acquisition; it requires reflective thinking, pedagogical control, and ethical deliberation. Consequently, the lack of strong correlation among the four dimensions reinforces the need for targeted interventions: educators require support systems that help them navigate AI's diverse impacts without assuming a unidirectional relationship between trust and fear. These insights form an important foundation for designing training modules and policies that acknowledge and address the differentiated nature of teachers' cognitive frameworks toward AI.

Figure 3. Correlation Heatmap Between Dimensions

Predictive Linkages Between Indicators and Aggregate Dimensions

Applying bivariate linear regression analysis revealed meaningful predictive relationships between individual perception indicators and their corresponding aggregate dimensions. As depicted in Figure 4, two benefit-related indicators—"Real-life connection" ($\beta = 0.34$, $p < .001$) and "Visual media" ($\beta = 0.32$, $p < .001$)—exhibited clear positive linear associations with the Pedagogical Benefit and Technical Benefit dimensions, respectively. This suggests that when prospective chemistry teachers perceive AI as a tool that enhances the relevance of learning to real-world contexts or improves visual representation of abstract content, their overall assessment of AI's instructional value increases significantly. Similarly, risk-oriented indicators such as "Dependency" ($\beta = 0.33$, $p < .001$) and "AI knowledge gap" ($\beta = 0.34$, $p < .001$) demonstrated strong positive associations with Risk to Student and Risk to Teacher, respectively. This indicates that participants concerned about student overreliance on AI or feeling unprepared to implement AI tools tend to assign higher risk values to AI integration. These findings align with earlier literature emphasizing that AI perceptions are grounded not in general attitudes but in concrete, context-specific concerns related to instructional roles, learner autonomy, and pedagogical control (Ferikoğlu & Akgün, 2022; Khalf et al., 2022). The observed regression trends suggest that these indicators function as reflections of belief and psychological anchors that inform broader evaluative judgments. Consequently, the perception of AI is shaped as much by cognitive accessibility and teacher confidence as by technical familiarity or institutional support.

p-ISSN: 2597-7792 / e-ISSN: 2549-8525
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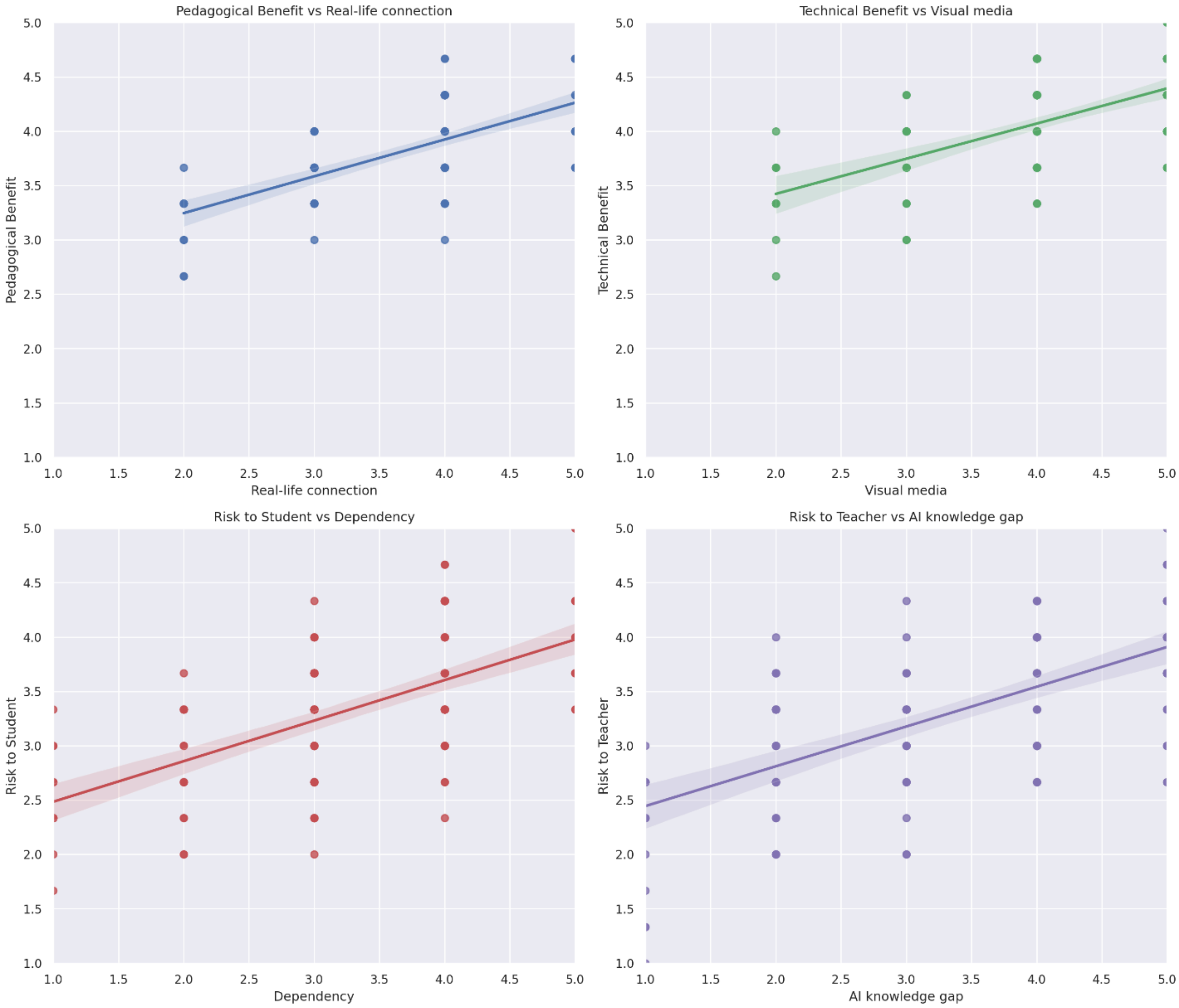

