Pre-Service Teachers' Readiness to Use Artificial Intelligence: Evidence from Kazakhstan

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***Abstract*—The use of Artificial Intelligence (AI) in the teaching and learning process is a key demand in higher education. It encourages Kazakhstani universities to actively seek the best ways to incorporate AI into learning, providing students with the highest quality educational experience. This study aims to determine the attitudes of pre-service teachers toward the integration of AI in educational practice. Additionally, it examines the dynamics of attitude changes toward AI following the completion of a training program. Using a quantitative survey and statistical methods, data from 320 students at a pedagogical university were analyzed. The results showed a generally positive attitude toward AI, especially on the scales of perceived usefulness and ease of use. Previous experience with AI was significantly correlated with the intention to use the technology in future professional activities. After completing a six-week training program, statistically significant improvements were recorded on all scales. The paper confirms the importance of pedagogical training in the field of AI and emphasizes the need to include such modules in teacher training programs. These findings align with the research objectives of the study. The study offers practical insights for educators and policymakers to enhance teaching techniques in Kazakhstan and beyond, promoting more successful, research-based AI teaching strategies. In conclusion, this study contributes to the emerging field of EdTech by filling a data gap in Central Asia, particularly in Kazakhstan.**

***Keywords*—artificial intelligence, teacher training, attitude, factors, Artificial Intelligence (AI) literacy, pre-service primary teachers**

I. Introduction

Efforts are currently underway across all areas of education to improve the quality and effectiveness of Kazakhstani education. One of the ways to improve the effectiveness of training in universities is the introduction of Artificial Intelligence (AI), which is one of the leading directions in the development of new information technologies in education [1]. The relevance of this paper is also driven by the practical needs of teacher preparation and pedagogical practice. In connection with the profound changes occurring in the education system and reflected in the methodological system of teaching within each educational area, it is becoming an urgent need to solve the problem of drawing up adequate requirements for the level of preparation of students for the use of AI, as well as determining objective variables for assessing their attitude [2]. The teaching community remains insufficiently aware of the challenges and concerns associated with the widespread adoption of AI, which both students and educators will inevitably encounter. Furthermore, a literature search in international databases [3] revealed that there aren't many studies that specifically link the adoption of AI with student satisfaction, particularly when it comes to higher education in Kazakhstan.

According to Almulla [4] and Rodway and Schepman [5], students' attitudes and feelings regarding their foundational training and the creation of a digital learning environment at a university are what determine their level of satisfaction with the use of AI. Additionally, Bucea-Manea-Ţoniş *et al.* [6] believe that there is a lot of didactic potential for AI in higher education, even though it is hard to gauge its capabilities. According to Mahmoud and Sørensen [7], AI is essential to achieving the goal of personalized learning of every student. This study is grounded in the Technology Acceptance Model (TAM) [8], which explains how Perceived Usefulness (PU) and Ease of Use (EOU) influence users' Behavioral Intention (BI) to adopt new technologies. TAM has been widely applied to understand educational technology acceptance, including in teacher training contexts.

Despite these advancements, AI knowledge is still not fully incorporated into teaching methods, which leads to new and complex issues [9]. Meta-analysis shows that limited research has been conducted on how Pre-Service Teachers (PSTs) perceive AI in their professional practice, particularly in non-Western and developing country contexts [10–12]. Many studies [13–15] have focused on the implementation or technological capabilities of AI systems, rather than on the attitudes, readiness, and pedagogical beliefs of PSTs. Furthermore, studies that have examined PSTs perceptions often generalize across educational levels or focus primarily on secondary education, leaving a gap in understanding how future primary educators—the first point of contact for many young learners—engage with this emerging technology [16]. This lack of focus on PSTs represents a critical gap in the literature. Specifically, little is known about how students view the technological accessibility of AI, what influences their opinions, and whether they believe they are ready to incorporate AI tools into their teaching [17–20]. Furthermore, the Central Asian region, including Kazakhstan, remains underrepresented in global education technology research,

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limiting the applicability of existing findings to diverse educational contexts [21, 22].

