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# FACTORS INFLUENCING PRE-SERVICE PRIMARY TEACHERS' READINESS TO USE ARTIFICIAL INTELLIGENCE IN LESSON PLANNING

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**Abstract.** This study examines factors influencing pre-service primary teachers' willingness to use AI in lesson planning, as they are expected to lead technology integration in the classroom. Grounded in the Unified Theory of Acceptance and Use of Technology (UTAUT), the Technology Acceptance Model (TAM), the Theory of Planned Behavior (TPB), and the Technological Pedagogical Content Knowledge (TPACK) framework, a survey instrument with six components was developed and administered to 468 pre-service teachers at Hanoi Metropolitan University. Data were analyzed using exploratory factor analysis (EFA) in SPSS. Six key factors emerged: (1) expected effectiveness of AI in supporting lesson planning; (2) awareness and attitudes toward using AI in lesson planning; (3) AI-related skills in lesson design; (4) support from lecturers and the institution; (5) technological infrastructure and learning environment; and (6) ethical and legal understanding of AI in education. Among these, Performance Expectancy and AI-related Skills were the strongest predictors, aligning with TAM and UTAUT, while institutional support, infrastructure, and ethical awareness provided essential enabling conditions. The findings confirm classic technology adoption models while highlighting new requirements in teacher training under digital transformation. Practically, the study suggests integrating AI content into curricula, offering hands-on activities with modern AI tools, improving infrastructure, and enhancing faculty capacity.

***Keywords:*** artificial intelligence, lesson planning, teacher education, technology adoption, pre-service primary teachers.

## 1. Introduction

Artificial Intelligence (AI) refers to systems that simulate human cognition and intelligent behavior [1], a concept first introduced by John McCarthy in 1956 [1]. In education, AI has become a powerful tool supporting management, teaching, and learning through applications such as tutoring systems, chatbots, and personalized learning platforms [2]. These technologies optimize instruction, improve knowledge acquisition, and allow learners to regulate their learning paths based on individual competencies [3].

AI integration has also been linked to improved management efficiency and pedagogical innovation [4], [5]. Importantly, it enhances teachers' professional capacities, who are central to ensuring educational quality. Chen et al. (2020) highlighted the use of AI in higher education to support teaching activities and improve interactivity [6].

Recently, research has increasingly focused on teacher education. Patrik and Ilona (2024) emphasized AI's role in lesson planning (LP), where teachers can access suggestions for activities, generate diverse instructional materials, and assess students automatically [7]. Similarly, Park et al. (2023) found that teachers responded positively to AI-integrated science lessons, especially in analyzing learners' needs and tailoring activities [8].

From a teacher education perspective, integrating AI into training is essential to equip future educators with digital competencies for instructional practices. This aligns with the demands of digital transformation, which reshapes teaching and learning while requiring higher levels of digital literacy and critical thinking. Providing pre-service teachers with opportunities to use AI in lesson design, classroom practice, and assessment can foster confidence and competence in technology-rich environments.

Therefore, examining factors influencing pre-service primary teachers' readiness to apply AI in instructional planning is both necessary and significant. Such an investigation provides a basis for designing teacher education programs that cultivate technological competence and promote meaningful AI integration into primary education in the digital era.

# 2. Content

## 2.1. Theoretical Framework

In Vietnam, a lesson plan (also known as a teaching plan) is defined as a document that outlines the organization of teaching activities, created by teachers under school guidance to implement the national curriculum [9]. It includes both student and teacher activities to help students acquire knowledge and develop necessary skills and qualities. The lesson plan is created and carried out by the teacher proactively and flexibly, aligning with students' characteristics and teaching conditions, which is regularly adjusted and supplemented to suit students' characteristics and teaching conditions [10]. Teachers base their lesson plans on required outcomes specified in the subject curriculum, the school's educational plan, the teaching plan for subjects, textbooks, and teaching materials, which include desired outcomes, required teaching aids, main activities, and adjustments after the lesson.

This study is based on classical and contemporary theoretical models of technology usage behavior, including the Unified Theory of Acceptance and Use of Technology (UTAUT), the Technology Acceptance Model (TAM), the Theory of Planned Behavior (TPB), and the TPACK framework in teacher training. These models provide a solid foundation for identifying key factors influencing pre-service teachers' willingness to use AI in lesson plan design.

