



Analysis of the Readiness of Prospective Elementary School Teachers in Integrating Artificial Intelligence in Science Learning

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Article Info	Abstract
Keywords: <i>AI readiness; Primary School Teacher Candidates; science learning; RAIS; Technology Self-Efficacy</i> Received: 12/06/2026 Revised: 19/08/2026 Accepted: 04/09/2026	Background: The determination of Artificial Intelligence (AI) as an optional subject in Permendikdasmen Number 13 of 2025 places prospective elementary school teachers as a central actor in policy implementation, but the empirical profile of the readiness of prospective elementary school teachers in integrating AI in science learning is not yet available in the Indonesian literature. Methods: A quantitative approach with a descriptive-correlational survey design was applied to 163 PGSD students of Universitas Pendidikan Indonesia from the main campus and five regional campuses, who were selected through purposive sampling. The Readiness for Artificial Intelligence Applications Scale (RAIS) instrument was used after limited modification (16 valid items, Cronbach's $\alpha = 0.921$). Data were analyzed with descriptive statistics and Spearman's Rho correlation using IBM SPSS Statistics version 21. Results: The overall readiness level of prospective elementary school teachers was in the High category ($M = 64.21$; $SD = 7.49$; 80.26%), with 96.9% of respondents in the High to Very High category. The profile per dimension showed ethical awareness as the strongest dimension (82.88%), followed by technology self-efficacy (81.23%), and student interaction as the most moderate dimension (78.07%). Correlation analysis revealed a significant positive relationship across all dimensional pairs ($p < 0.01$), with the strongest correlation between student interaction and ethical awareness ($p = 0.509$). Conclusion: Prospective elementary school teacher candidates at UPI demonstrate adequate AI readiness for the implementation of the 2025 Curriculum policy, with ethical awareness as the strongest dimension and student interaction as the most moderate dimension that needs to be strengthened through strengthening pedagogical experience.

INTRODUCTION

The development of Artificial Intelligence (AI) in the last decade has fundamentally changed the educational landscape, with the integration of AI in learning evolving from just a tool to a system capable of supporting personalization, automated assessment, and adaptive feedback

(Chiu et al., 2023). Various AI applications, such as adaptive tutoring systems, automated assessment, and generative content platforms, have been shown to increase learning effectiveness at various levels and across disciplines (Almasri, 2024; Antonio, 2025). Nonetheless, the use of AI in education shows significant inequality between countries. Li et al (2025) report that as of 2023, only about 8% of educational institutions in low-income countries have implemented AI-based tools, while in high-income countries the figure reaches 47%. This inequality shows that realizing AI's potential in education is not determined solely by technology availability, but by the readiness of the education ecosystem, with teachers as central actors in the integration process (Aravantinos et al., 2026).

Recent studies confirm that teacher readiness is a critical factor in the adoption of AI in educational environments. Kaufman et al (2025) reported that only about 25% of educators were utilizing AI-based tools in learning in the 2023–2024 school year in the United States, while a systematic review by Aravantinos et al (2026) found that technical training alone was inadequate to support effective AI integration. Successful integration requires a combination of pedagogical knowledge, positive attitudes, organizational support, and ongoing professional training. The findings align with those of Gouseti et al (2024), who confirm that teachers' AI competencies are multidimensional and cannot be reduced to technical skills alone. Further, the ethical dimension becomes crucial given that AI in the classroom has implications for student data privacy, algorithmic bias, and educators' professional responsibilities (Nguyen et al., 2023; Porayska-Pomsta et al., 2023). Thus, teacher preparation for the AI era demands the formation of holistic competencies that cover technological, pedagogical, and ethical dimensions simultaneously. This readiness is further supported by mastery of subject-matter content and comprehension of the academic context, since a solid grasp of disciplinary content enables prospective teachers to critically evaluate and pedagogically adapt AI-generated information rather than accepting it uncritically (Wen & Wen, 2024).