The initial and crucial step in applying the principles of artificial intelligence is transforming the professional attitudes and competency levels of teachers [23]. However, limited research has examined how pre-service teachers, especially in developing countries, perceive their role and practical application in classrooms [24]. Nevertheless, despite these challenges and many others, AI in Kazakhstan represents a promising scientific avenue that can help address numerous intricate educational issues [25].

Data specific to Central Asia, including post-Soviet countries, facilitates understanding of how different educational contexts impact the adoption of AI techniques and helps expand its focus beyond global perspectives [26]. However, there is limited research on how pre-service teachers, particularly in post-Soviet countries, perceive their role and the practical application of AI in the classroom [27]. Additionally, this study is important for growing global interest in AI in the context of Kazakhstan's educational reforms [28]. In addition to the Technology Acceptance Model (TAM), this study also acknowledges the broader sociotechnical and ethical dimensions of AI integration in education. Recent scholarship highlights concerns regarding algorithmic bias, data privacy, and the digital divide, especially in under-resourced educational systems [29–31]. The pedagogical implications of AI adoption are also significant: while AI can support personalized and adaptive learning, it may inadvertently reinforce existing inequalities if access, training, and ethical considerations are not adequately addressed [32, 33]. By situating this research within these wider debates, the study aims to contribute not only to the practical understanding of AI adoption among pre-service teachers but also to the ongoing discourse on equitable and responsible use of AI in education. In light of the existing literature, the following research questions were formulated:

A. Research Questions

Q1: How is the attitude of pre-service teachers toward the integration of AI into education formed and transformed under the influence of various factors?

B. Research Objectives

This study aims to examine the attitudes of PSTs toward the use of AI in educational practice. In addition, it investigates the dynamics of changes in attitudes toward AI after completing the training program.

II. Materials and Methods

A. Data Collection and Sample

This study utilized a quantitative survey design [34] to collect and analyze data on pre-service teachers' attitudes toward AI in educational settings. The statistical analysis of attitudes, trends, and correlations among variables was facilitated by the survey's effectiveness in gathering standardized data from a substantial number of respondents. To determine the attitudes of PSTs toward integrating AI into educational practice, we invited participants from universities in Kazakhstan offering accredited undergraduate programs for preparing future teachers. Only one institution—Abai Kazakh National Pedagogical University (Abai University)—responded to our invitation. The initial target population included 360 students; however, due to accessibility constraints, the study ultimately focused on a sample of 320 students. Most respondents were aged 21–23 years (79.7%), and 30.3% reported previous experience with AI tools. Table 1 presents the demographic characteristics of the study participants.

Table 1. Demographic characteristics of study participants

Variable	Category	Frequency (n)	Percentage (%)
Gender	Female	260	81.3%
	Male	60	18.7%
Age	21–22 years	140	43.8%
	23 years	115	35.9%
	24 years and above	65	20.3%
	Mean (SD)	22.6 (1.2)	-
Year of study	Final (4th) year	320	100%
Prior exposure to AI tools	Yes	97	30.3%
	No	223	69.7%
Frequency of AI tools usage	Never	150	46.9%
	Rarely	85	26.6%
	Sometimes	60	18.8%
	Missing / No response	25	7.7%
	Total	320	100%

The authors' development of the AI learning tools attitude scale [34] was used to gather the data (see Table A1). The researchers developed the initial pool of items, consulting existing scales to ensure content relevance and coverage. The questionnaire was piloted with a small group of pre-service teachers (n = 25). Based on their feedback, redundant and unclear items were removed or revised. The scale structure was informed by the TAM, which identifies Perceived Usefulness (PU), perceived Ease of Use (EOU), and Behavioral Intention (BI) as key predictors of users' acceptance of new technologies [35]. These constructs were directly operationalized in the corresponding subscales of the instrument. TAM was selected for its established relevance and parsimonious structure, which aligns well with the study's focus on initial perceptions and intentions of pre-service teachers. Although more comprehensive models like UTAUT offer additional variables (e.g., social influence, facilitating conditions), TAM remains a widely used and validated framework in EdTech contexts, particularly for early-stage technology adoption. To adapt TAM to the specific context of AI adoption among pre-service teachers in Kazakhstan, a fourth subscale—Concerns and Reservations about AI (R-CRA)—was added to capture risk perceptions, which have been highlighted as a critical attitudinal component in emerging EdTech literature [36].