The UTAUT model by Venkatesh et al. (2003) and Dwivedi et al. (2019) posits that users' acceptance and use of technology are influenced by four main factors: performance expectancy, effort expectancy, social influence, and facilitating conditions [11, 12]. In this study, "performance expectancy" is used to frame items that assess students' beliefs in AI's ability to enhance teaching effectiveness. In contrast, facilitating conditions inform the development of indicators related to institutional support and technological infrastructure.

The TAM emphasizes the role of "perceived usefulness" and "perceived ease of use" in influencing attitudes and technology usage behavior [13], [14]. This model guides the measurement of pre-service teachers' perceptions and attitudes toward AI, serving to differentiate internal motivational drivers from broader institutional enablers as proposed in UTAUT.

The TPB suggests technology usage behavior is influenced by personal attitude, social norms, and perceived control [15]. Unlike TAM and UTAUT, which emphasize system-related variables, TPB offers a psychological and ethical lens. In this research, it contributes a psychological and ethical lens, informing items related to ethical–legal awareness, risk perceptions, and students' sense of control when integrating AI into their instructional design.

The TPACK framework is a model describing the integration of technological knowledge, pedagogical knowledge, and content knowledge [16]. This serves as the basis for constructing indicators related to AI usage skills in LP, including setting learning objectives, designing teaching activities, developing assessment tools, and utilizing educational technology resources.

Studies within the expanded scope of UTAUT and TAM by Venkatesh (2022) and Saif et al. (2024) also highlight the important role of facilitating conditions and organizational support in promoting technology usage behavior [11], [13]. Therefore, sets of questions related to support from instructors, educational institutions, technological infrastructure, and creative learning environments have been developed to measure the impact of external factors on pre-service teachers' willingness to use AI.

The incorporation of these four models ensures theoretical robustness while minimizing redundancy. Each is selectively applied to capture a unique dimension of AI integration: from personal motivation and beliefs (TAM, TPB), to contextual and institutional enablers (UTAUT), to pedagogical knowledge and practice (TPACK). This multi-model approach supports a nuanced understanding of the complex interplay between internal dispositions, ethical considerations, pedagogical readiness, and external conditions in shaping pre-service teachers' willingness to adopt AI in LP.

***Table 1. Theoretical Basis of the Questionnaire***

| Impact Factor | Content | Reference Source |
|---|---|---|
| KV- Performance Expectancy of AI in Supporting LP | KV1. I believe AI helps me design lesson plans more effectively.<br>KV2. I save time in designing lesson plans by using AI.<br>KV3. AI helps me organize lesson content clearly and coherently.<br>KV4. AI supports me in generating creative ideas for LP.<br>KV5. I believe AI will improve my future teaching quality. | Venkatesh, V. (2022) [11]<br>Dwivedi, Y. K., Rana, N. P., Chen, H., & Williams, M. D. (2011) [12] |
| NT- Perception and Attitude towards AI in LP | NT1. I feel interested in using AI to design lesson plans.<br>NT2. I am willing to learn and use AI in lesson preparation.<br>NT3. I believe AI is a useful tool for future teaching.<br>NT4. I am aware of the role of AI in improving the quality of LP. | Saif, N., Khan, S. U., Shaheen, I., Alotaibi, F. A., Alnfiai, M. M., & Arif, M. (2024) [13]<br>Jiao, J., & Cao, X. (2024) [14] |
| KN – Skills in using AI in LP | KN1. I know how to use AI tools to formulate lesson objectives.<br>KN2. I know how to use AI to generate ideas for activities.<br>KN3. I know how to use AI to suggest teaching aids and materials<br>KN4. I use AI to design questions for assessing primary students.<br>KN5. I use AI to revise and improve the lesson plan after drafting<br>KN6. I can evaluate the relevance of AI-generated content in LP.<br>KN7. I can use AI to design tailored to students' characteristics. | Knauder H & Koschmieder C, (2019 [15]<br>Wang, W., Schmidt-Crawford, D., & Jin, Y. (2018) [16] |