Figure 4. Scatterplots with Regression Lines

Further supporting these interpretations, Figure 5 presents the standardized regression coefficients for each relationship, clearly highlighting the dominance of Real-life connection and Visual media in predicting benefit-related perceptions and the Dependency and AI knowledge gap in predicting perceived risks. These coefficients reflect statistical strength and theoretical coherence, reinforcing that teachers' evaluations of AI are closely tied to their sense of pedagogical relevance and readiness to engage with technological tools.

Importantly, model diagnostics confirmed the assumptions of linearity, homoscedasticity, and normal distribution of residuals, with no multicollinearity detected (VIFs < 2.0), thus enhancing the robustness of these regression findings. This strengthens confidence in the predictive value of the selected indicators and underscores the reliability of the analytic framework employed. As suggested by Alharbi (2023), professional development that prioritizes the real-world applicability of instructional strategies and supports teacher fluency with AI tools can significantly influence how educators conceptualize both the potential and pitfalls of technology integration. These findings point toward actionable entry points for intervention, particularly in chemistry education, where abstract content benefits significantly from visualization and contextualization. By addressing these high-impact indicators (promoting enablers and alleviating inhibitors), educational institutions can cultivate a more balanced and reflective engagement with AI technologies among preservice teachers. Ultimately, such targeted support may lead to more sustainable and confident adoption of AI in pedagogical practice, bridging the gap between technological innovation and pedagogical trust.