Table 2 presents the reliability data for the AI learning attitude scale.

To enrich PSTs' attitudes toward AI in educational contexts, a structured six-week training program was developed and implemented (see Table 3). The program was delivered through interactive workshops, hands-on sessions, and guided discussions. Regular participation of teacher candidates in the training program was ensured. A detailed description of the weekly modules, learning objectives, and instructional methods is provided in Table A2.

The data collection procedure consisted of several consecutive stages, covering the period before and after the intervention implementation. Table 4 outlines the data collection process.

Table 2. The AI learning attitude scale's factor structure and reliability

Subscale	Number of items	Cronbach's (α)	McDonald's ω	Mean factor loading (EFA)
Perceived Usefulness (PU) of AI in education	4	0.88	0.89	0.72
Ease of Use (EOU) of AI tools	4	0.85	0.86	0.69
Behavioral Intention (BI) to use AI	4	0.87	0.88	0.71
Concerns and Reservations regarding AI integration (R-CRA) *(reversed)*	4	0.79	0.80	0.65
Total scale	16	0.91	0.92	—

Table 3. Content of training program

Week	Focus area
1	Introduction to AI: concepts, history, applications
2	Global trends and exemplars of AI in education
3	Hands-on exploration of AI-based educational tools
4	Pedagogical integration: designing AI-enhanced learning activities
5	Ethical, legal and social implications of classroom AI
6	Reflection, evaluation and future action planning

Table 4. Summary of data collection procedures

Step	Description
Data collection period	February–April 2024 (8 weeks). Pre-test administered in late February; post-test conducted mid-April, following the six-week intervention.
Location	Abai Kazakh National Pedagogical University, Kazakhstan
Participants	Final-year pre-service teacher candidates
Survey administration method	In-person administration during regularly scheduled academic sessions
Informed consent	Obtained from all participants prior to data collection. Anonymity and confidentiality were strictly maintained.
Time required	Approximately 15–20 minutes per respondent for each administration (pre and post)
Data screening	Responses with more than 20% missing data were excluded from analysis
Final sample size	320 valid responses retained

The research questions were addressed by aligning the quantitative data analysis with each question. Data analysis methods were mapped to the corresponding research questions to ensure comprehensive coverage of the study. Table 5 details the data analysis procedures for each research question.

Table 5. Data analysis methods mapped to research questions

Research question	Analytical procedure	Key variables
1	Descriptive statistics (M, SD, %)	PU, PEOU, BI, R-CRA
2	One-way ANOVA	Gender, age, prior AI exposure × attitude subscales
3	Paired-samples t-test	Pre- vs. post-scores on each subscale
4	Pearson correlations; multiple regression	BI (DV) predicted by PU, PEOU, R-CRA, demographics
All analyses were conducted in SPSS v29 with α = .05. Effect sizes were reported as Cohen's d (t-tests) and η² (ANOVA)		

Table 6. PSTs' attitudes toward AI integration

Subscale	M	SD	Strongly disagree (%)	Disagree (%)	Neutral (%)	Agree (%)	Strongly agree (%)
PU	4.21	0.58	2.5	3.7	10.2	58.9	24.7
EOU	4.03	0.66	3.1	6.0	12.5	55.0	23.4
BI	4.15	0.62	1.9	4.4	11.0	59.7	23.0
R-CRA (rev.)	2.48	0.77	26.0	31.9	20.3	15.6	6.2
Total	4.02	0.61	—	—	—	—	—

Referring to Table 6, participants reported generally positive attitudes across most subscales. These findings indicate that, while participants demonstrated readiness and a positive outlook toward the adoption of AI in educational settings, addressing their reservations through targeted training and ethical discussions remains essential to fostering full acceptance [37, 38].

III. Result and Discussion

Table 6 presents the descriptive statistics and frequency distributions of PSTs' attitudes toward AI integration.

Table 7 presents the findings of the one-way ANOVA.