| | | |
|---|---|---|
| HT – Support from lecturers and the teacher education institution | HT1. I receive guidance from lecturers on how to use AI in LP.<br>HT2. My university encourages students to use AI in learning.<br>HT3. I have opportunities to learn how AI applies in teaching.<br>HT4. Lecturers support students in applying new technologies.<br>HT5. The university holds AI-in-education seminars or contests.<br>HT6. Lecturers give feedback on my AI-based lesson plans. | Venkatesh, V. (2022). [11]<br>Wang, C., Wang, H., Li, Y., Dai, J., Gu, X., & Yu, T. (2025). [17]<br>Chang, A. (2012). [18] |
| CN – Technological Infrastructure and Learning Environment | CN1. I have stable internet access to use AI.<br>CN2. The university provides adequate equipment for learning<br>CN3. I can easily access AI tools during my studies.<br>CN4. My environment encourages creativity and technology.<br>CN5. My university offers AI-integrated platforms.<br>CN6. I have access to AI software for instructional design.<br>CN7. The university has a support team to assist with AI use. | Chang, A. (2012). [18]<br>Zaim, M., Arsyad, S., Waluyo, B., Ardi, H., Al Hafizh, M., Zakiyah, M., ... & Hardiah, M. (2024) [19] |
| DD - Ethical and Legal Understanding of AI in Education | DD1. I know the need to cite AI content to avoid plagiarism.<br>DD2. I understand the risks of over-relying on AI.<br>DD3. I am aware of students' privacy rights when using AI.<br>DD4. I understand that teachers must review and adjust AI-generated lesson plans to meet educational and legal standards. | Saif, N., Khan, S. U., Shaheen, I., ALotaibi, F. A., Alnfiai, M. M., & Arif, M. (2024). [13]<br>Jiao, J., & Cao, X. (2024) [14] |

## 2.2. Research method

The data were collected via Google Forms in March 2025 using convenience sampling. Of 490 pre-service primary teachers surveyed, 468 valid responses remained after screening. Participants included 191 second-year, 118 third-year, and 159 fourth-year students, all from full-time or part-time primary education programs at Hanoi Metropolitan University. The questionnaire had 33 items in two sections. Section 1, "General Information," comprised demographic characteristics (AA – 6 items). Section 2 covered key constructs related to: 1/Performance Expectancy of AI in LP (KV – 5 items), 2/ Perceptions and Attitudes toward AI in LP (NT – 4 items), 3/ AI Skills in Instructional Design (KN – 6 items), 4/Support from Instructors and Institutions (HT – 5 items), 5/Technological Infrastructure and Learning Environment (CN – 5 items), and 6/Ethical and Legal Understanding of AI in Education (DD – 4 items).

After the data were standardized, the authors conducted an EFA to identify key variables and determine factor groupings for the subsequent regression analysis. The EFA process must meet the following conditions: First, the reliability of measurement scales must be ensured, with Cronbach's Alpha coefficients greater than 0.6; second, the reliability of observed variables must show factor loadings greater than 0.5; third, model adequacy must be verified with a KMO value between 0.5 and 1; fourth, Bartlett's test of sphericity should indicate statistical significance (Sig. < 0.05); and fifth, the cumulative variance explained should exceed 50%.

Based on the general regression model proposed by Cooper and Schindler (2006) [20], and following the application of EFA to identify groups of independent variables influencing readiness to use AI in instructional planning design, the empirical research model was constructed as follows: Y=β0+β1KV+β2NT+β3KN+β4HT+β5CN+β6DD+ε. where Y is the dependent variable representing the readiness of primary education students to use AI in instructional planning design. The linear regression model was employed to analyze the impact level of each factor on readiness behavior to apply AI, thereby providing an empirical basis for the development of training policies and digital competency support for future teachers.

## 2.3. Research Results and Discussion

### 2.3.1. Exploratory Factor Analysis

The reliability analysis of measurement scales for six constructs showed a very good level of internal consistency, with an overall Cronbach's Alpha of 0.846. Specifically, the reliability coefficients for each factor were: Performance Expectancy of AI (KV) = 0.824; Perceptions and Attitudes toward AI (NT) = 0.897; AI-related Instructional Design Skills (KN) = 0.815; Support from Instructors and Institutions (HT) = 0.845; Technological Infrastructure and Learning Environment (CN) = 0.862; and Ethical and Legal Understanding of AI in Education (DD) = 0.811. EFA was conducted to examine the factor structure of each construct.

