JSSER
www.jsser.org

Journal of Social Studies Education Research

Sosyal Bilgiler Eğitimi Araştırmaları Dergisi

2026:17 (2), 200-222

The Impact of Artificial Intelligence and STEM Applications on Pre-Service Teachers' Learning Motivation and Individual Innovativeness: A Quasi-Experimental Study

Elmira Mirzaliyeva [1] , Nazeket Kaliyeva [2] , Beisen Assylmurat [3] & Saule Tazhibayeva[4]

Abstract

The current research aims to examine the effect of AI & STEM applications on pre-service teachers' learning motivation and individual innovativeness. It was conducted using a quasi-experimental design with experimental and control groups and pre-test–post-test measurements. The study group consisted of 64 undergraduate students taking a teaching practice course at the Faculty of Education of a state university in Almaty, with 32 students from each group. During the six-week application period, AI & STEM-based teaching applications were implemented in the experimental group. The existing curriculum was continued in the control group. The experimental group applications were planned within a three-stage process consisting of AI awareness and STEM integration. An AI-supported design workshop, microteaching, and reflective evaluation sessions. The Learning Motivation Scale, developed by Noe and Wilk (1993) and the Individual Innovation Scale, developed by Hurt, Joseph, and Cook (1977) were used as data collection tools. Since a significant difference was found between the pre-test learning motivation scores of the groups, Analysis of Covariance (ANCOVA) was applied in the post-test comparison. In the comparison of individual innovation, an independent samples t-test was used. The research findings indicate that students in the experimental group who participated in AI&STEM applications achieved statistically significantly higher post-test scores than students in the control group in terms of both learning motivation and individual innovation skills. According to Cohen's classification, the effect size for learning motivation was found to be large ($\eta^2 = 0.147$). This result shows that AI&STEM integration makes a significant contribution to teacher training processes. In this context, its integration into higher education programs is recommended.

Keywords: *Artificial intelligence in education, STEM integration, Learning motivation, Individual innovativeness, Teacher education, quasi-experimental design*

Introduction

The integration of artificial intelligence (AI) technologies into the field of education has accelerated in recent years and has begun to fundamentally transform teaching and learning processes. In today's world, where personalized and interactive approaches are replacing

[1] *Branch of the Joint Stock Company of the National Center for Advanced Training "Orleu" Institute of Professional Development in Zhambyl Region, Kazakhstan, e-mail: mirzaliyeva_e@orleu.edu.kz*
[2] *L. N. Gumilyov Eurasian National University, doctoral student of "Training of teachers of the Kazakh language and literature", Kazakhstan, e-mail: nazeket.kalieva.81@mail.ru*
[3] *L.N. Gumilyov Eurasian National University, Kazakhstan, e-mail: assylmurat.beisen@gmail.com*
[4] *Corresponding Author, L.N. Gumilyov Eurasian National University Republic of Kazakhstan, e-mail: tazhibaeva_szh@enu.kz*

traditional educational paradigms, intelligent systems provided by AI can adapt to students' individual needs and enrich the learning experience (Chauke et al., 2024; Chen et al., 2020; Makeleni et al., 2023; Zhai et al., 2021). In this context, STEM education, encompassing Science, Technology, Engineering, and Mathematics, has also begun to be reshaped with AI-supported tools. Significant opportunities have emerged in developing students' analytical thinking, problem-solving, and innovation capacities (Madden et al., 2013; Hussin et al., 2019). Research shows that AI-enriched STEM environments provide students with an interdisciplinary perspective and enable them to produce more competent solutions to complex real-world problems (Leon et al., 2025; Tassilova et al., 2025). With the increasing use of AI, there has also been a noticeable increase in studies integrating STEM and AI. This transformation is not limited to changes in content and tools, but also profoundly affects the pedagogical competencies of teachers (Alenezi & Alenezi, 2025; Ng et al., 2023; Shabalala, 2024). In such an environment, training prospective teachers in terms of AI literacy and STEM competencies has become important for both national and international education systems (Lee & Perret, 2022; Mirzaliyeva et al., 2025; Ussainova et al., 2025).

With the penetration of AI technologies into educational environments, the effects on students' intrinsic motivation towards learning have also come to the forefront of researchers' attention. Motivation is considered one of the main driving forces of the learning process, and this effect is seen to be even more pronounced, especially in technology-supported environments (Daher & Thabet, 2025; Galindo-Domínguez et al., 2025). AI systems can provide personalized feedback by identifying students' individual interests, learning speed and conceptual gaps. Thus, they can increase participation and continuity in the learning process (Halkiopoulos & Gkintoni, 2024; Imran et al., 2025). In addition, the problem-based and project-oriented approaches inherent in STEM education foster students' curiosity and prepare the ground for them to internalize their motivation (Borowczak et al., 2025). Despite all these developments, the number of studies that experimentally measure the effect of AI and STEM integration on student motivation is still quite limited. This limitation poses a significant obstacle to translating theoretical knowledge in the field into practice and creates areas of uncertainty for curriculum designers and policymakers.

The rapid transformation of today's business and social life places innovation skills at the center of education. The concept of individual innovation refers to an individual's tendency and capacity to adopt and apply new ideas, methods, or technologies, and developing this characteristic in prospective teachers is critically important for raising generations that can respond to the needs of the 21st century (Avsec & Savec, 2021; Şahin & Dursun, 2022). AI-supported learning environments offer students experiences that go beyond mere information transfer, encouraging exploration and creation. The literature emphasizes that these experiences are directly related to innovative thinking (Daher & Thabet, 2025; Erbilgin et al., 2024; Verdenhofa et al., 2024; Zhan et al., 2022). However, it is noteworthy that experimental research examining the impact of AI and STEM applications on individual innovation, particularly in the sample of prospective teachers, remains quite limited. This gap in the literature is the starting point of the present research and necessitates addressing the subject with an experimental design.