These challenges are manifested in the context of education in Indonesia, where progressive policy direction has not been balanced by readiness for implementation in the field. Through the Regulation of the Minister of Primary and Secondary Education Number 13 of 2025, the government officially included Coding and Artificial Intelligence as optional subjects in the curriculum starting from the 2025/2026 school year, implemented gradually beginning in Grade 5 of elementary school, Grade 7 of junior high school, and Grade 10 of senior high school/vocational school (Kemendikdasmen, 2025). However, this ambitious policy has not been balanced by adequate educator preparedness, as shown by various studies revealing a significant gap in the digital competence of elementary school teachers, especially in the use of AI-based technology in the classroom (Asriyanik et al., 2025). Existing limited studies show that the use of AI in Indonesia is still concentrated on basic uses such as virtual assistants and the development of learning instruments (Fajriati et al., 2024; Saputro et al., 2024). Meanwhile, substantive integration in learning is still very limited. Research in Indonesian primary schools confirms that teachers' ability to implement digital learning models is still predominantly influenced by their technical competence and innovative communication capacity, not just the availability of infrastructure (Kasmad et al., 2022). This gap between policy ambition and actual conditions is becoming increasingly urgent to be bridged, especially at the elementary school level, which is the starting point for policy implementation.

These challenges become even more complex in elementary science education. Science learning requires students to understand abstract concepts, develop critical thinking skills, and solve problems through a scientific approach (Septiani & Fatonah, 2024). These characteristics are conceptually relevant to strengthen through interactive simulations, visualizations of scientific phenomena, and AI-based virtual experiments (Almasri, 2024). In addition, integrating technology

into science learning through the STEAM approach has been proven to improve the critical thinking skills of elementary school students (Fazriyah et al., 2025). Science learning in elementary school also requires strategies that develop science process skills and foster students' active involvement in learning (Putri et al., 2024). However, the integration of AI in science learning faces specific challenges: the need for pedagogical competencies that differ from other subjects, the risk of misconceptions due to unverified AI outputs, and the demands of higher ethical awareness given that science concerns the formation of children's scientific ways of thinking (Porayska-Pomsta et al., 2023). At the elementary school level, this challenge is compounded by limited infrastructure and variations in teacher competencies (Aini et al., 2024), and the characteristics of elementary school students as a vulnerable group to data privacy risks, algorithmic bias, and exposure to age-inappropriate content. In this context, the readiness of Elementary School Teacher Education (PGSD) students as prospective AI implementers in science classes is strategically important to study empirically.

Analysis of the readiness of prospective teachers requires a theoretical framework that can comprehensively map AI competencies. The Technological Pedagogical Content Knowledge (TPACK) framework has long been the cornerstone of technology integration in learning because it emphasizes the integration of technological, pedagogical, and content knowledge (Mishra & Koehler, 2006), and in its development expanded to accommodate AI-specific competencies such as human-machine dialogue understanding, automated assessment, and adaptive feedback (Mishra et al., 2023). However, AI-TPACK-based instruments emphasize more professional knowledge of active teachers, making them less suitable for prospective teachers who do not have professional teaching experience. In this context, the Readiness for Artificial Intelligence Applications Scale (RAIS) developed by Ramazanoglu & Akin (2025) is a more relevant alternative, as it is specifically designed to measure readiness for AI adoption by integrating three dimensions simultaneously. First, technology self-efficacy, which represents an individual's confidence in using AI effectively (Nordlöf et al., 2019). Second, student interaction, which reflects the ability to facilitate meaningful learning through AI (Holmes & Tuomi, 2022). Third, ethical awareness, which relates to privacy, data security, and responsibility in the use of AI technologies (Huang, 2023; Nguyen et al., 2023). The integration of these three dimensions into one measurement framework is an advantage of RAIS over other instruments that tend to map readiness only partially.

Although studies on teacher AI readiness are growing rapidly globally, the existing literature still leaves some interrelated empirical gaps. Initial studies in Indonesia by Purnama et al (2025) used the RAIS framework to map the AI readiness of active teachers in Balinese schools and found a disparity in readiness between teachers in urban and rural areas. The study provides an important foundation, but it still leaves three unaddressed gaps. First, studies in Indonesia are still dominated by a sample of active teachers (Fathurrachman & Saputri, 2025; Purnama et al., 2025). Meanwhile, the mapping of the readiness of prospective teachers, especially PGSD students who will become implementers of AI policies in the elementary school curriculum starting from the 2025/2026 school year, has not been carried out systematically. The context of prospective teachers is important because their psychological characteristics and training needs differ from those of active teachers. Second, existing studies tend to discuss AI readiness in the context of general learning or across subjects, while elementary science learning has its own epistemic characteristics (scientific reasoning, experimentation, and the risk of misconceptions about AI outputs) that require separate consideration in AI adoption. An empirical profile of the readiness of prospective elementary school teachers for the specific context of science learning is not yet available in the Indonesian literature. Third, the study of RAIS in Indonesia and in the ASEAN region (Bautista et al., 2024), So far, it is purely descriptive, while the analysis of interdimensional relationships (technology self-efficacy, student interaction, ethical awareness) has not been

explored, even though mapping the correlation between dimensions is important to identify the drivers and inhibitors of AI readiness that are useful in designing more targeted educational interventions.