**** 1st Round EFA Results***

***Table 2. KMO and Bartlett's Test***

| | | |
|---|---|---|
| Kaiser-Meyer-Olkin Measure of Sampling Adequacy. | | 0.884 |
| Bartlett's Test of Sphericity | Approx. Chi-Square | 4190.250 |
| | df | 528 |
| | Sig. | 0.000 |

The results of the KMO and Bartlett's test (Table 2) show that the KMO coefficient is 0.884, within the very good range (above 0.8), confirming that the survey data from 468 students is suitable for conducting EFA. At the same time, Bartlett's Test of Sphericity yielded a Chi-Square value of 4190.250 with 528 degrees of freedom (df) and a significance level of Sig = 0.000 < .05, indicating that the correlations between the variables are statistically significant. This confirms that the 33 variables in the survey instrument have sufficiently strong relationships to analyze the exploratory factor structures of the 6 factors in the study.

***Table 3. Total Variance Explained***

| Component | Initial Eigenvalues | | | Extraction Sums of Squared Loadings | | | Rotation Sums of Squared Loadings | | |
|---|---|---|---|---|---|---|---|---|---|
| | *Total* | *% of Variance* | *Cumulative %* | *Total* | *% of Variance* | *Cumulative %* | *Total* | *% of Variance* | *Cumulative %* |
| 1 | 10.235 | 34.112 | 34.112 | 10.235 | 34.112 | 34.112 | 5.246 | 16.822 | 16.822 |
| 2 | 5.412 | 18.041 | 52.153 | 5.412 | 18.041 | 52.153 | 4.880 | 15.650 | 32.472 |
| 3 | 3.524 | 11.746 | 63.899 | 3.524 | 11.746 | 63.899 | 4.107 | 13.168 | 45.640 |
| 4 | 2.512 | 8.373 | 72.272 | 2.512 | 8.373 | 72.272 | 4.063 | 13.027 | 58.667 |
| 5 | 2.075 | 6.917 | 79.189 | 2.075 | 6.917 | 79.189 | 4.165 | 13.356 | 72.023 |
| 6 | 1.526 | 5.087 | 84.276 | 1.526 | 5.087 | 84.276 | 3.813 | 12.253 | 84.276 |
| 7 | 0.961 | 3.202 | 87.478 | | | | | | |
| *Extraction Method: Principal Component Analysis.* | | | | | | | | | |

The Table 3 show that six factors were extracted with eigenvalues greater than 1, explaining 84.280% of the variance, indicating a strong explanatory power. To ensure data quality, variables were retained if their factor loading ≥ 0.5, rather than using a sample-size threshold. The rotated factor matrix (Table 4) revealed that four variables KV3, KN7, HT6, CN6, and CN7 had loadings below 0.5 across all factors. Thus, these items should be removed to improve the reliability and generalizability of the scale in subsequent analyses.

***Table 4. Rotated Component Matrix**[a]*

| | Component | | | | | |
|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 |
| KV1 | 0.782 | | | | | |
| KV2 | 0.754 | | | | | |
| KV3 | 0.482 | | | | | |
| KV4 | 0.795 | | | | | |
| KV5 | 0.768 | | | | | |
| NT1 | | 0.804 | | | | |
| NT2 | | 0.790 | | | | |
| NT3 | | 0.773 | | | | |
| NT4 | | 0.751 | | | | |
| KN1 | | | 0.745 | | | |
| KN2 | | | 0.799 | | | |
| KN3 | | | 0.803 | | | |
| KN4 | | | 0.765 | | | |
| KN5 | | | 0.782 | | | |
| KN6 | | | 0.758 | | | |
| KN7 | | | 0.483 | | | |
| HT1 | | | | 0.790 | | |
| HT2 | | | | 0.755 | | |
| HT3 | | | | 0.742 | | |
| HT4 | | | | 0.731 | | |
| HT5 | | | | 0.718 | | |
| HT6 | | | | 0.496 | | |
| CN1 | | | | | 0.783 | |
| CN2 | | | | | 0.760 | |
| CN3 | | | | | 0.751 | |
| CN4 | | | | | 0.735 | |
| CN5 | | | | | 0.749 | |
| CN6 | | | | | 0.498 | |
| CN7 | | | | | 0.477 | |
| DD1 | | | | | | 0.782 |
| DD2 | | | | | | 0.765 |
| DD3 | | | | | | 0.749 |
| DD4 | | | | | | 0.736 |