Table 7. The results of the variations in AI attitudes

Demographic variable	Subscale	F	p-value
Gender	PU	2.13	0.146
	EOU	1.89	0.170
	BI	0.78	0.378
	R-CRA	4.21	0.041*
Age group (21–22, 23, 24+)	PU	3.67	0.027*
	EOU	2.44	0.089
	BI	1.02	0.362
	R-CRA	5.03	0.008
Prior exposure to AI	PU	6.45	0.012*
	EOU	4.73	0.031*
	BI	5.88	0.016*
	R-CRA	0.94	0.333

Note: $p < 0.05$ (*), $p < 0.01$ (**).

The PU subscale showed significant differences by age group, highlighting how age affects perceptions of the risks and benefits of using AI. When examining the influence of prior experience with AI, significant differences were found in the PU, EOU, and BI subscales. These findings imply that participants' attitudes toward AI become more favorable after using relevant tools [39, 40].

The means and standard deviations for each demographic variable's attitude toward the AI subscales are presented in Table 8.

Table 8. DS: Individual demographic group means and standard deviations for attitude subscales

Demographic variable	Group	PU	EOU	BI	R-CRA
Gender	Female	4.21±0.83	4.35±0.74	4.18±0.81	3.42±0.85
	Male	4.06±0.78	4.28±0.71	4.11±0.77	3.72±0.90
Age group	21–22	4.05±0.81	4.32±0.72	4.10±0.79	3.31±0.83
	23	4.25±0.76	4.34±0.75	4.17±0.80	3.51±0.87
	24+	4.30±0.79	4.22±0.70	4.15±0.74	3.81±0.89
Prior AI exposure	Yes	4.35±0.70	4.45±0.66	4.32±0.73	3.49±0.82
	No	4.08±0.81	4.23±0.75	4.09±0.78	3.53±0.88

Referring to Table 8, the means and standard deviations for the AI attitude subscales by demographic variables are presented. Women display slightly higher values for perceived usefulness and behavioral intention to use AI compared to men. Conversely, men exhibit slightly higher scores on the wariness and concern scale, which may indicate greater apprehension about the potential risks associated with AI implementation.

By age group, there is a tendency for both perceived usefulness and concerns about AI risks to increase with age;

participants aged 24 and older show the highest mean values (PU = 4.30; R-CRA = 3.81), suggesting a more mature and balanced assessment of AI technologies.

Students with prior experience working with AI provide the most positive ratings across all scales, particularly with PU = 4.35 and BI = 4.32, confirming the significant influence of personal experience on attitudes toward AI use in educational practice.

Fig. 1 show that participants with previous AI experience score higher on the PU, EOU, and BI subscales, indicating a more positive attitude toward AI tools. Similarly, males and older age groups have slightly higher scores on the R-CRA subscale, which may reflect differences in risk perception and resistance to AI adoption.

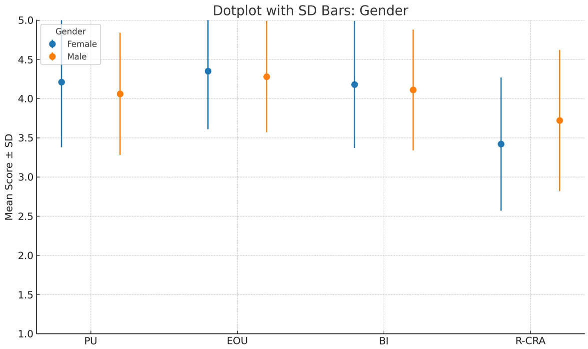

Fig. 1. Dotplot with SD bars for gender.

The structured AI training program had a significant and positive impact on pre-service teachers' readiness and willingness to use AI. For example, Verma *et al.* [41] and Alenezi [42] found that AI tools significantly increased student engagement in teacher training programs and enhanced pedagogical content knowledge. Similarly, teacher candidates who engaged with structured AI learning modules demonstrated improvements in classroom management and lesson planning skills [43]. These findings align with constructivist learning theories [44], which suggest that learners' ability to construct knowledge is enhanced through active engagement with interactive and multimodal content.

Fig. 2 illustrates the changes in attitudes toward AI before and after the training.