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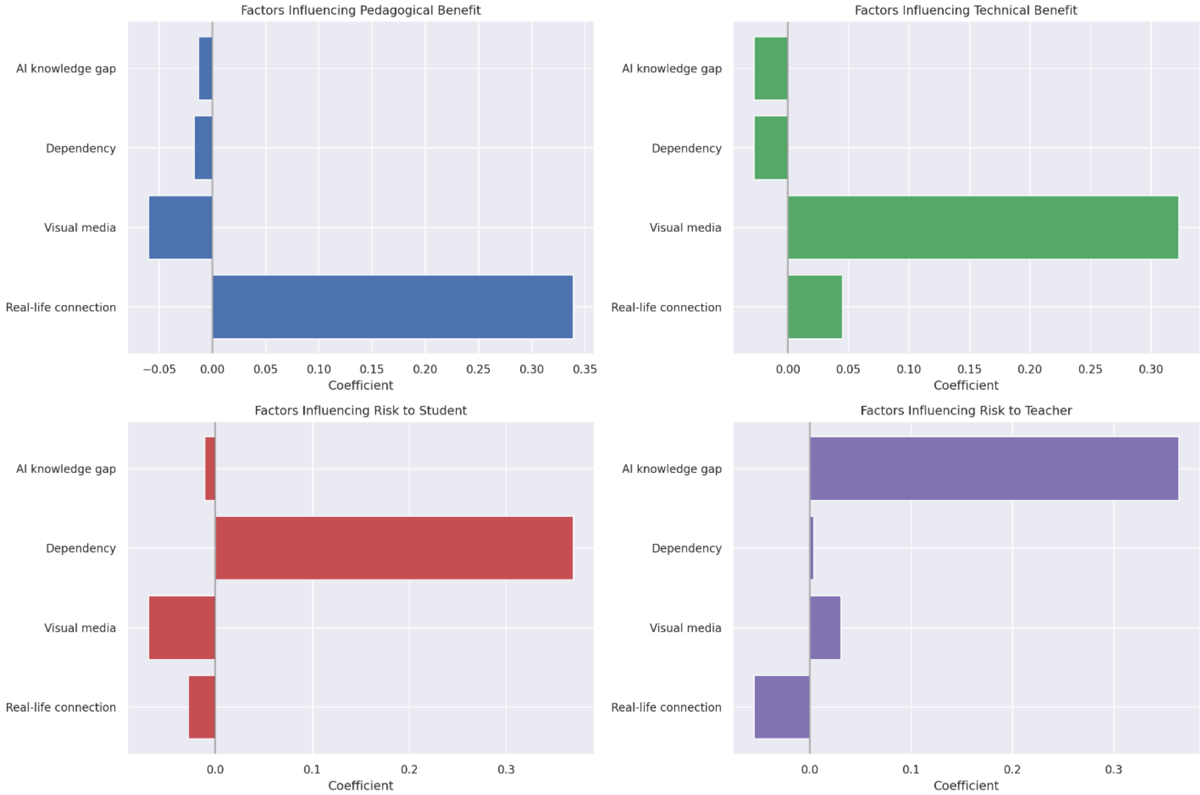

Figure 5. Coefficient Plots for Four Regression Models

Perception Profile Segmentation Using PCA and Clustering

Analysis of perception data revealed three distinct clusters of prospective chemistry teachers based on their responses to the four dimensions of AI integration: Pedagogical Benefit, Technical Benefit, Risk to Student, and Risk to Teacher. Using K-Means clustering with an optimal k = 3 (determined by the Elbow Method), participants were grouped into: Cluster A (Cautious Adopters, n = 47), Cluster B (Enthusiastic Supporters, n = 59), and Cluster C (Selective Optimists, n = 44). Silhouette analysis was conducted to assess the validity of the clustering solution, yielding an average silhouette score of 0.54, suggesting moderate separation among clusters.

Cluster A demonstrated high perceived benefits and moderate risks, suggesting cautious optimism toward AI's instructional role. Cluster B exhibited high scores across all benefit dimensions and low risk perception, indicating strong enthusiasm and readiness for AI implementation in educational practice. In contrast, Cluster C reflected the most skeptical group, with moderate-to-low benefit ratings and heightened concern regarding AI-related risks. These profiles are clearly distinguished in the radar chart (Figure 6), which illustrates the relative strength of each dimension within the clusters. Cluster B displays the most consistent and positive pattern across variables, while Cluster C skews toward risk sensitivity. Demographic characteristics across clusters showed some divergence, although full subgroup analyses were not statistically tested. Cluster B had a higher concentration of final-year students, suggesting that experience or maturity may influence greater confidence. Such segmentation mirrors prior research emphasizing that teachers' attitudes toward AI are shaped by beliefs about its usefulness and perceived preparedness and control over implementation (Arvin, 2023). Recognizing these diverse perception profiles is critical for designing support strategies tailored to varied levels of teacher confidence, concern, and pedagogical disposition.