Based on these three gaps, this study aims to analyze the overall level of readiness of prospective elementary school teachers to integrate AI into science learning, examine their readiness across the dimensions of technology self-efficacy, student interaction, and ethical awareness, and analyze the relationships among these three dimensions. This study extends the RAIS approach previously applied to active teachers in Indonesia (Purnama et al., 2025) to the context of prospective primary school teachers and a specific field of study (science), and introduces interdimensional correlational analysis as a new approach to mapping AI readiness in Indonesian literature. The results of this study are expected to make an empirical contribution to designing an educational curriculum for prospective teachers that is more responsive to the AI era, developing specific AI training materials for elementary science learning, and identifying strategies to strengthen ethical awareness of the use of AI in elementary schools.

METHODS

This study uses a quantitative approach with a descriptive-correlational survey design. The descriptive design was used to map the level of readiness of prospective elementary school teachers in integrating Artificial Intelligence (AI) in Natural Sciences learning, while the correlational component was used to analyze the relationship between the dimensions of prospective teachers' readiness (Creswell & Creswell, 2018). Measurements are made at a single point in time without intervention or manipulation of variables. The research population includes all students of the Elementary School Teacher Education Study Program (PGSD) at Universitas Pendidikan Indonesia (UPI), spread across six campuses: the main campus of Bumi Siliwangi and five regional campuses (Purwakarta, Serang, Sumedang, Cibiru, and Tasikmalaya). UPI was chosen as the research locus because it is one of the largest Education Personnel Education Institutions (LPTK) in Indonesia with a geographical distribution that covers urban and regional areas, thus allowing for a variety of respondent characteristics with a relatively homogeneous curriculum.

The study population consisted of 2022-cohort students of the Elementary School Teacher Education Program (PGSD) at Universitas Pendidikan Indonesia (UPI) who had completed the Program Penguatan Profesional Kependidikan (P3K) and were distributed across six UPI campuses. The sample was selected using a non-probability sampling technique with a purposive sampling approach, selecting respondents based on criteria relevant to the research objectives (Etikan et al., 2016; Sugiyono, 2019). The inclusion criteria include: (1) active PGSD UPI students of the class of 2022; (2) have completed the P3K program; and (3) have experience in the use of digital technology for learning. Data collection was carried out through a personal contact approach by contacting prospective respondents who met the inclusion criteria directly through private messages. Based on the contact list obtained by the researchers, 350 students were contacted. Of these, 163 students responded and met the inclusion criteria and were used as the research sample. The response rate obtained was 46.6%. The distribution of samples by campus is presented in Table 1.

Table 1. Distribution of Research Respondents by Campus

Campus	Quantity (n)	Percentage
Universitas Pendidikan Indonesia Bumi Siliwangi	21	12.88%
Universitas Pendidikan Indonesia Regional Campus Purwakarta	76	46.63%
Universitas Pendidikan Indonesia Regional Campus Cibiru	11	6.75%
Universitas Pendidikan Indonesia Regional Campus Sumedang	29	17.79%
Universitas Pendidikan Indonesia Regional Campus Tasikmalaya	10	6.13%
Universitas Pendidikan Indonesia Regional Campus Serang	16	9.82%
Total	163	100.00%