A review of the literature reveals that the vast majority of studies on AI and STEM education are descriptive, correlational, or systematic reviews. This stands out as a significant methodological limitation in establishing causal relationships (Chen et al., 2020; Zhai et al., 2021). Studies examining the impact of AI on student motivation are mostly evaluated at the higher education level and within the context of general academic achievement. Dimensions such as intrinsic motivation, self-efficacy, and learning continuity, which are components of motivation, are not addressed separately (Daher & Thabet, 2025; Leon et al., 2025; Shi & Zhang, 2025). Similarly, research on individual innovation skills is mostly evaluated within the framework of technology adoption. The specific effect of STEM and AI integration on innovation is examined in a limited number of studies (Mumcu, 2022; Yuksel, 2015). In this context, the present research aims to fill these gaps with an experimental approach and to make an original contribution to the literature. The scarcity of experimental studies that simultaneously address both the motivation and individual innovation dimensions of AI and STEM integration for prospective teachers clearly highlights the unique value and scientific importance of this research.

Artificial Intelligence and STEM Integration in Teacher Education

The integration of AI into STEM education within teacher training programs has become a priority research agenda in contemporary educational science. In this integration process, the fundamental expectation is not only that prospective teachers become familiar with technological tools, but also that they acquire the competencies to use these tools effectively from a pedagogical perspective

(Alenezi & Alenezi, 2025; Mirzaliyeva et al., 2025; Sun et al., 2024). The integration of AI applications into STEM courses enriches prospective teachers' conceptual understanding processes and strengthens their problem-solving skills. This integration has been shown to have positive effects on interdisciplinary thinking (Ayanwale & Sanusi, 2023; Tedre et al., 2021). The multi-layered structure of STEM fields, combined with the data processing, pattern recognition, and adaptive learning features offered by AI, creates an environment that contributes to the professional development of prospective teachers (Beek & Straub, 2024; Borowczak et al., 2025; Tassilova et al., 2025). Overcoming attitudes and prejudices towards technology integration is considered a critical aspect of program design. Research shows that prospective teachers' perceptions of AI tools vary depending on the program content and practical experiences. This necessitates that teacher training programs be structured in a flexible and contextual manner (Alshammari & Al-Enezi, 2024; Leon et al., 2025; Lee & Perret, 2022). Implementing STEM and artificial intelligence integration in the classroom guides prospective teachers towards metacognitive processes such as critical inquiry, analytical evaluation, and reflective practice. These processes are known to deepen professional competence.

For the effective integration of AI and STEM in teacher training programs, both theoretical foundations and practical infrastructure must be robust. AI's contribution to teacher education is not limited to enriching content knowledge but also encompasses pedagogical content knowledge (PCK) components, increasing prospective teachers' capacity to integrate technology into their lessons (Lee & Perret, 2022; Tedre et al., 2021). In this process, AI-supported intelligent tutoringl systems (ITS) provide students with real-time feedback and identify individual learning difficulties, enabling prospective teachers to make more informed decisions in both their learning and teaching practices (Koedinger et al., 2013). Furthermore, various studies have shown that STEM-focused project-based learning experiences, when supported by AI tools, strengthen prospective teachers' interdisciplinary collaboration and creative problem-solving skills (Hussin et al., 2019; Sun et al., 2023). Moreover, it has been observed that prospective teachers' attitudes towards AI and STEM integration are shaped not only by cognitive factors but also by affective and contextual variables. This necessitates the adoption of a multidimensional approach in program design (Ayanwale & Sanusi, 2023; Borowczak et al., 2025). In this context, for AI and STEM integration to gain a lasting and functional place in the teacher training process, theoretical frameworks, application environments, and assessment practices need to be designed in a consistent and integrated manner (Wulff et al., 2025).

Learning Motivation in AI-Supported Educational Environments

The question of how student motivation is shaped in AI-assisted learning environments is increasingly on the agenda of educational science researchers. Studies in this field reveal that personalized content, real-time feedback, and adaptive learning experiences offered by AI positively influence students' intrinsic motivation (Daher & Thabet, 2025; Galindo-Domínguez et al., 2025). When evaluated within the framework of self-determination theory, AI systems are seen to contribute to the internalization of motivation by strengthening students' perceptions of competence, autonomy, and relatedness. This contribution is particularly evident in AI applications in STEM contexts (Shi & Zhang, 2025; Imran et al., 2025). Intelligent tutoring systems and learning analytics tools can monitor students' strengths and weaknesses in academic processes and adjust content accordingly. Thus, increasing student expectations of success and fostering their motivation (Halkiopoulos & Gkintoni, 2024; Ndiangui & Koklu, 2024; Xu et al., 2024).

The impact of AI-powered environments on motivation manifests as a multidimensional dynamic that is not limited to the cognitive dimension but also encompasses the student's emotional engagement in the learning process and self-regulatory behaviors (Al Malki et al., 2025; Popenici & Kerr, 2017; Seo et al., 2021). Some studies point out that the positive effect of AI on motivation occurs under specific contextual conditions and may not manifest at the same level in every learning environment. This finding reinforces the need for experimental research (Borowczak et al., 2025; Pertiwi et al., 2024; Zamri et al., 2025). Indeed, studies that address the impact of AI and STEM integration on student motivation through a controlled experimental design play a critical role in overcoming methodological limitations in the field.

Innovation Skills and Individual Innovativeness in Pre-Service Teachers

Individual innovativeness is defined as an individual's tendency to adopt new ideas, products, or processes, and it is based on a comprehensive research tradition drawing on Rogers' (1962) diffusion theory of innovation (Yuksel, 2015). In the context of prospective teachers, individual innovativeness manifests itself as openness to technological tools and new teaching methods, and a willingness to integrate these tools into their professional practice. Exposure to AI and STEM applications is seen to strengthen this tendency (Avsec & Savec, 2021). AI-supported learning processes encourage prospective teachers to explore, experiment, and produce original solutions beyond routine knowledge acquisition. This creates experiential environments that foster innovative behavior (Ibrahim et al., 2025; Verdenhofa et al., 2024; Yordudom et al., 2026; Zhan et al., 2022).