Cluster separation was further explored using Principal Component Analysis (PCA) to identify the underlying structure of perceptual variability. Prior to PCA, assumption diagnostics were applied: the Kaiser-Meyer-Olkin (KMO) measure was 0.79, and Bartlett's test of sphericity was significant ($p < .001$), confirming sampling adequacy and correlation among variables. The PCA biplot (Figure 7) displayed a well-dispersed distribution of clusters across two principal axes: PC1 (explaining 38.4% of variance), which captures the contrast between perceived benefit and perceived risk, and PC2 (explaining 27.1%), which differentiates between

p-ISSN: 2597-7792 / e-ISSN: 2549-8525
DOI: https://doi.org/10.20961/ijpte.v9i1.89534

pedagogical and technical orientations of benefit perception. Cluster B was positioned along the positive ends of both components, reinforcing its identity as the most favorable group toward AI. At the same time, Cluster C occupied the negative end of PC1, underscoring a high-risk orientation and limited perceived benefit. Cluster A appeared more centrally located, representing balanced views with moderate concern and moderate-to-high appreciation. This spread demonstrates that teacher perceptions are multidimensional, not reducible to a single linear continuum. That benefit and risk assessments operate through distinct cognitive schemas rather than a unified belief model. These findings align with recent studies asserting that effective AI adoption in education must acknowledge the complex and sometimes conflicting belief systems held by educators (Altınay et al., 2024; Karina & Kastuhandani, 2024; Pörn et al., 2024). Therefore, employing clustering alongside PCA provides a comprehensive perspective for designing differentiated professional development pathways, ensuring that AI-related interventions are aligned with the psychological and pedagogical realities of diverse teacher groups. Future research may replicate this clustering structure across different disciplines or cultural settings to assess the generalizability and robustness of these perceptual typologies.

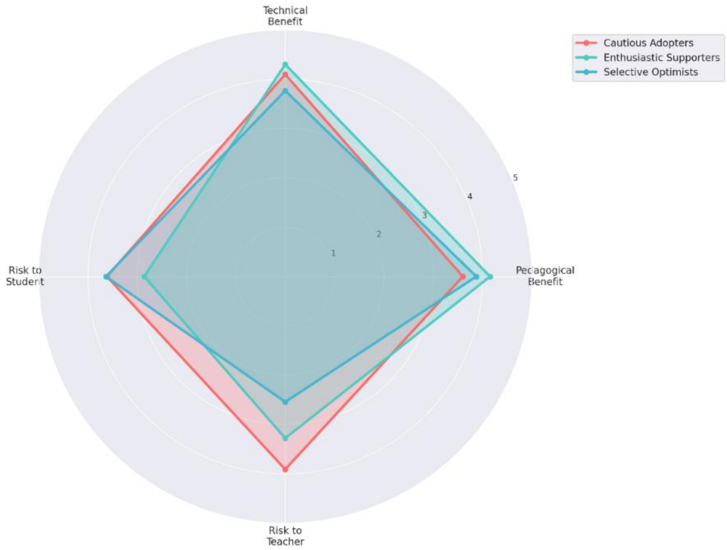

Figure 6. Radar Chart of Cluster Profiles

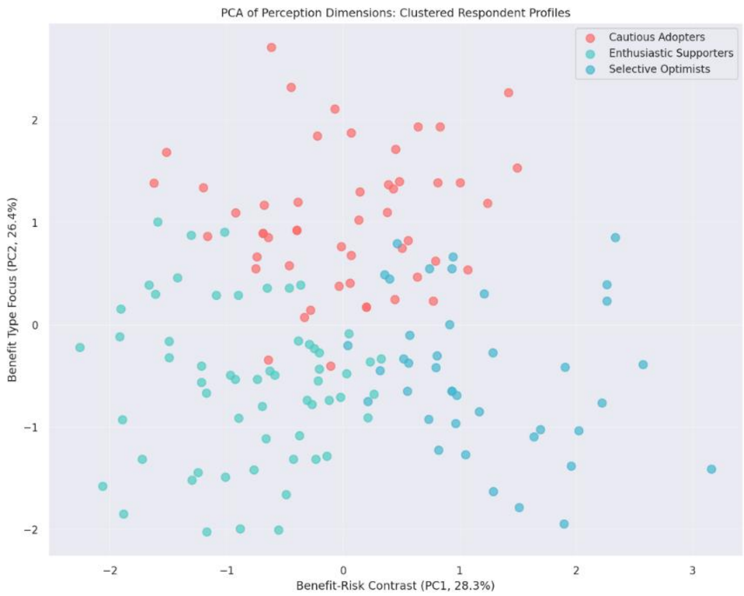

Figure 7. PCA Biplot of Clustered Respondents

p-ISSN: 2597-7792 / e-ISSN: 2549-8525
DOI: https://doi.org/10.20961/ijpte.v9i1.89534