The data collection instrument in this study uses the Readiness for Artificial Intelligence Applications Scale (RAIS) developed by Ramazanoglu & Akin (2025). The original RAIS instrument consisted of 19 statements that measured three dimensions of AI readiness: technology self-efficacy (6 items), student interaction (7 items), and ethical awareness (6 items). In the original study, RAIS showed good psychometric properties with a Kaiser-Meyer-Olkin (KMO) value of 0.903 and Cronbach's Alpha of 0.892 (technology self-efficacy = 0.833; student interaction = 0.835; ethical awareness = 0.885). Responses were measured using a five-level Likert scale, from "strongly disagree" (score 1) to "strongly agree" (score 5), with an inverse score for negative items (Likert, 1932). Given that the original instrument was developed in the Turkish context, limited modifications were made for use in Indonesia through two stages. The first stage involved translating the instrument into Indonesian by the researcher while maintaining the semantic meaning of each item. The second stage involved content validity using the Index of Item Objective Congruence (IOC) formula involving three experts: science learning experts, educational technology experts, and Artificial Intelligence experts. Eligibility criteria were set at an IOC value of ≥ 0.5 (Rovinelli & Hambleton, 1976). The results of the assessment showed that all 19 items met the eligibility criteria and were extended to empirical testing.

Empirical validity and reliability tests were conducted on 30 UPI PGSD students who were separated from the main sample of the study to avoid estimation bias. According to Johanson & Brooks as cited in Bawatanaya et al (2025), a minimum of 30 respondents is recommended for a preliminary study. Therefore, 30 students were used for the preliminary testing of the adapted RAIS instrument. The validity test used the Pearson Product Moment correlation, with an item considered valid if $r > r_{\text{table}}$ at a significance level of $\alpha = 0.05$ ($r_{\text{table}} = 0.361$ for $n = 30$). The test results showed three dropped items: P3 ($r = 0.045$), P14 ($r = 0.295$), and P17 ($r = 0.284$). The Pearson Product Moment item total correlation coefficients for these items were below the r_{table} threshold of 0.361, indicating weak correlations between the item scores and the total score. P3 and P17 were negative items that were appropriately reverse-scored. However, their wording may have led to different interpretations among respondents, resulting in responses that were less consistent with the intended constructs. P14, although positively worded, showed relatively limited response variability, which may have reduced its ability to discriminate levels of ethical awareness. Accordingly, the final instrument consisted of 16 valid items. The final instrument grid is shown in Table 2.

Table 2. Research Instrument Grid (After Validity Test)

Dimension	Item No	Dropped Items	Valid Amount
Technology self-efficacy	1,2,3,4,5,6	3	5
Student interaction	7,8,9,10,11,12,13	-	7
Ethical awareness	14,15,16,17,18,19	14,17	4
TOTAL		3	16

Reliability tests were carried out on 16 valid items using Cronbach's Alpha coefficient, with interpretation criteria: > 0.90 very reliable; 0.80–0.90 highly reliable; 0.70–0.80 reliable; < 0.70 is less reliable (Nunnally & Bernstein, 1994). The results of the analysis showed a total Cronbach's Alpha value of 0.921 (Table 3), so the instrument was classified as very reliable and suitable for use as a data collection tool. Data collection was carried out online through a closed questionnaire distributed using Google Form from April 29 to May 16, 2026. Before filling out the questionnaire, respondents were given information about: (1) the purpose of the research; (2) the nature of participation is voluntary and can be terminated at any time; (3) confidentiality and anonymity of data; and (4) the use of data solely for academic purposes. Informed consent is obtained electronically on the first page of the questionnaire before the respondent can proceed to the question items, in accordance with applicable research ethics principles.

Table 3. Reliability Test Results

Cronbach's Alpha	Number of Items	Remarks
0.921	16	Highly Reliable

Data analysis was carried out in four stages using IBM SPSS Statistics version 21. The first stage involved testing data normality using the Kolmogorov-Smirnov test to determine the appropriate correlation analysis: if the data are normally distributed ($p > 0.05$), Pearson Product Moment correlation is used, while if the data are not normally distributed ($p < 0.05$), Spearman's Rho correlation is used as a non-parametric test (Field, 2013). The second stage is an overall descriptive statistical analysis to address the first research objective, including minimum, maximum, mean, median scores, modes, standard deviations, and percentage distributions. The third stage is a descriptive statistical analysis per dimension (technology self-efficacy, student interaction, and ethical awareness) to address the second research objective. The fourth stage is an interdimensional correlational analysis to address the third research objective, with the power of correlation interpreted according to Cohen (1988): small (0.10–0.29), medium (0.30–0.49), and large (≥ 0.50). The results of the descriptive analysis were classified into five readiness-level categories based on the percentage of achievement of the maximum score (score/maximum score $\times 100\%$), following the criteria developed by Riduwan (2013). A similar categorization approach has been applied in various descriptive studies of basic education in Indonesia to measure the level of educational variables, such as learning motivation among PGSD students (Nasrah & Muafiah, 2020). The complete categorization is presented in Table 4.