Table 9 presents the results of a paired samples t-test comparing pre- and post-training attitudes toward AI among pre-service teachers.

Table 9. Results for attitudes before and after training

Subscale	Pre-training mean (SD)	Post-training mean (SD)	t	df	*p*-value	Cohen's d
PU	3.45 (0.58)	4.12 (0.47)	−15.84	319	< 0.001	0.89
EOU	3.62 (0.55)	4.08 (0.50)	−11.27	319	< 0.001	0.63
BI	3.38 (0.65)	4.05 (0.53)	−14.42	319	< 0.001	0.81
R-CRA	2.89 (0.73)	2.35 (0.69)	9.76	319	< 0.001	0.55

[1] Cohen's d calculated as $t / \sqrt{n}$, where $n = 320$. Effect sizes indicate medium (R-CRA) to large effects (PU, BI), supporting the substantial impact of the training intervention.

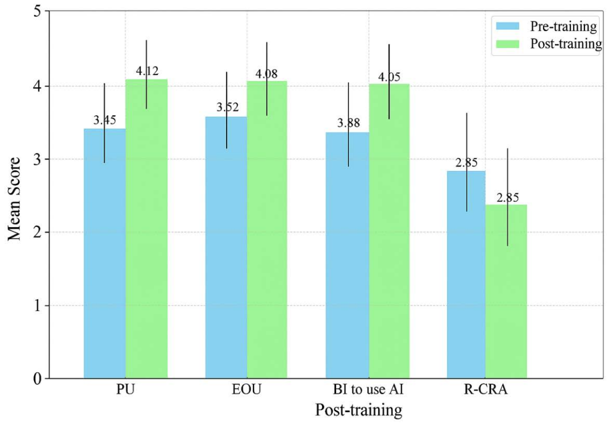

Fig. 2. Mean subscale scores pre- and post-training.

The diagram clearly demonstrates a statistically significant improvement in all positive scales (PU, EOU, and BI), along with a decrease in wariness as measured by the R-CRA scale following the training. This indicates that the training program had a positive impact on participants' perceptions and acceptance of AI.

Table 10 presents the correlation matrix (Pearson's r).

Table 10. Correlation matrix (Pearson's r)

Variables	1	2	3	4	5
BI (1)	1				
PU (2)	**0.64** ($p < 0.001$)	1			
EOU (3)	**0.58** ($p < 0.001$)	0.55 ($p < 0.001$)	1		
R-CRA (rev.) (4)	**0.42** ($p < 0.001$)	0.37 ($p < 0.001$)	0.33 ($p < 0.01$)	1	
Prior AI exposure (binary) (5)	**0.30** ($p < 0.01$)	0.25 ($p < 0.01$)	0.28 ($p < 0.01$)	0.19 ($p < 0.05$)	1

All indicators demonstrate positive and statistically significant relationships with each other. The strongest correlation is observed between BI and PU, $r = 0.64$ ($p < 0.001$). Significant correlations are also found between BI and EOU ($r = 0.58$, $p < 0.001$), as well as BI and the reverse-coded caution scale ($r = 0.42$, $p < 0.001$). Prior experience with AI shows weaker, yet still significant, positive relationships with all main subscales, including BI ($r = 0.30$, $p < 0.01$). These results indicate a close association between attitudes toward AI and prior experience, underscoring the importance of these factors in understanding the behavioral intentions of the study participants.

Fig. 3 presents a heat map of the correlation matrix illustrating the relationships among the main AI attitude subscales. All correlations are statistically significant, with cell brightness and color reflecting the strength and direction of these relationships, thereby facilitating visual interpretation of the data.

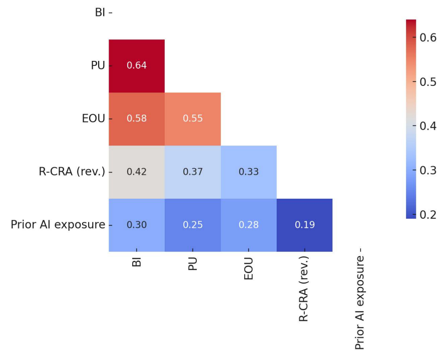

Fig. 3. Correlation matrix of attitude variables and prior AI exposure.