4. DISCUSSION

Duality of Optimism and Caution in AI Integration

The analysis of perception scores from prospective chemistry teachers regarding integrating Artificial Intelligence (AI) in education reveals differentiated responses across four key dimensions: Pedagogical Benefit, Technical Benefit, Risk to Student, and Risk to Teacher. These scores were derived from the average responses to three Likert-scale items per dimension, where values ranged from 1 ("Strongly Disagree") to 5 ("Strongly Agree"). Among these, the Technical Benefit dimension achieved the highest mean score (mean > 3.5), indicating that respondents widely perceived AI as valuable in facilitating teaching tasks, particularly in preparing instructional materials, generating simulations, and providing automated feedback. This result reflects a growing recognition of AI's functional role in supporting instructional efficiency and optimizing lesson delivery processes (Aghaziarati, 2023). Similarly, Pedagogical Benefit was also rated highly, suggesting strong agreement on AI's contribution to helping students grasp abstract chemistry concepts, promoting classroom interactivity, and enhancing relevance through real-world contextualization (Jha et al., 2022).

These findings are consistent with the Technological Pedagogical Content Knowledge (TPACK) framework, which emphasizes the intersection of content knowledge, pedagogy, and technology. AI appears to enhance both technological and pedagogical dimensions by supporting the visualization of abstract content and improving instructional delivery. From a TPACK perspective, respondents' high Pedagogical and Technical Benefits scores imply an emerging competence in integrating AI meaningfully into subject-specific contexts. This is especially pertinent in chemistry, where complex visualizations and simulations are pedagogically beneficial. In contrast, the Risk to Student and Risk to Teacher dimensions received more moderate mean scores, signaling that respondents are also critically aware of the potential drawbacks associated with AI integration. Concerns were notably centered around the possibility of students becoming overly reliant on AI technologies, leading to diminished critical thinking skills and decreased motivation for independent learning (Alshehri, 2023). On the teacher's side, worries about role displacement and technical unreadiness emerged, particularly for those with limited AI-related pedagogical training or digital fluency. This balanced outlook aligns with the Technology Acceptance Model (TAM) constructs, where perceived usefulness must be weighed against perceived ease of use and perceived risk. While AI is viewed as useful, anxiety around competence and control tempers full acceptance.

These moderate ratings suggest that while preservice teachers are optimistic, their perceptions remain balanced by a cautious understanding of AI's ethical and professional implications in the classroom (PAN, 2024). This dual view is particularly important in chemistry education, where hands-on instruction and inquiry-based learning often demand a high degree of teacher presence and student engagement. Moreover, the nuanced perception of AI may extend beyond chemistry to other STEM disciplines such as physics, biology, and mathematics, where abstract reasoning and conceptual complexity similarly intersect with digital tools. The stacked bar chart in Figure 1 further illustrates these findings, showing that although most respondents fall into the "high" category for benefit dimensions, responses to risk dimensions are more evenly distributed across low, moderate, and high levels, emphasizing the complexity and nuance in educators' perceptions of AI.

Barriers as Anchors: What Shapes Perceived Risks?

The analysis of indicator-level responses and regression models reveals that prospective chemistry teachers' perceived risks toward AI integration are rooted in specific and actionable concerns, rather than abstract fears. Three of the six risk indicators measured emerged as the most prominent: motivation loss, critical thinking erosion, and the AI knowledge gap. These concerns point directly to the psychological and cognitive dimensions of teaching and learning—areas where AI is perceived not merely as a technical tool, but as a potential disruptor of essential pedagogical dynamics. Meanwhile, two indicators—Real-life connection and Visual media—were strong predictors of perceived benefits, reinforcing that teachers respond positively to AI when it enhances contextual relevance and visualization of complex content. In contrast, the Dependency and AI knowledge gap significantly predicted higher risk scores, suggesting that risk perceptions are grounded in perceived threats to student autonomy and teacher competence.