Table 4. Categorization of Readiness Levels
(Riduwan, 2013)

Percentage Range	Category
81% – 100%	Very High
61% – 80%	High
41% – 60%	Medium
21% – 40%	Low
0% – 20%	Very Low

RESULT AND DISCUSSION

This section presents the results of the data analysis and discusses them in a structured manner according to the three research objectives. The first sub-section reports the results of the normality prerequisite test, the second sub-section presents the AI Readiness of Prospective

Elementary Teacher Candidates (Objective 1), the third sub-section presents the readiness profile reviewed from three dimensions (Objective 2), and the fourth sub-section presents the results of the analysis of interdimensional relationships (Objective 3). Each sub-section ends with a discussion that connects the findings with the theoretical framework and previous research. Before the main analysis was performed, the Kolmogorov-Smirnov normality test was applied to all four score variables to determine the appropriate type of correlation test. The test results are presented in Table 5.

Table 5. Kolmogorov-Smirnov Normality Test Results

Variable	N	KS Statistic	Sig. (p)	Interpretation
TSE (Technology Self-Efficacy)	163	1.206	0.109	Normal ($p > 0,05$)
SI (Student Interaction)	163	1.661	0.008	Not Normal ($p < 0,05$)
EA (Ethical Awareness)	163	1.718	0.005	Not Normal ($p < 0,05$)
TOTAL AI Readiness	163	1.393	0.041	Not Normal ($p < 0,05$)

Table 5 shows that only the TSE dimension is normally distributed ($p = 0.109 > 0.05$), while the SI dimensions ($p = 0.008$), EA ($p = 0.005$), and TOTAL score ($p = 0.041$) do not meet the normality assumption. Since three of the four variables were not normally distributed, interdimensional correlational analysis for the third research objective was performed using Spearman's Rho coefficient as a non-parametric test that did not require the assumption of normality (Field, 2013). The first research objective focused on an overview of the readiness level of prospective elementary school teachers in integrating AI in science learning as a whole. The results of the descriptive statistical analysis are presented in Table 6, while the frequency distribution of the readiness category is shown in Table 7.

Table 6. Descriptive Statistics of Overall AI Readiness Score

Statistics	Value
N (number of respondents)	163
Minimum Score (theoretical range: 16–80)	31.00
Score Maximum	79.00
Mean	64.21
Median	65.00
Mode	62.00
Standard Deviation	7.49
Average Percentage = $(64.21 / 80) \times 100\%$	80.26%
Category	High

Table 6 shows that the average AI readiness score of prospective elementary school teachers is 64.21 (SD = 7.49) out of a theoretical maximum score of 80, with an empirical score range between 31 and 79. The average achievement percentage of 80.26% placed the overall profile in the High category (61%–80%) according to the criteria of Riduwan (2013). The median value of 65.00 is slightly higher than the mean, indicating a slightly left-skewed distribution. In addition, the distribution had multiple modes, with SPSS reporting 62.00 as the smallest modal value.

Table 7. Frequency Distribution of Overall AI Readiness Levels

Category	Range	Frequency (n)	Percentage (%)
Very High	81% – 100%	83	50.9
High	61% – 80%	75	46.0
Medium	41% – 60%	4	2.5
Low	21% – 40%	1	0.6
Very Low	0% – 20%	0	0.0
Total	—	163	100.0

Table 7 reveals that the majority of prospective UPI elementary school teachers are in the Very High (50.9%) and High (46.0%) categories, so that cumulatively 96.9% of respondents have achieved an adequate or better level of AI readiness. Only 3.1% of respondents were in the Medium to lower category, and none were in the Very Low category. These findings indicate that overall, prospective teachers of UPI Elementary School have good readiness to implement AI in science learning, in line with the policy of the Minister of Education Number 13 of 2025, which requires the introduction of AI in the elementary school curriculum starting from the 2025/2026 school year.