The project-based and interdisciplinary nature of STEM education offers prospective teachers the opportunity to confront real-life problems, and in this process, it lays the groundwork for the systematic development of innovative thinking (Leon et al., 2025). However, it is observed that the vast majority of studies on prospective teachers' innovation skills are addressed only within the framework of technology acceptance or ICT competencies, and experimental studies that directly measure the specific impact of AI and STEM integration in this context remain quite limited (Avsec & Savec, 2021; Mumcu, 2022).

Research Objective and Questions

The aim of this research is to examine the impact of AI & STEM applications on the learning motivation and individual innovation skills of students in the Faculty of Education. To this end, the study sought answers to the following questions:

- To what extent do AI & STEM applications in the Faculty of Education (experimental group) affect students' learning motivation compared to applications based on the existing curriculum (control group)?
- To what extent do AI & STEM applications in the Faculty of Education (experimental group) affect students' individual innovation skills compared to applications based on the existing curriculum (control group)?

Method

Research Design

This research was designed using a quasi-experimental pre-test–post-test design with experimental and control groups. In this design, participants are not randomly assigned to groups. Both groups are pre-tested before the intervention and then only the experimental group receives the experimental intervention. After the completion of the experimental intervention, both groups are post-tested to assess the effectiveness of it (Creswell & Creswell, 2017). The quasi-experimental design of the research is schematically presented below in Table 1.

Table 1

Research Design

Group	Pre-test	Treatment	Post-test
Experimental	O_1	X (AI&STEM)	O_2
Control	O_1	—	O_2

X = AI & STEM interventions (experimental intervention); O_1 = Pre-test; O_2 = Post-test; — = No intervention.

As seen in Table 1, the research encompassed a six-week implementation period. Conducted within the scope of the teaching practice course at the Faculty of Education. This process involved applying AI & STEM-based applications to the experimental group and the existing curriculum to the control group for the same duration. Pre-test and post-test measurements were administered simultaneously to both groups.

Research Group

The research was conducted with undergraduate students enrolled in teaching practice at the Faculty of Education of a state university in Almaty. The group was determined using purposive sampling, and a total of 64 students participated, with 32 students from each group. The experimental group consisted of 20 female and 12 male students while the control group consisted of 19 female and 13 male students. The two groups were considered to be comparable regarding distribution of gender and size.

Experimental Procedure

The research was conducted over six weeks with undergraduate students taking a teaching practice course at a state university. In the first week, data collection instruments were administered simultaneously to both groups as pre-tests. From the second week onwards, for five weeks, AI & STEM-based teaching practices were implemented in the experimental group. The existing curriculum was continued for the same period in the control group. The simultaneous, paper-based administration of the measurement instruments to both groups was chosen to minimize potential application bias between the groups. At the end of the sixth week, post-test measurements were completed. The pre-test and post-test data were compared to evaluate the impact of AI & STEM applications on students' learning motivation and individual innovation skills.

AI & STEM Implementation Process in the Experimental Group

AI & STEM teaching:

- Sessions 1-2: AI awareness and STEM integration
- Sessions 3-4: AI-assisted design workshop applications
- Sessions 5-6: Microteaching

Sessions 1-2 – Pedagogical Introduction to AI and STEM

The first two sessions were structured to enable prospective teachers to approach AI and STEM concepts from a pedagogical perspective. The course began with the question, “How would the classroom environment change if AI were a teacher?” Students, in small groups, discussed the potential roles, opportunities, and ethical risks of AI in teaching. This was followed by a brief theoretical framework. The interdisciplinary nature of STEM and the importance of technology integration in the context of teaching practice were explained. Students learned through experience how OpenAI-based text generation tools or applications such as Microsoft Copilot could provide support in lesson planning. In the practical part of the week, groups developed an AI-supported STEM lesson outline, addressing a teaching practice theme. A reflective evaluation activity was conducted at the end of the process.

Sessions 3-4 – AI-Powered STEM Design Workshop

In these two sessions, students participated in a design workshop where they transformed theoretical knowledge into practical application. The course focused on the problem of "Smart classrooms and learning outcomes," asking prospective teachers to design an innovative STEM solution to this real-life problem. Groups analyzed the problem, considering science, mathematics, engineering, and technology dimensions together, and planned how to integrate AI tools into the process. For instance, they used Canva's AI features for visual design and material production, and the Scratch platform for basic coding and simulation. At this stage, students not only used technology but also evaluated its pedagogical suitability. At the end of the session, each group gave a short "design presentation" to share their ideas and receive peer feedback.

Sessions 5-6 – Microteaching and Reflective Assessment

In the last two sessions, micro-teaching process applications were carried out, where the developed AI & STEM lesson designs were put into practice. Each group presented their prepared lesson in a classroom setting with a short application. Other students participated in the activities by taking on the role of secondary school students. During this application, the pedagogical use of AI tools, the level of increasing student participation, and the integrity of STEM integration were observed. At the end of the lesson, feedback was given via structured observation forms, and strengths and areas for improvement were discussed. In the final stage, students evaluated the impact of this experience on their motivations, career visions, and innovative thinking processes by writing individual reflective journals.

In the control group, a traditional six-session teaching practice process was conducted. This involved classic lesson plan writing and microteaching without the use of AI and STEM technological tools. The control group was first structured to allow prospective teachers to experience the traditional instructional planning process. Students were asked to select a learning objective aligned with the National Education curriculum and prepare a classic lesson plan for that objective. The plan was structured to include the following steps: aim-outcome writing, introduction-development-conclusion sections, teaching methods and techniques, material selection, and assessment. During this process, students utilized textbooks, teacher's guides, and printed academic resources. They did not use digital or AI-supported tools. Instructional design was largely based on lecturing, question-and-answer, and discussion techniques. Each prospective teacher presented their lesson plan in a 10-15 minute application. Other students assumed the student role. Traditional teaching techniques such as lecturing, question-and-answer, and whiteboard explanations were predominantly used during the lesson. At the end of the application, an evaluation was conducted using structured observation forms. The evaluation criteria were: The study focused on the clarity of the subject matter, classroom management, time management, and the appropriateness of the assessment methods.

After six sessions of teaching practice conducted in the experimental groups, the Learning Motivation Scale and the Innovation Scale were administered to both groups simultaneously as post-tests.