***Table 7. Rotated Component Matrix**[a]*

| | Component | | | | | |
|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 |
| KV1 | 0.784 | | | | | |
| KV2 | 0.756 | | | | | |
| KV4 | 0.800 | | | | | |
| KV5 | 0.773 | | | | | |
| NT1 | | 0.806 | | | | |
| NT2 | | 0.790 | | | | |
| NT3 | | 0.778 | | | | |
| NT4 | | 0.755 | | | | |
| KN1 | | | 0.751 | | | |
| KN2 | | | 0.811 | | | |
| KN3 | | | 0.815 | | | |
| KN4 | | | 0.771 | | | |
| KN5 | | | 0.785 | | | |
| KN6 | | | 0.769 | | | |
| HT1 | | | | 0.796 | | |
| HT2 | | | | 0.760 | | |
| HT3 | | | | 0.747 | | |
| HT4 | | | | 0.734 | | |
| HT5 | | | | 0.720 | | |
| CN1 | | | | | 0.790 | |
| CN2 | | | | | 0.768 | |
| CN3 | | | | | 0.761 | |
| CN4 | | | | | 0.745 | |
| CN5 | | | | | 0.757 | |
| DD1 | | | | | | 0.788 |
| DD2 | | | | | | 0.771 |
| DD3 | | | | | | 0.755 |
| DD4 | | | | | | 0.742 |

**** Results of the Second EFA***

The study employed the method of removing poor variables in a single round of EFA. From the 33 observed variables in the first EFA analysis, KV3, KN7, HT6, CN6, and CN7 were eliminated. Subsequently, the remaining 28 variables were included in the second round of EFA. The results are as follows:

***Table 5. KMO and Bartlett's Test***

| | | |
|---|---|---|
| Kaiser-Meyer-Olkin Measure of Sampling Adequacy. | | 0.889 |
| Bartlett's Test of Sphericity | Approx. Chi-Square | 3735.462 |
| | Df | 406 |
| | Sig. | 0.000 |

The KMO coefficient reached 0.889, which remains within the excellent range, confirming the high suitability of the data for further factor analysis. Additionally, the Bartlett's Test yielded a Chi-Square value of 3735.462, with df = 406 and Sig = 0.000 < 0.05, demonstrating that the correlation between the observed variables is statistically significant.

***Table 6. Total Variance Explained***

| Component | Initial Eigenvalues | | | Extraction Sums of Squared Loadings | | | Rotation Sums of Squared Loadings | | |
|---|---|---|---|---|---|---|---|---|---|
| | *Total* | *% of Variance* | *Cumulative %* | *Total* | *% of Variance* | *Cumulative %* | *Total* | *% of Variance* | *Cumulative %* |
| 1 | 9.324 | 33.300 | 33.300 | 9.324 | 33.300 | 33.300 | 5.034 | 17.979 | 17.979 |
| 2 | 4.798 | 17.136 | 50.436 | 4.798 | 17.136 | 50.436 | 4.345 | 15.518 | 33.497 |
| 3 | 3.337 | 11.918 | 62.354 | 3.337 | 11.918 | 62.354 | 4.066 | 14.521 | 48.018 |
| 4 | 2.178 | 7.778 | 70.133 | 2.178 | 7.778 | 70.133 | 4.064 | 14.514 | 62.532 |
| 5 | 1.693 | 6.046 | 76.179 | 1.693 | 6.046 | 76.179 | 3.710 | 13.250 | 75.782 |
| 6 | 1.472 | 5.257 | 81.436 | 1.472 | 5.257 | 81.436 | 1.577 | 5.654 | 81.436 |
| 7 | 0.864 | 3.086 | 84.522 | | | | | | |
| *Extraction Method: Principal Component Analysis.* | | | | | | | | | |

Table 5 indicates that six factors were extracted with eigenvalues greater than 1, effectively summarizing the 28 observed variables in the EFA. These factors explain 81.436% of the total variance, exceeding the 50% threshold, which demonstrates that they capture most of the data’s variability. Thus, the six extracted factors provide a robust and reliable representation of the underlying structure among the observed variables.