The high level of readiness may partly be explained by the generational characteristics of the respondents. The PGSD students in the sample belong to Generation Z, who are known as digital natives with intense exposure to technology from an early age (Bautista et al., 2024). They grew up with various AI-based services such as virtual assistants, recommendation systems, and generative chatbot applications that have become part of academic and social routines. This experience forms a relatively strong digital literacy, which is the foundation for readiness to adopt AI in a professional context as an aspiring educator. This is relevant to the findings in the context of PGSD UPI, which show that students' literacy skills, including prospective teachers, are an important foundation in the development of their professional competencies, where strong literacy is positively correlated with an understanding of the underlying values of responsible educational practices (Wulan & Fajrussalam, 2022). These findings align with Antonio (2025), who found that preservice science teachers showed good AI-TPACK competence after being exposed to structured pedagogical experience. These findings also align with Purnama et al (2025), who reported that AI readiness is related to technical ability, institutional support, technological infrastructure, school facilities, and access to training and technology. Their findings indicate that AI readiness depends not only on individual familiarity with technology but also on the support and resources available to teachers.

The second research objective focuses on mapping the AI readiness profile of prospective elementary school teachers based on three dimensions: technology self-efficacy (TSE), student interaction (SI), and ethical awareness (EA). Descriptive statistics per dimension are presented in Table 8, while the categorical distribution is presented in Table 9.

Table 8. Descriptive Statistics of AI Readiness Score by Dimension

Dimensions	Min	Max	Mean	SD	Max Score	Mean Percentage (%)	Category
Technology Self-Efficacy (TSE)	8.00	25.00	20.31	2.93	25	81.23	Very High
Student Interaction (SI)	12.00	34.00	27.33	3.62	35	78.07	High
Ethical Awareness (EA)	9.00	20.00	16.58	2.39	20	82.88	Very High

Table 8 shows a three-dimensional comparative profile of AI readiness. The Ethical Awareness (EA) dimension occupies the highest position with an average percentage of 82.88%, followed by Technology Self-Efficacy (TSE) at 81.23%, and Student Interaction (SI) as the most moderate dimension with 78.07%. Both EA and TSE dimensions are in the Very High category, while SI is in the High category and remains below the threshold for the Very High category. It should be noted that these differences between dimensions are descriptive and the difference is relatively thin (78–83%), so the claim that one dimension is significantly higher than another cannot be affirmed without additional inferential tests. This pattern reveals the important characteristics of prospective elementary school teachers, who are more confident in individual aspects (technical competence and personal ethical awareness) than in pedagogical interaction with students.

Table 9. Category Frequency Distribution per Dimension

Category	TSE n (%)	SI n (%)	EA n (%)
Very High	74 (45.4)	51 (31.3)	80 (49.1)
High	80 (49.1)	102 (62.6)	71 (43.6)
Medium	7 (4.3)	9 (5.5)	12 (7.4)
Low	2 (1.2)	1 (0.6)	0 (0.0)
Very Low	0 (0.0)	0 (0.0)	0 (0.0)
Total	163 (100.0)	163 (100.0)	163 (100.0)

Table 9 reinforces the findings of Table 8. The Ethical Awareness (EA) dimension has the highest proportion in the Very High category (49.1%), and none of the respondents are in the Low category, indicating that ethical awareness of the use of AI is evenly strong among prospective elementary school teachers. In contrast, the Student Interaction (SI) dimension had the lowest proportion of Very High (31.3%), with most respondents (62.6%) classified in the High category. The Technology Self-Efficacy (TSE) dimension shows a more balanced distribution with 45.4% Very High and 49.1% High, but has the highest proportion of the Low category (1.2%).

The finding that Ethical Awareness is the strongest dimension is an interesting contrast to the international literature. In a study (Bautista et al., 2024) in the Philippines, there are actually weaknesses in the ethical aspect among preservice teachers. The high Ethical Awareness (EA) score in this study may also relate to the professional preparation respondents gained through the Program Penguatan Profesional Kependidikan (P3K). All respondents had completed P3K before participating in this study. This shared professional preparation may strengthen their awareness of professional responsibility, including responsible use of technology in learning. However, this study did not directly examine the effect of P3K on Ethical Awareness. Therefore, P3K may be a contributing factor behind the high EA score rather than its direct cause. These findings align with Nguyen et al (2023), who affirm that ethical awareness is a fundamental prerequisite for adopting AI in education.