Data Collection Tools

Individual Innovativeness Scale

To assess students' perceptions of individual innovativeness skills, the Individual Innovativeness Scale developed by Hurt, Joseph, and Cook (1977) was used. The scale was adapted into Kazakh by the researchers. The scale consists of a total of 20 items, 12 of which are scored positively (items 1, 2, 3, 5, 8, 9, 11, 12, 14, 16, 18, and 19) and 8 of which are scored negatively (items 4, 6, 7, 10, 13, 15, 17, and 20). The items are answered using a five-point Likert-type rating scale ranging from "Strongly Disagree" (1) to "Strongly Agree" (5). The individual innovativeness score is calculated by subtracting the total score obtained from the negative items from the total score obtained from the positive items and adding 42 points to this value. The minimum score obtainable from the scale is 14, and the maximum score is 94. In this research, the raw scores were divided by the number of items (20) to convert them into individual innovation skill perception scores ranging from 1 to 5. As a result of the confirmatory factor analysis carried out within the scope of the adaptation study, it was determined that the scale exhibits a single-factor structure and the internal consistency coefficient is $\alpha = 0.85$.

Learning Motivation Scale

To measure the learning motivation levels of students, the 17-item Learning Motivation Scale developed by Noe and Wilk (1993) was used. The scale was adapted from Turkish to Kazakh by the researchers. Exploratory Factor Analysis (EFA) performed on the Kazakh form revealed that the scale has a unidimensional structure. The Cronbach alpha internal consistency coefficient of this Likert-type scale, which is rated between "Strongly Disagree" (1) and "Strongly Agree" (5), was calculated as $\alpha = 0.81$.

Data Analysis

Data analysis was performed using SPSS 27 software. To apply parametric tests, it was first examined whether the data met the assumption of normal distribution. The skewness coefficient for the learning motivation pre-test data was calculated as 0.21, and the kurtosis coefficient as -0.16. The skewness coefficient for the individual innovativeness pre-test data was determined as -0.41, and the kurtosis coefficient as 0.23. According to Tabachnick and Fidell (2007), skewness and kurtosis coefficients between -1.5 and +1.5 indicate that the data meets the assumption of normal distribution. The obtained coefficients are within this range. The assumption of normal distribution was also tested using the Kolmogorov-Smirnov test. A p-value > 0.05 was obtained for both pre-test data sets, thus confirming that the assumption of normal distribution is met. Since a statistically significant difference was found between the pre-test learning motivation scores of the groups, pre-test scores were controlled as a common variable in the comparison of post-test learning motivation scores, and One-Way Analysis of Covariance (ANCOVA) was applied. According to Field (2024), when differences are observed in the initial scores of the participants, pre-test scores should be statistically controlled in post-test comparisons between groups. In the comparison of individual innovativeness post-test scores, since no significant difference was found between the pre-test scores, an independent samples t-test was used.

Findings

The findings are presented in line with the two research questions of the study. First, descriptive statistics for the pre-test and post-test scores of the experimental and control groups are reported. Then, the results related to Research Question 1 and Research Question 2 are presented separately.

To examine the impact of AI & STEM applications on students' learning motivation, the pre-application motivation levels of the experimental and control groups were first compared. The findings from the pre-test data, administered simultaneously to both groups, are presented below in Table 2.

Table 2

Comparison of Pre-test Learning Motivation Scale Scores of the Groups

Scale	Group	N	Mean	SD	t	p
Learning Motivation	Experimental	32	3,23	0,67	-2,091	0,041*
	Control	32	3,55	0,54		

$*p<0,05$

As presented in Table 2, the pre-test learning motivation scores of the experimental and control groups differed significantly before the intervention. An independent samples t-test revealed a statistically significant difference between the two groups ($t = -2.091$; $p = 0.041 < 0.05$). The mean pre-test score for the experimental group was 3.23, while the mean score for the control group was 3.55. This significant difference in learning motivation levels between the groups before the experimental interventions necessitated the use of baseline scores as a control variable in the post-test comparison. Therefore, Analysis of Covariance (ANCOVA) was used to compare post-test learning motivation scores between the groups.

The adjusted post-test mean scores and descriptive statistics, calculated after statistically controlling for pre-test scores using analysis of covariance, are presented in Table 3.

Table 3

Descriptive Statistics and Adjusted Mean Scores for Group Learning Motivation Post-Test

Group	Mean	Adj. Mean	SD	N
Experimental	4,20	4,21	0,33	32
Control	3,96	3,95	0,27	32

Adj. Mean = Adjusted mean calculated by controlling for pretest scores.

As shown in Table 3, the raw post-test mean scores were calculated as 4.20 for the experimental group and 3.96 for the control group. When pre-test scores were controlled the adjusted mean scores were 4.21 for the experimental group and 3.95 for the control group. This pattern indicates a significant difference in favor of the experimental group after the intervention. The statistical significance of this difference was tested using the ANCOVA test, and the results are presented in Table 4.

Table 4

ANCOVA Results Regarding the Learning Motivation of the Groups in the Post-Test

Source	SS	df	MS	F	p	Partial η²
Corrected Model	,967	2	0,484	5,273	0,008**	0,147
Intercept	29,346	1	29,346	319,886	<0,000***	0,840
Pretest (Covariate)	0,072	1	0,072	0,781	0,380	0,013
Group	0,967	1	0,967	10,542	0,002**	0,147
Error	5,596	61	0,092			
Total	1073,286	64				
Corrected Total	6,563	63				

*SS = Sum of squares; MS = Mean square. **p < .01; ***p<.001*

As presented in Table 4, after controlling for pre-test scores, the post-test learning motivation scores differed significantly between the experimental and control groups, F(1, 61) = 10.542, p =

.002, partial $\eta^2 = .147$. This effect size indicates a large practical impact according to Cohen's (1988) guidelines. In other words, participation in the six-week AI&STEM intervention was associated not only with statistically significant gains in learning motivation, but also with a substantively meaningful difference in favor of the experimental group.