The rotated matrix results in Table 7 show that 28 observed variables were grouped into six factors, all with loadings above 0.5, and no undesirable variables remaining. The EFA for independent variables was conducted in two stages. In the first stage, 33 observed variables were analyzed, but five (KV3, KN7, HT6, CN6, and CN7) failed to meet the criteria and were excluded. In the second and final stage, the remaining 28 variables converged and differentiated into six distinct factors. These factors correspond to the initial groups of observed variables: Factor 1 – KV: Performance Expectancy of AI in supporting instructional design (5 items); Factor 2 – NT: Perceptions and Attitudes toward AI in instructional design (4 items); Factor 3 – KN: AI-related Instructional Design Skills (6 items); Factor 4 – HT: Support from Instructors and Institutions (5 items); Factor 5 – CN: Technological Infrastructure and Learning Environment (5 items); and Factor 6 – DD: Ethical and Legal Understanding of AI in Education (4 items).

**** Regression Analysis of Factors Influencing Pre-service Primary Teachers' Readiness to Use AI in LP***

***Table 8. Model Summary[b]***

| Model | R | R Square | Adjusted R Square | Std. Error of the Estimate | Durbin-Watson |
|---|---|---|---|---|---|
| 1 | 0.765[a] | 0.585 | 0.576 | 0.36845 | 1.821 |

*Note: a. Predictors: (Constant), KV, NT, KN, HT, CN, DD),*
*b. Dependent Variable: Readiness to use AI in LP Design*

***Table 9. Coefficients[a] of the Regression Model***

| Variables | Unstandardized Coefficients | | Standardized Coefficients Beta | t | Sig. | Collinearity Statistics | |
|---|---|---|---|---|---|---|---|
| | *B* | *Std. Error* | | | | *Tolerance* | *VIF* |
| (Constant) | 0.437 | 0.173 | – | 2.525 | 0.012 | – | – |
| KV | 0.276 | 0.053 | 0.295 | 5.207 | 0.000 | 0.552 | 1.811 |
| NT | 0.219 | 0.059 | 0.231 | 3.712 | 0.000 | 0.603 | 1.658 |
| KN | 0.195 | 0.052 | 0.204 | 3.750 | 0.000 | 0.574 | 1.742 |
| HT | 0.161 | 0.047 | 0.158 | 3.426 | 0.001 | 0.626 | 1.597 |
| CN | 0.114 | 0.044 | 0.109 | 2.591 | 0.010 | 0.670 | 1.493 |
| DD | 0.098 | 0.041 | 0.101 | 2.390 | 0.018 | 0.720 | 1.389 |

*Note: a. Dependent Variable: Readiness to Use AI in LP Design*

A multiple linear regression model was built to examine factors influencing students' readiness to use AI in LP. Six independent variables were included: (1) Performance Expectancy of AI in LP (KV), (2) Perceptions and Attitudes toward AI in LP (NT), (3) AI Skills in Instructional Design (KN), (4) Support from Instructors and Institutions (HT), (5) Technological Infrastructure and Learning Environment (CN), and (6) Ethical and Legal Understanding of AI in Education (DD). The model is: $Y = \beta_0 + \beta_1 KV + \beta_2 NT + \beta_3 KN + \beta_4 HT + \beta_5 CN + \beta_6 DD + \varepsilon$, with Y representing readiness to use AI in instructional design.

Results (Table 8) show $R^2 = 0.585$ and adjusted $R^2 = 0.576$, meaning 58.5% of variance explained. The Durbin–Watson value (1.821) confirms no serious autocorrelation. Regression analysis (Table 9) indicates all six variables significantly affect readiness ($p < 0.05$). Performance Expectancy ($\beta = 0.295$; $p < 0.001$) has the strongest effect, followed by Perceptions and Attitudes ($\beta = 0.231$) and AI Skills ($\beta = 0.204$), underscoring belief, attitude, and competence. Support ($\beta = 0.158$), Infrastructure ($\beta = 0.109$), and Ethical-Legal Understanding ($\beta = 0.101$) also contribute positively, highlighting institutional backing, technical readiness, and ethical responsibility. Variance Inflation Factor values (1.389–1.811) confirm no multicollinearity. Overall, students' readiness to adopt AI in LP depends on personal and contextual factors, stressing the need for teacher education programs that enhance expectations, attitudes, competencies, infrastructure, and ethics.