On the other hand, the Student Interaction dimension, as the most moderate profile, provides an important signal for the development of prospective teachers' competence. These dimensions include the ability to facilitate classroom discussions with AI, guide students in using AI for science experiments, and design learning activities that involve AI as a student partner (Ramazanoglu & Akin, 2025). The low score in this dimension can be explained from the perspective of the respondents' characteristics: they are indeed still prospective teachers who have just completed P3K, so direct experience in facilitating students in the context of AI is still limited. Holmes & Tuomi (2022) assert that the ability to facilitate students' interaction with AI requires repetitive pedagogical experiences that are difficult to obtain through theory lectures alone. Thus, the SI dimension becomes an obstacle that needs to be addressed through strengthening field experience practices.

High Technology Self-Efficacy (TSE), as well as the small proportion of the Low category in this dimension, illustrates that technical confidence capital is adequate. Good technical confidence is consistent with Bandura (1997), who places self-confidence as a predictor of performance, and with Nordlöf et al (2019), who found that technology self-efficacy was positively correlated with the readiness for technology integration. However, the fact that TSE has the highest proportion of the Low category (1.2%) indicates the existence of a minority of prospective teachers who are technically behind and who need to be accompanied through remedial training before field practice.

The third research objective focuses on the relationship between the three dimensions of AI readiness. Given that the results of the normality test showed that two of the three dimensions were not normally distributed, the correlational analysis was performed using Spearman's Rho coefficient. The results of the analysis are presented in Table 10.

Table 10. AI Readiness Interdimensional Correlation Matrix

Dimensions	TSE	SI	EA
Technology Self-Efficacy (TSE)	1.000	—	—
Student Interaction (SI)	0.407**	1.000	—
Ethical Awareness (EA)	0.476**	0.509**	1.000

Remarks: ** Significant correlation at the level of 0.01 (2-tailed). The interpretation of the power of correlation refers to Cohen (1988): small (0,10–0,29), medium (0,30–0,49), and large ($\geq 0,50$).

Table 10 shows that all dimensional pairs are positively and significantly correlated at the 0.01 level. The strongest correlation was found between Student Interaction and Ethical Awareness ($p = 0.509$, $p < 0.01$) which belonged to the large category according to Cohen (1988), followed by the correlation of Technology Self-Efficacy with Ethical Awareness ($p = 0.476$, $p < 0.01$) and the correlation of Technology Self-Efficacy with Student Interaction ($p = 0.407$, $p < 0.01$) which was in the medium category. No dimension pairs showed a very high correlation ($p > 0.70$), so the three dimensions still measure different aspects of AI readiness despite being interrelated, indicating good construct validity on the RAIS instrument.

The correlation pattern stores important pedagogical information. The strongest correlation between SI and EA suggests that prospective teachers' ability to facilitate students' interaction with AI evolves along with their ethical awareness. Prospective teachers who are more aware of ethical aspects (student data privacy, algorithmic bias, and the responsibility of supervising AI output) tend to be more pedagogically prepared to manage AI-based learning in the classroom. These findings are particularly relevant for the primary school context because elementary school students are a vulnerable group to the ethical risks of using AI, without ethical awareness, pedagogical interactions with AI can potentially harm students (Porayska-Pomsta et al., 2023). The implication is that the educational curriculum of prospective elementary school teachers needs to integrate pedagogical and ethical competencies simultaneously, not as two separate materials.

The moderate correlation between TSE and SI ($p = 0.407$) reflects another important finding: personal technical competence does not automatically transform into a student's ability to facilitate. This pattern is in line with the UTAUT2 framework (Cabero-Almenara et al., 2024). The difference between effort expectancy (individual technical ease) and facilitating conditions (contextual support and pedagogical competence for real implementation in the classroom) is that personal technical mastery is not enough without competency support to facilitate learning. More specifically, the DigCompEdu framework (Momdjian et al., 2025) explicitly separates educators' personal digital competencies from the competencies needed to facilitate students' digital learning; their study of preservice teachers in Lebanon shows a gap between the two aspects that is consistent with the findings of this study. Prospective teachers may be very proficient in using AI for themselves, but still have difficulty in designing effective learning scenarios for elementary school students. This pattern is also relevant to the TPACK framework (Mishra & Koehler, 2006), which places the integration of technology, pedagogy, and content as separate competencies that need to be developed synergistically. Mishra et al (2023) further affirm that in the era of generative AI, the TPACK framework needs to be expanded to accommodate AI-specific pedagogical skills such as facilitating prompt-based inquiry, evaluating AI outputs, and managing misinformation from AI.