To answer the second question of the study, the perceptions of individual innovation skills of the experimental and control groups were evaluated before and after the intervention. Pre-test findings regarding the innovation scores of the groups at the beginning of the intervention are presented in Table 5.

Table 5

Comparison of Pre-test Individual Innovativeness Scale Scores of the Groups

Scale	Group	N	Mean	SS	t	p
Individual Innovativeness	Experimental	32	3,62	0,59	-0,101	0,920
	Control	32	3,64	0,46		

As shown in Table 5, the mean individual innovativeness scores of the experimental and control groups were calculated as 3.62 and 3.64 respectively, before the experimental applications began. According to the independent samples t-test results, no statistically significant difference was found between the two groups ($t = -0.101$; $p = 0.920 > 0.05$). This finding indicates that both groups had equivalent initial conditions regarding individual innovativeness levels before starting the experimental applications. Since there was no significant difference in the pre-test innovativeness scores of the groups, it was decided to use the independent samples t-test for the post-test comparison. The analysis results regarding the post-test findings are presented in Table 6.

Table 6

Comparison of the Groups' Final Test Individual Innovativeness Scale Scores

Scale	Group	N	Mean	SS	t	p
Individual Innovativeness	Experimental	32	3,95	0,56	2,162	0,035*
	Control	32	3,67	0,45		

*$p < .05$.

As presented in Table 6, the post-test individual innovativeness scores were significantly higher in the experimental group than in the control group. The mean score for the experimental group was 3.95, while the mean score for the control group was 3.67. This difference between the groups was found to be statistically significant ($t = 2.162$; $p = 0.035 < 0.05$). This finding indicates that students participating in AI & STEM applications achieved significantly higher scores in terms of their perception of individual innovation skills after the experimental process, compared to their peers continuing with the current curriculum.

In summary, the findings related to Research Question 1 showed that the AI&STEM intervention had a statistically significant positive effect on students' learning motivation after controlling for pre-test differences. The findings related to Research Question 2 showed that students in the experimental group also reported significantly higher post-test individual innovativeness scores than those in the control group. Overall, the results suggest that the intervention was associated with improvements in both motivational and innovation-related outcomes.

Discussion and Conclusion

This research aims to examine the effects of artificial intelligence and STEM applications on the learning motivation and individual innovation skills of faculty of education students using a quasi-experimental design. According to the research findings, the learning motivation levels of the experimental group students who participated in AI & STEM applications were significantly higher compared to the control group students. Similarly, after the completion of the experimental process, it was determined that the perceptions of individual innovation skills of the students in the experimental group were also significantly different from those in the control group. Taken together, these findings suggest that the integration of AI and STEM may hold substantial pedagogical potential in the context of teacher training. In this discussion section, these findings are interpreted within the framework of the relevant literature, the theoretical and practical contributions of the research are evaluated, the limitations of the study are addressed, and suggestions are made for future research and applications.

Interpretation of the Findings

According to the first finding, students in the experimental group, where AI & STEM applications were implemented, exhibited significantly higher learning motivation at the end of the experimental process compared to control group students, where the existing curriculum was continued. This finding remains valid even after controlling for pre-test scores through covariance analysis, taking into account that the experimental and control groups had different initial motivation levels before the intervention. The resulting effect size shows that the implemented intervention had a practically significant and strong impact on learning motivation. This finding is consistent with studies suggesting that AI-supported learning environments offer personalized experiences that foster students' intrinsic motivation. Indeed, Daher and Thabet (2025) demonstrated through systematic review findings that AI environments consistently have positive effects on student motivation. Galindo-Domínguez et al. (2025), in their longitudinal study conducted within the framework of self-determination theory, reported that AI-supported interventions significantly increased learning motivation in young people. It is known that project-based and interdisciplinary learning experiences in the context of STEM increase students' curiosity and participation levels. Borowczak et al. (2025) confirmed the supportive role of these integration processes on motivation in experimental contexts. Shi and Zhang (2025), on the other hand, explained from the perspective of self-determination theory that students' perceptions of self-efficacy and psychological resilience have a decisive function on motivation in AI-based contexts. The findings of the current study are consistent with the aforementioned literature and confirm the potential of AI & STEM integration to strengthen the motivation of prospective teachers through an experimental design.

According to the second finding of the study, while the individual innovation skill perceptions of the experimental and control groups showed a similar distribution before the application. After the completion of the experimental process, the innovation scores of the students in the experimental group increased significantly compared to the students in the control group. This finding provides a unique contribution to the literature by directly revealing the effect of AI & STEM applications on individual innovation through a controlled design. Avsec and Savec (2021), in their studies examining the innovative behavior patterns of prospective teachers, found that learning environments supporting technology integration strongly predicted the development of these skills. Verdenhofa et al. (2024), in their study conducted in Latvia, Ukraine, and Spain, emphasized that AI left significant positive traces on students' creativity and innovation. Zhan et al. (2022) revealed that product-based pedagogy significantly increased students' innovative thinking skills in the context of an AI course. Leon et al. (2025) reported that presenting AI in STEM education within an interdisciplinary framework produced strong effects on students' innovation and participation levels. Mumcu (2022) and Şahin and Dursun (2022) have shown that individual innovation is strongly related to technology adoption processes and that this context is sensitive to educational interventions. The findings of the present research are consistent with these studies and suggest that AI & STEM integration may support the development of pre-service teachers' innovation skills.

Implications of the Findings

The findings of this research hold significant implications, both theoretically and practically. On a theoretical level, the study adds an experimental layer of evidence to the literature on the role of artificial intelligence in education, validating the impact of AI & STEM integration on learning motivation and individual innovativeness through a controlled design. In this respect, the research partially fills the experimental gap noted in the review studies by Chen et al. (2020) and Zhai et al. (2021). From a self-determination theory perspective, it is found that AI & STEM applications can simultaneously foster students' perceptions of competence, autonomy, and relatedness, thereby paving the way for the internalization of intrinsic motivation (Galindo-Domínguez et al., 2025). In terms of individual innovativeness, this finding, drawing on Rogers' diffusion of innovation theory, demonstrates that innovativeness is not a static personality trait, but rather a tendency that can be developed through appropriate learning environments (Yuksel, 2015; Mumcu, 2022). Regarding implementation, the study concludes that integrated AI & STEM modules should be systematically included in the curricula of pedagogy faculties and teacher training programs. It is critical that these modules are not limited to simply introducing technological tools, but are supported by applications that encourage prospective teachers to use AI pedagogically in real classroom contexts (Lee & Perret, 2022; Ayanwale & Sanusi, 2023). Education policymakers should consider these findings and update teacher training standards and accreditation criteria, which could pave the way for a systemic transformation.