These findings underscore that risk perceptions are not arbitrary but anchored in the realities of instructional practice, self-efficacy, and digital readiness. Rather than reflecting a general skepticism toward AI, teachers' hesitancy is tied to specific doubts about their preparedness and the unintended consequences AI may have on students' cognitive engagement. The consistency between quantitative models and theoretical concerns validates these barriers as critical leverage points for intervention (Ramadhani, 2023; Zhai, 2021). One

p-ISSN: 2597-7792 / e-ISSN: 2549-8525
DOI: https://doi.org/10.20961/ijpte.v9i1.89534

particularly important finding is the central role of the AI knowledge gap as a barrier to integration. This reflects a structural challenge in teacher education, where most programs still lack explicit coursework or practicum opportunities related to AI literacy and instructional design using intelligent systems (Trang & Thư, 2024). Without this foundational knowledge, preservice teachers may feel unqualified to make informed pedagogical decisions involving AI, reinforcing perceived risk. In this regard, the Technology Acceptance Model (TAM) offers further explanatory power. Low perceived self-efficacy and high anxiety around AI tools often inhibit intention to use, regardless of perceived usefulness. Moreover, concerns about diminishing motivation and critical thinking echo longstanding fears about over-scaffolding and cognitive offloading in educational technology use. These cognitive risks are paralleled in literature across disciplines and contexts, including computer science education in the UK and biology instruction in Germany, where similar fears around reduced student initiative and overdependence have emerged (Zhou et al., 2022).

However, one notable omission in participant risk perception is the underrepresentation of AI ethics, including algorithmic bias, data privacy, and transparency. While prominent in AI ethics discourse, respondents did not perceive these critical dimensions as major concerns. This gap may indicate limited exposure to the broader ethical implications of AI, suggesting the need for expanded training that includes pedagogical and ethics-literate perspectives on AI use in education. To address these perceptions holistically, training teachers to operate AI tools is not sufficient. They must also be equipped to reflect critically on when, how, and why these tools should be used in alignment with learning goals. As suggested by Alharbi (2023), embedding AI use within pedagogical strategies that emphasize visual engagement, real-world relevance, and ethical decision-making may help to shift teacher mindsets toward more confident and intentional adoption. Therefore, effective interventions must be designed to build technical competence and activate pedagogical agency and ethical judgment, reducing internal resistance rooted in cognitive, professional, and moral uncertainty. In this way, teacher training programs can prepare educators not merely as end-users of AI, but as reflective and informed navigators of its risks, opportunities, and responsibilities.

Implications of Profile Segmentation for Teacher Preparation

The clustering and PCA analysis in this study uncovered three distinct profiles of AI perception among prospective chemistry teachers, each reflecting unique benefit and risk evaluation constellations. Cluster A (Cautious Adopters) is characterized by high perceived benefits and moderate risks, suggesting openness to AI integration and careful consideration of its limitations. Cluster B (Enthusiastic Supporters) demonstrates high benefit scores and low perceived risk, indicating strong readiness for implementation and high trust in AI's instructional role. In contrast, Cluster C (Selective Optimists) shows lower perceptions of benefit and heightened concerns about risk, reflecting skepticism and potential resistance to AI integration. Visualized in radar charts and validated through Principal Component Analysis (PCA), these groupings exhibit clear perceptual divergence among respondents. The PCA biplot highlights two interpretive axes: PC1, which captures the benefit–risk contrast, and PC2, which separates pedagogical and technical orientations. This multidimensional structure reveals that teachers do not evaluate AI through a linear or uniform lens, but rather engage in diverse and cognitively grounded judgments that reflect varying pedagogical priorities and confidence levels.