Based on this pattern, Ethical Awareness (EA) appears to act as a connecting dimension between the three: EA correlates most strongly with SI ($p = 0.509$) and also quite strongly with TSE ($p = 0.476$). Conceptually, this pattern indicates that ethical awareness is correlated with both technical mastery and pedagogical ability, although the causal relationship between the three cannot be inferred from this correlational design. In practical terms, this correlation pattern is consistent with the idea that ethical awareness can bridge individual competencies into

responsible pedagogical practice in the classroom. For LPTKs such as UPI, these findings provide an empirical basis for considering AI ethical literacy as an important component of the AI curriculum for prospective elementary school teachers. By strengthening EA, interventions on the TSE and SI dimensions are expected to be more targeted as they show statistically significant linkages.

CONCLUSION

This study analyzes the readiness of prospective elementary school teachers to integrate Artificial Intelligence into science learning using the three-dimensional framework of the Readiness for Artificial Intelligence Applications Scale (RAIS) of Ramazanoglu & Akin (2025). Based on the analysis of 163 PGSD students at Universitas Pendidikan Indonesia across six campuses, three main conclusions were obtained. First, prospective UPI elementary school teachers as a whole have a high level of AI readiness, with an average percentage of 80.26%; 96.9% of respondents are in the High or Very High category, and no respondents are in the Very Low category. Second, among the three dimensions, ethical awareness is the strongest profile (82.88%, Very High), followed by technology self-efficacy (81.23%, Very High), and student interaction as the most moderate dimension (78.07%, High), so it is identified as a readiness bottleneck. Third, the three dimensions are positively and significantly correlated ($p < 0.01$), with the strongest correlation between student interaction and ethical awareness ($p = 0.509$), placing ethical awareness as the connecting dimension between technical competence and pedagogical ability. The pedagogical implication of this study is the need to strengthen student interaction through structured pedagogical experiences that involve facilitating elementary school students with AI, while maintaining and deepening ethical awareness as the foundation of the AI curriculum for prospective teachers. LPTK is recommended to integrate ethical and pedagogical competencies simultaneously, rather than separately, given their strong correlation. Remedial technical training should also be provided to a minority of prospective teachers (around 3%) who are still in the Medium and below category. This study has limitations that need to be considered in interpreting the findings. First, the sampling technique is non-probability (purposive sampling), so generalization to the national PGSD student population needs to be done carefully. Second, the cross-sectional design does not allow cause-and-effect inference between variables; The correlations found describe relationships, not causality. Third, the RAIS instrument used was adapted through limited modification (translation + IOC) without formal back-translation or confirmatory factor analysis, so the psychometric properties of the Indonesian version of the instrument still need further validation. Fourth, the data are self-reported, so the readiness reported by respondents may differ from actual competencies when teaching practices with AI are carried out in real classrooms. Further research is recommended to: (1) conduct full psychometric validation of the Indonesian version of the RAIS instrument through exploratory and confirmatory factor analysis; (2) expanding the sample to other LPTK in Indonesia using probability sampling techniques; (3) using longitudinal design to map the development of AI readiness throughout the study period of prospective teachers; and (4) complementing self-reported measurement with actual performance assessments when prospective teachers carry out AI-based learning in elementary schools.

DECLARATION OF GENERATIVE AI

During the preparation of this work, the author(s) used ChatGPT to assist with composing sentences and brainstorming ideas throughout the writing process, and used Grammarly Pro to check grammar, spelling, and overall language accuracy. After using these tools, the author(s)

reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

CONFLICTING INTEREST STATEMENT

The authors declares that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

FUNDING INFORMATION STATEMENT

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

AUTHORSHIP CONTRIBUTION STATEMENT

Fiddini Nafa Eka Rohmaningsih: Conceptualization, Methodology, Investigation, Formal Analysis, Data Curation, Writing - Original Draft, Visualization. **Fitri Nuraeni:** Supervision, Validation, Writing - Review & Editing. **Nenden Permas Hikmatunisa:** Supervision, Validation, Writing - Review & Editing.

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