A distinctive contribution of the present study lies in the structured three-stage design of the intervention, which combined AI awareness, AI-supported STEM design workshops, and microteaching-based reflective practice. Rather than treating AI as a stand-alone technological tool, this model embedded AI within a pedagogically sequenced teacher education experience. In this respect, the study contributes an implementable instructional framework for integrating AI into STEM-oriented teacher preparation.

Limitations

The current research presents several limitations that must be considered when interpreting its findings. First, it was conducted at the Faculty of Educationof a single state university in Almaty, and the sample size was limited to 32 students in each group. This restricts the generalizability of the findings to different contexts. The limitation of the experimental application to a six-week period constitutes a significant constraint in terms of monitoring the long-term effects of the AI & STEM intervention. The significant difference in pre-test scores of learning motivation between the two groups before the intervention shows that the groups were not fully equalized in terms of initial conditions. Though this difference was statistically controlled through covariance analysis, this should be carefully considered in the interpretations. The fact that the measurement tools used were solely self-report-based does not completely eliminate potential sources of bias, such as the social desirability effect. The fact that the research was conducted within a single cultural and institutional context should also be considered as a factor limiting the transfer of results to different educational systems. All these limitations stand out as methodological priorities that should be considered in the design of future research. Another limitation is that the study did not include a delayed post-test. Therefore, although the intervention appears to have strengthened participants' individual innovativeness in the short term, it remains unclear whether these gains would be sustained over time.

Recommendations

The findings of this research allow for the development of a series of recommendations for both practical application and future research. It is suggested that developers of teacher training programs incorporate AI & STEM integrated learning experiences as mandatory course content, presenting both theoretical and practical components of these modules. Future research should conduct multicenter experimental studies with large samples across different countries and teacher training levels to enhance the reliability and generalizability of the findings. Adopting longitudinal designs with follow-up measures to assess the persistence of effects on motivation and innovation will significantly deepen the body of knowledge in this field. The use of mixed methods approaches will allow qualitative data accompanying quantitative findings to provide richer explanations of the process. Researchers examining variables such as technology self-efficacy, prior experience, and disciplinary field that may mediate the impact of AI & STEM applications on motivation and innovation will strengthen the mechanistic understanding. Policymakers reflecting these research findings in national teacher training strategies and accreditation frameworks could create a lasting impact at the systemic level. Increasing institutional investments by universities in AI infrastructure and designing continuous professional development programs for prospective teachers should also be considered a strategic priority in this context. In addition, future implementations may adapt the AI&STEM model to other academic disciplines such as language teacher education, social sciences education, and arts-based teacher preparation. Such cross-disciplinary adaptations would help determine whether the motivational and innovation-related benefits observed in this study can be replicated beyond STEM-oriented instructional contexts.

Conclusion

The present research examined the impact of AI & STEM applications on the learning motivation and individual innovation skills of Faculty of Education students and found significant differences in favor of the experimental group for both variables. These findings provide a unique contribution to the literature by supporting the pedagogical value of AI and STEM integration in the context of teacher training with experimental evidence. By addressing these two variables simultaneously and within a controlled experimental framework, the research fills a methodological gap that previous descriptive and correlational studies have failed to fill. The finding that prospective teachers' individual innovation skills can be developed through appropriate learning environments demonstrates that this trait is not merely a personality tendency and is open to educational interventions (Avsec & Savec, 2021). The findings also confirm that personalized learning environments offered by AI play a decisive role in the internalization of motivation (Imran et al., 2025; Galindo-Domínguez et al., 2025). The fact that the research was conducted within the context of a Faculty of Education and with groups having different initial conditions brings with it limitations that need to be considered in interpreting the findings. This indicates the need for further research on the subject with larger and more diversified samples in future studies.

References

Al Malki, M, Washahi, Q. A., & Al Farsi, A.R. (2025). Omani Pre-Service Teachers' Preparedness and Perceptions of Integrating Artificial Intelligence into Classrooms. *Journal of Social Studies Education Research, 16*(4), 265-297. https://jsser.org/index.php/jsser/article/view/6933/761

Alenezi, A., & Alenezi, A. (2025). Knowledge and Teaching with Artificial Intelligence: Stem Vs. Humanities. *Comunicar: Revista Científica de Comunicación y Educación*, (82), 116-126. https://doi.org/10.5281/zenodo.15996228

Alshammari, A., & Al-Enezi, S. (2024). Role of artificial intelligence in enhancing learning outcomes of pre-service social studies teachers. *Journal of Social Studies Education Research*, *15*(4), 163-196. https://jsser.org/index.php/jsser/article/view/5787/699

Avsec, S., & Savec, V. F. (2021). Predictive Modelling of Pre-Service Science and Technology Teachers' Innovative Behaviour. *Journal of Baltic Science Education*, *20*(2), 171–183. https://doi.org/10.33225/jbse/21.20.171

Ayanwale, M. A., & Sanusi, I. T. (2023). Perceptions of STEM vs. non-STEM teachers toward teaching artificial intelligence. Paper presented at the 1-5. https://doi.org/10.1109/AFRICON55910.2023.10293455

Beek, A., & Straub, J. (2024). Outreach as Research Activism: Using STEM Outreach as a bridge to Social Change. *Journal of Culture and Values in Education, 7*(3), 130-146. https://doi.org/10.46303/jcve.2024.32

Borowczak, A. C., Kilty, T. J., & Borowczak, M. (2025). Building successful STEM partnerships in education: Strategies for enhancing collaboration. *Education Sciences, 15*(7), 893. https://doi.org/10.3390/educsci15070893

Chauke, T., Mkhize, T., Methi, L., & Dlamini, N. (2024). Postgraduate Students' Perceptions on the Benefits Associated with Artificial Intelligence Tools on Academic Success: In Case of ChatGPT AI tool. *Journal of Curriculum Studies Research, 6*(1), 44-59. https://doi.org/10.46303/jcsr.2024.4

Chen, L., Chen, P., & Lin, Z. (2020). Artificial intelligence in education: A review. *IEEE access*, *8*, 75264-75278. doi: 10.1109/ACCESS.2020.2988510

Creswell, J. W., & Creswell, J. D. (2017). *Research design: Qualitative, quantitative, and mixed methods approaches*. Sage publications.