Table 11 presents a regression analysis identifying factors influencing future teachers' intention to use AI. Multicollinearity was assessed using VIF values, all of which were below 2.0, indicating no concerns regarding multicollinearity.

Table 11. Multiple regression analysis (DV = BI to use AI)

Predictor variable	B	SE B	Beta (β)	t	*p*-value
PU	0.41	0.06	0.45	6.83	< 0.001
EOU	0.27	0.07	0.31	3.86	< 0.001
R-CRA (reverse coded)	0.18	0.05	0.22	3.21	0.002
Prior AI exposure	0.12	0.04	0.15	2.75	0.006
Gender (0 = Male, 1 = Female)	0.05	0.04	0.06	1.21	0.228
Age	−0.02	0.03	−0.03	−0.66	0.511

The results show that all main variables—Perceived Usefulness (PU), Ease of Use (EOU), and reservations about AI (R-CRA)—are significant positive predictors of behavioral intention. Prior experience with AI also has a significant impact. However, gender did not have a statistically significant effect. Thus, the primary factors determining future teachers' willingness to use artificial intelligence are their perceptions of its usefulness and ease of use, their level of caution, and previous experience with AI.

Fig. 4 presents the standardized regression coefficients (Beta). Statistically significant predictors ($p < 0.05$) are highlighted in blue, while nonsignificant predictors are shown in gray. The most influential factors are Perceived Usefulness (PU) and Ease of Use (EOU), followed by reservations about AI (R-CRA) and prior AI experience. Age and gender did not significantly influence the intention to use AI.

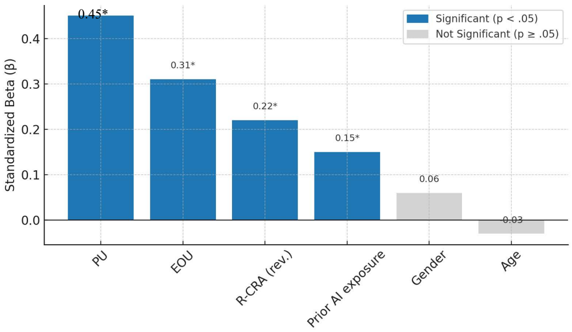

Fig. 4. Standardized beta coefficients predicting BI.

Thus, the integration of AI positively impacted key educational outcomes for the participants, ultimately preparing them to utilize AI in the classroom both ethically and effectively. These results provide further evidence of the importance of developing AI education initiatives. The training enhanced the environment for incorporating AI by improving technical proficiency, reducing anxiety, and increasing perceived value. Overall, participants demonstrated a generally positive attitude toward AI, with perceived usefulness and ease of use rated particularly highly. The majority agreed with statements reflecting the potential benefits of AI for learning.

The improvement across all scales following the targeted training program confirms the effectiveness of short-term, structured training in increasing future teachers' readiness to use AI in practice [45]. These findings align with Nazaretsky [46], who also observed a significant increase in teachers' professional confidence after completing AI modules. Similarly, Falebita and Kok [47] showed that self-efficacy and confidence in using AI are key factors influencing teacher readiness, which is further supported in this study by the significant impact of perceived usefulness and ease of use on behavioral intention. Scherer [48] emphasized the importance of pedagogical attitudes beyond technical training. Therefore, the results underscore the need to integrate targeted AI modules into teacher training programs, combining practical application with critical reflection on the ethical and social implications of AI.

Furthermore, it is important to situate these findings within the cultural, institutional, and policy context of Kazakhstan. The country's recent national strategies for digital transformation and educational reform emphasize the integration of advanced technologies, including AI, to modernize teaching and learning processes. However, challenges related to institutional readiness, infrastructure disparities, and socio-cultural attitudes toward technology can influence how future teachers perceive and adopt AI. This study highlights that while Kazakhstani pre-service teachers show positive attitudes toward AI, their perceptions are inevitably shaped by these broader socio-technical factors. Recognizing this contextual influence is crucial for developing culturally relevant and effective AI training programs that align with Kazakhstan's educational policies and address local needs and concerns.