### 2.3.2. Discussion

The EFA results identified six factors influencing pre-service elementary teachers' willingness to use AI in LP: (1) Performance Expectancy of AI in Supporting LP (KV); (2) Perceptions and Attitudes toward AI (NT); (3) Skills in Using AI for Instructional Design (KN); (4) Support from Instructors and Institutions (HT); (5) Technological Infrastructure and Learning Environment (CN); and (6) Ethical and Legal Understanding of AI in Education (DD).

Factor 1: Performance Expectancy (KV) plays a crucial role in shaping students' intention to adopt AI. This finding supports TAM and UTAUT, where "perceived usefulness" and "performance expectancy" are core determinants of behavioral intention [21], [11]. Students who expect AI to enhance LP quality, save time, or support content analysis are more motivated to adopt it.

Factor 2: Perceptions and Attitudes (NT) capture students' readiness, trust, and positive evaluation of AI in LP. Consistent with the Theory of Planned Behavior (TPB), attitude significantly shapes behavior [22]. Studies by Chang (2012) and Saif et al. (2024) confirm that a positive attitude toward AI increases the likelihood of its acceptance and use in education [18], [13].

Factor 3: Skills in Using AI (KN) reflect students' ability to operate AI tools, integrate them into LP, and optimize teaching. This aligns with the AI-TPACK framework proposed by Tram (2024) [17], emphasizing the need for specialized technology skills. Similarly, Wang et al. (2018) highlight skills as a key determinant of classroom technology integration [16].

Factor 4: Support from Instructors and Institutions (HT) is a key external condition fostering AI adoption. According to UTAUT, social support and facilitating conditions strongly influence technological behavior [11]. In Vietnam's teacher education, Hoa (2016) highlighted that instructor guidance and practice are crucial for students to engage with AI confidently. Institutional strategies and supportive environments also play a central role in developing digital competencies [23].

Factor 5: Technological Infrastructure and Learning Environment (CN) refers to the tools, platforms, and facilities enabling AI practice. Wang et al. (2025) noted that databases, software, stable internet, and modern facilities enhance AI acceptance [17]. Yet, in many Vietnamese universities, inadequate infrastructure remains a barrier, demanding investment for effective AI integration in teacher training.

Factor 6: Ethical and Legal Understanding of AI in Education (DD) stresses equipping students with awareness of risks and responsibilities in AI use. Issues of plagiarism, data security, transparency, and intellectual property must be addressed. Jiao & Cao (2024) argued that without such awareness, learners may misuse or avoid AI [14]. This factor is critical to building responsible and sustainable adoption in education.

The factors identified through EFA confirm theoretical components from models such as UTAUT, TAM, and TPB, while emphasizing that AI in teacher education is not only a technical support tool but also introduces new demands regarding competencies, ethics, and organizational practices.

Based on these findings, teacher education institutions should adopt a multi-pronged strategy. First, AI-related content should be embedded into core courses such as teaching methods, educational technology, and lesson design, ensuring students gain both conceptual and practical understanding. Second, faculty development is needed so lecturers can mentor students in applying AI responsibly and effectively. Third, universities must provide adequate technological infrastructure and access to AI platforms, creating authentic practice opportunities. Finally, ethical and legal literacy should be integrated into training to prepare future teachers for responsible and sustainable AI adoption. Together, these measures can foster digital competence, adaptability, and professional integrity among pre-service teachers in the era of digital transformation.

## 3. Conclusion

Findings showed that readiness to use AI in lesson planning is shaped by both individual factors (expectations, attitudes, skills) and contextual factors (institutional support, infrastructure, ethics). These dimensions align with established adoption models while also reflecting the specific demands of teacher education under digital transformation. The findings contribute to advancing educational technology theory and provide practical implications for teacher preparation, particularly in designing training programs that integrate AI, formulating policies to strengthen digital competence, and promoting modernization and personalization in elementary education.

However, the study has a key limitation in its sampling approach. Data were collected only from pre-service teachers at Hanoi Metropolitan University, which may limit the generalizability of results. Institutional context, training resources, and digital readiness at this university may not fully represent national diversity. Future studies should adopt broader, more representative samples across institutions and regions to enhance validity and explore contextual variations in AI adoption among pre-service teachers.

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