Daher, W., & Thabet, E. A. (2025). Students' Motivation in the Artificial Intelligence Environment: A Systematic Review. *International Journal of Interactive Mobile Technologies*, *19*(11). https://doi.org/10.3991/ijim.v19i11.55139

Erbilgin, E., Tarman, I., Tarman, B. (2024). Correction to: Using Limited Resources to Teach Core Ideas from STEM and Social Studies. In: Tillman, D.A. (eds) Exploring Perspectives on Creativity Theory and Research in Education. Creativity Theory and Action in Education, vol 8. Springer, Cham. https://doi.org/10.1007/978-3-031-55416-2_17

Field, A. (2024). *Discovering statistics using IBM SPSS statistics*. Sage publications limited.

Galindo-Domínguez, H., Delgado, N., Urruzola, M., Etxabe, J., & Campo, L. (2025). Using Artificial Intelligence to Promote Adolescents' Learning Motivation. A Longitudinal Intervention From the Self-Determination Theory. *Journal of Computer Assisted Learning*, *41*(2), e70020. https://doi.org/10.1111/jcal.70020

Halkiopoulos, C., & Gkintoni, E. (2024). Leveraging AI in E-learning: Personalized learning and adaptive assessment through cognitive Neuropsychology—A systematic analysis. *Electronics (Basel), 13*(18), 3762. https://doi.org/10.3390/electronics13183762

Hurt, H. T., Joseph, K., & Cook, C. D. (1977). Scales for the measurement of innovativeness. *Human Communication Research*, 4, 58-65.

Hussin, H., Jiea, P. Y., Rosly, R. N. R., & Omar, S. R. (2019). Integrated 21st century science, technology, engineering, mathematics (STEM) education through robotics project-based learning. *Humanities & Social Sciences Reviews*, *7*(2), 204-211. https://doi.org/10.18510/hssr.2019.7222

Ibrahim, A., Alorani, O., Shane, M., Jafar, A. & Ajlouni, A. (2025). The Relationship Between Pre-service Teachers' Self-Efficacy in Teaching SWDs, Intensity of ChatGPT Use, and Their Perceived Practicum Stress. *Journal of Social Studies Education Research, 16*(4), 86-108. https://jsser.org/index.php/jsser/article/view/6938/755

Imran, H., Nadeem, S., Khan, M. L., & Qureshi, U. (2025). Impact of Artificial Intelligence Personalized Learning on Student Motivation and Academic Performance. *SOCIUM Учредители: Jomard Publishing*, *2*(1), 49–58. https://doi.org/10.62476/soc.2149

Koedinger, K. R., Brunskill, E., Baker, Ryan S. J. d., McLaughlin, E. A., & Stamper, J. (2013). New potentials for Data-Driven intelligent tutoring system development and optimization. *The AI Magazine, 34*(3), 27-41. https://doi.org/10.1609/aimag.v34i3.2484

Lee, I., & Perret, B. (2022, June). Preparing high school teachers to integrate AI methods into STEM classrooms. In *Proceedings of the AAAI conference on artificial intelligence* (Vol. 36, No. 11, pp. 12783-12791). https://doi.org/10.1609/aaai.v36i11.21557

Leon, C., Lipuma, J., & Oviedo-Torres, X. (2025, July). Artificial intelligence in STEM education: A transdisciplinary framework for engagement and innovation. In *Frontiers in Education* (Vol. 10, p. 1619888). Frontiers. https://doi.org/10.3389/feduc.2025.1619888

Madden, M. E., Baxter, M., Beauchamp, H., Bouchard, K., Habermas, D., Huff, M., ... & Plague, G. (2013). Rethinking STEM education: An interdisciplinary STEAM curriculum. *Procedia Computer Science*, *20*, 541-546. https://doi.org/10.1016/j.procs.2013.09.316

Makeleni, S., Mutongoza, B., & Linake, M. (2023). Language Education and Artificial Intelligence: An Exploration of Challenges Confronting Academics in Global South Universities. *Journal of Culture and Values in Education, 6*(2), 158-171. https://doi.org/10.46303/jcve.2023.14

Mirzaliyeva, E., Ussenova, G., Mamayeva, G., & Yelubay, A. (2025). The Effects of Artificial Intelligence and STEM-Based Education in Social Classes. *Journal of Social Studies Education Research, 16*(4), 298-325. https://jsser.org/index.php/jsser/article/view/7059/762

Mumcu, F. (2022). Is Personal Innovativeness Decisive in Preservice Teachers' ICT Competencies? *Instructional Technology and Lifelong Learning*, *3*(1), 1–18. https://doi.org/DOI:%252010.52911/itall.1101391

Ndiangui, P., & Koklu, O. (2024). Understanding Barriers to STEM: Teachers' Insights on African American Underrepresentation. *Research in Social Sciences and Technology, 9*(3), 26-44. https://doi.org/10.46303/ressat.2024.45

Ng, D.T.K., Leung, J.K.L., Su, J. *et al.* Teachers' AI digital competencies and twenty-first century skills in the post-pandemic world. *Education Tech Research Dev* **71**, 137–161 (2023). https://doi.org/10.1007/s11423-023-10203-6

Noe, R. A., & Wilk, S. L. (1993). Investigation of the factors that influence employees' participation in development activities. *Journal of Applied Psychology*, *78* (2), pp: 291-302.