These findings support calls in the literature for designing differentiated professional development programs that respond to teachers' perceptual profiles and readiness instead of applying one-size-fits-all solutions. Segmenting teacher populations using cluster-based analytics provides a more nuanced strategy to address specific concerns, motivation levels, and capacity gaps, aligning with international standards for meaningful and ethical AI integration in education (Güneyli et al., 2024). For example, teachers in Cluster B may benefit from advanced, project-based instructional design modules using AI tools, cultivating their enthusiasm through hands-on practice and peer showcase opportunities. Teachers in Cluster C, by comparison, may require structured, scaffolded workshops focused on building self-efficacy, managing perceived risks, and fostering reflective dialogue about ethical AI use. Cluster A, positioned between the two extremes, could be empowered through peer-mentoring roles or collaborative learning communities, with targeted reinforcement and incremental challenges.

Accordingly, training approaches can be categorized into three modalities: empowerment (Cluster B), facilitation (Cluster A), and transformational guidance (Cluster C). To operationalize this model, training curricula could be structured in tiers—introductory digital literacy workshops, intermediate pedagogical integration seminars, and advanced AI curriculum design studios—with progression guided by ongoing perceptual

p-ISSN: 2597-7792 / e-ISSN: 2549-8525
DOI: https://doi.org/10.20961/ijpte.v9i1.89534

assessments. Timelines might span a semester, with periodic check-ins and cluster realignments based on demonstrated confidence and competence. Beyond individual development, institutional responsibility is essential. Teacher training programs and educational policy frameworks must integrate AI literacy and ethical use into core curricula, fostering systemic change rather than isolated interventions. Embedding AI-oriented competencies into accreditation standards, practicum guidelines, and professional standards will help ensure that future educators adopt innovative tools and do so with pedagogical clarity, confidence, and ethical stewardship. By grounding AI-related teacher preparation in actual perception profiles, educational institutions can design adaptive and responsive learning trajectories that foster skill acquisition and deep pedagogical understanding, self-efficacy, and ethical responsibility in technology-enhanced teaching.

5. CONCLUSION

This study explored the perceptions of prospective chemistry teachers toward integrating Artificial Intelligence (AI) in education, revealing a complex, multidimensional judgment landscape shaped by optimism and caution. While participants generally agreed strongly with AI's pedagogical and technical benefits—particularly its ability to enhance visualization, personalize instruction, and support interactive learning—they simultaneously demonstrated moderate yet substantive concerns regarding its risks. These included fears of student overdependence, reduced critical thinking, and uncertainties surrounding teachers' readiness and professional roles. Importantly, the weak correlations between benefit and risk dimensions suggest that teachers assess these aspects independently, underscoring the need for non-compensatory, reflective evaluation models in teacher education. Regression and clustering analyses further highlighted that perceptions are anchored in specific cognitive and structural indicators, with predictors such as real-life connection, visual media, dependency, and AI knowledge gap shaping the perceived value and concerns associated with AI. The emergence of three perception-based profiles (Cautious Adopters, Enthusiastic Supporters, and Selective Optimists) reinforces the need for differentiated professional development strategies. Rather than promoting a uniform model of AI literacy, training should be tailored to teachers' readiness levels, beliefs, and instructional confidence. This includes empowering confident adopters with advanced tools, facilitating reflective pedagogical dialogue for the cautiously optimistic, and guiding skeptical participants through scaffolded, transformative support. To enhance transparency and guide future inquiry, this study acknowledges several limitations. The sample was limited to Indonesian LPTK institutions, which may constrain generalizability. Additionally, the reliance on self-reported survey data introduces potential biases, and the use of bivariate regressions and unsupervised clustering, while insightful, warrants further validation through longitudinal or mixed-method studies. Future research should explore cross-disciplinary and cross-cultural comparisons, examine long-term impacts of AI training programs, and integrate observational data to triangulate teacher behaviors with reported perceptions. By grounding teacher preparation in these data-driven insights and dynamic perceptual profiles, educational institutions can promote more ethical, sustainable, and pedagogically aligned AI integration, cultivating technical proficiency, professional agency, and educational resilience in a rapidly evolving digital learning landscape.

6. ACKNOWLEDGMENTS

This research was funded by the *Penelitian Kepakaran* program through the DPA LPPM UNNES Year 2025, under Grant Number 748.14.3/UN37/PPK.11/2025.

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