A. Limitations of the Study

While the study offers valuable insights into pre-service teachers' attitudes toward AI integration in Kazakhstan, several limitations should be acknowledged. First, the research was conducted at a single institution (Abai Kazakh National Pedagogical University), which may limit the generalizability of the findings to other universities or regions within Kazakhstan. Second, the sample consisted exclusively of final-year pre-service teachers, potentially overlooking the perspectives of students at earlier stages of their training. Third, the reliance on self-reported survey data introduces the possibility of response bias, as participants may provide socially desirable answers rather than reflecting their true attitudes or behaviors. Additionally, the study's quantitative design, while effective for measuring trends and correlations, does not capture the depth of participants' experiences or the nuanced factors influencing their attitudes, which qualitative methods could have explored. Finally, the relatively short duration of the intervention (six weeks) may not be sufficient to assess long-term changes in attitudes or sustained behavioral intentions regarding AI use in educational practice.

IV. Conclusion

This study examined the attitudes of future teachers toward the integration of AI in educational practice. A key factor in shaping a positive attitude was previous experience with AI: participants who had already used AI tools demonstrated a higher level of readiness to implement them in the future. This highlights the need to provide pedagogical students with opportunities for practical mastery of AI within an educational context. The six-week training program developed and implemented in this study had a significant impact on changing participants' attitudes: after its completion, scores on all positive scales increased significantly, while wariness toward AI decreased. These results confirm the effectiveness of short-term, content-rich educational interventions in developing digital and pedagogical readiness for AI use.

The study addresses a gap in empirical data in Central Asia, particularly Kazakhstan, contributing to the understanding of how developing countries can adapt teacher preparation to the challenges of digital transformation. Based on these findings, it is recommended that AI-related modules be included in formal teacher training curricula, with emphasis on practical application, ethical considerations, and critical thinking. Future research should expand geographically to include other regions and universities and employ mixed methods to better understand the factors influencing AI integration in educational practice.

APPENDIX

Table A1. Attitude scale toward AI Learning

Subscale	Item statement
Perceived usefulness	AI tools can enhance students' learning experiences in the classroom.
	Using AI can help me deliver more personalized instruction.
	I believe AI can help reduce my teaching workload by automating routine tasks.
	AI can improve students' academic performance.
Ease of use	AI tools are easy to use for classroom activities.
	I feel confident navigating basic features of AI-powered educational tools.
	Learning to operate AI applications would be easy for me.
	I find AI technologies user-friendly for educational purposes.
Behavioral intention	I intend to integrate AI tools into my future lessons.
	I am interested in learning more about how to use AI in education.
	I would recommend AI tools to my colleagues.
	I plan to actively seek out AI-based resources for my teaching.
Concerns & reservations	I am concerned that AI could replace the teacher's role in the classroom.
	I worry about ethical issues related to using AI with students.
	I believe AI might increase inequality among students with different access to technology.
	I am hesitant to use AI because of data privacy concerns.

Table A2. Detailed description of the six-week AI training intervention

Week	Module title	Learning objectives	Instructional methods
1	Introduction to AI	Understand basic AI concepts, history, and applications	Interactive lecture, multimedia presentations
2	Global trends & exemplars	Explore global AI trends in education, analyze successful case studies	Group discussions, case study analysis
3	Hands-on exploration	Gain practical experience with AI-based educational tools	Hands-on workshops, tool demonstrations
4	Pedagogical integration	Design AI-enhanced learning activities	Collaborative lesson planning, peer feedback
5	Ethical, legal & social Implications	Reflect on ethical and social concerns related to AI in education	Guided debates, scenario-based discussions
6	Reflection & future planning	Evaluate learning, plan future integration of AI in teaching practice	Reflective journaling, action plan development

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Conceptualization, NM and SN; methodology, YM; software, LO; validation, RB, SA and NM; formal analysis, SN; investigation, YM; resources, LO; data curation, RB; writing—original draft preparation, SA; writing—review and editing, NM; visualization, SN; supervision, YM; project administration, LO; funding acquisition, SA. All authors have read and agreed to the published version of the manuscript.

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