Pertiwi, R. W. L., Kulsum, L. U., & Hanifah, I. A. (2024). Evaluating the impact of artificial intelligence-based learning methods on students' motivation and academic achievement. *International Journal of Post Axial: Futuristic Teaching and Learning*, 49–58. https://doi.org/10.59944/postaxial.v2i1.279

Popenici, S. A., & Kerr, S. (2017). Exploring the impact of artificial intelligence on teaching and learning in higher education. *Research and practice in technology enhanced learning*, *12*(1), 22. https://doi.org/10.1186/s41039-017-0062-8

Seo, K., Tang, J., Roll, I., Fels, S., & Yoon, D. (2021). The impact of artificial intelligence on learner-instructor interaction in online learning. *International Journal of Educational Technology in Higher Education, 18*(1)https://doi.org/10.1186/s41239-021-00292-9

Shabalala, N. (2024). Elevating STEM Learning: Unleashing the Power of AI in Open Distance eLearning. *Research in Social Sciences and Technology, 9*(3), 269-288. https://doi.org/10.46303/ressat.2024.59

Shi, S., & Zhang, H. (2025). EFL students' motivation predicted by their self-efficacy and resilience in artificial intelligence (AI)-based context: From a self-determination theory perspective. *Learning and Motivation*, *91*, 102151. https://doi.org/10.1016/j.lmot.2025.102151

Sun, Y., Ni, C.-C., & Lin, R. (2023). From stereotype to reality: A pilot study on the use of science, technology, engineering, and mathematics and STEAM in design education in Taiwan. *Frontiers in Education (Lausanne)*, *8*, 1098584. https://doi.org/10.3389/feduc.2023.1098584

Sun, F., Tian, P., Sun, D., Fan, Y., & Yang, Y. (2024). Pre-service teachers' inclination to integrate AI into STEM education: Analysis of influencing factors. *British Journal of Educational Technology*, *55*(6), 2574-2596. https://doi.org/10.1111/bjet.13469

Şahin, F., & Dursun, Ö. (2022). Does innovativeness matter in technology adoption? Addressing pre-service teachers' intention to use ITs. *Journal of Educational Technology and Online Learning*, *5*(3), 676–693. https://doi.org/10.31681/jetol.1125238

Tabachnick, B. G., & Fidell, L. S. (2007). *Experimental designs using ANOVA* (Vol. 724). Belmont, CA: Thomson/Brooks/Cole.

Tassilova, N. A., Shashayeva, G. K., Yernazarova, Z. S., Akhmetova, A. I., Arynov, Z. M., & Karimova, Z. K. (2025). Communication technologies in STEM education: A systematic review. *Eurasia Journal of Mathematics, Science and Technology Education*, *21*(10), em2719. https://doi.org/10.29333/ejmste/17178

Tedre, M., Toivonen, T., Kahila, J., Vartiainen, H., Valtonen, T., Jormanainen, I., & Pears, A. (2021). Teaching machine learning in K-12 classroom: Pedagogical and technological trajectories for artificial intelligence education. *IEEE Access, 9*, 110558-110572. https://doi.org/10.1109/ACCESS.2021.3097962

Ussainova, G., Seitmuratov, A., Issayeva, G., Shamsudinova, G., & Zhanseitova, L. (2025). Redesigning Instructional Design with an AI-Incorporated ADDIE Model for 21st Century Education. *Journal of Curriculum Studies Research, 7*(2), 498-521. https://doi.org/10.46303/jcsr.2025.31

Verdenhofa, O., Kinderis, R., & Berjozkina, G. (2024). AI as a creative partner: How artificial intelligence impacts student creativity and innovation: Case study of students from Latvia, Ukraine and Spain. *Baltic Journal of Economic Studies*, *10*(5), 111–119. https://doi.org/10.30525/2256-0742/2024-10-5-111-119

Wulff, P., Mientus, L., Nowak, A., & Borowski, A. (2025). AI in STEM Teacher Education: Inquiry into Capabilities of an Emerging Technology. *International Journal of Technology in Education and Science*, *9*(4), 597-618. https://doi.org/10.46328/ijtes.5105

Xu, Q., Liu, Y., & Li, X. (2025). Unlocking student potential: How AI-driven personalized feedback shapes goal achievement, self-efficacy, and learning engagement through a self-determination lens. *Learning and Motivation*, *91*, 102138. https://doi.org/10.1016/j.lmot.2025.102138

Yordudom, T., Nui-Suk, C., Imjai, N., Sumiati, S., & Aujirapongpan, S. (2026). Developing open innovation competency in Gen Z entrepreneurship students: Roles of absorptive capacity, AI literacy and algorithmic thinking skills. *The International Journal of Management Education*, *24*(1), 101326. https://doi.org/10.1016/j.ijme.2025.101326

Yuksel, I. (2015). Rogers' diffusion of innovation model in action: Individual innovativeness profiles of pre-service teachers in Turkey. *Croatian Journal of Education-Hrvatski Casopis Za Odgoj I Obrazovanje*, *17*(2). https://doi.org/doi:10.15516/cje.v17i2.871

Zamri, M. N., Zaki, M., Nazri, N. Z. M., Suhaimi, A. A. M., Rasak, N. T. S., Masri, H. M., & Hafiz, M. (2025). The impact of artificial intelligence on specialized learning motivation in higher education: A conceptual paper. *Internatıonal Journal Of Modern Educatıon (IJMOE)*, *7*(25), 911–930.

Zhai, X., Chu, X., Chai, C. S., Jong, M. S. Y., Istenic, A., Spector, M., ... & Li, Y. (2021). A Review of Artificial Intelligence (AI) in Education from 2010 to 2020. *Complexity*, *2021*(1), 8812542. https://doi.org/10.1155/2021/8812542

Zhan, Z., Shen, W., & Lin, W. (2022). Effect of product-based pedagogy on students' project management skills, learning achievement, creativity, and innovative thinking in a high-school artificial intelligence course. *Frontiers in Psychology*, *13*, 849842. https://doi.org/10.3389/fpsyg.2022.849842