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NÓRA VERONIKA NÉMETH¹, ZHUBANDYKOVA AKGUL²,
TUKENOVA KAPIZA², ASSILBAYEVA FATIMA^{3*}

¹University of Debrecen (Debrecen, Hungary)

²Kazakh National Woman's Teacher Training University (Almaty, Kazakhstan)

³Abai Kazakh National Pedagogical University (Almaty, Kazakhstan)

*Address of correspondence: Fatima Assilbayeva, Candidate of Pedagogical Sciences,
Abai Kazakh National Pedagogical University, Dostyk Str., 13, Almaty, 050000 Republic of Kazakhstan,
<https://orcid.org/0000-0002-0965-8314>, E-mail address: assilbayeva.fatima@gmail.com

Exploring Factors Influencing the Development of Students' Reflective Skills in Artificial Intelligence-Supported Learning

Abstract

Introduction. The article examines the factors influencing students' reflective skills in AI-based learning in higher education. Artificial intelligence (AI) has become an important component of the digital transformation of education, providing opportunities to enhance efficiency, accessibility, and flexibility of learning. In this context, the development of students' reflective and metacognitive skills has become an increasingly important research area. The study *aimed* to identify key factors associated with students' reflective skills in AI-based learning environments and to empirically examine the relationships among these factors. **Methodology and Methods.** The study employed quantitative research design and Partial Least Squares Structural Equation Modeling (PLS-SEM). The sample comprised 234 students from Abai Kazakh National Pedagogical University and Kazakh National Women's Teacher Training University. The model included four factors: perceived usefulness of AI, perceived ease of use, AI usage, and AI feedback. The *results* revealed a weak positive relationship between perceived usefulness of AI and students' reflective skills, while perceived ease of use, AI usage, and AI feedback demonstrated weak negative relationships. These findings indicate that AI use alone does not ensure the development of students' reflective thinking. Effective integration of AI into higher education should therefore be supported by reflective tasks, critical thinking activities, and metacognitive strategies. **Scientific novelty.** The study empirically examines the relationships between AI-related learning factors and students' reflective skills, demonstrating the limited explanatory value of technology use alone and highlighting the importance of pedagogical and metacognitive conditions. **Practical significance.** The findings support the integration of reflective tasks, critical thinking, self-assessment, and metacognitive activities into AI-supported learning environments. The study provides a basis for developing pedagogically grounded approaches to the effective integration of AI technologies in higher education.

Keywords: higher education, artificial intelligence, reflective skills, digital education, AI-based learning, metacognitive skills, PLS-SEM analysis.

Introduction. Currently, the rapid development of digital technologies in higher education is introducing significant changes to the content and organization of the educational process (Mary, D., & Joyce, M., 2024). In particular, introducing artificial intelligence technologies into the educational system is considered one of the most important factors in modernizing the educational environment and increasing the efficiency, accessibility, and

quality of the learning process (Ayeni, O. et al., 2024).

Learning systems based on artificial intelligence allow students to form individual learning trajectories, personalize educational materials, and optimize educational outcomes (Ifraheem, S. et al., 2024). At the same time, AI technologies are expanding the intellectual capabilities of digital educational platforms (Kosaraju, D., 2022). This improves students'

learning motivation, participation in the learning process, and academic results (Peng, Q., 2024). The integration of artificial intelligence technologies into the educational system effectively offers new opportunities, such as distance learning, the creation of multimodal learning environments, and expanded access to educational services. Such changes will affect the sustainable development of the higher education system and lay the foundation for a digital education ecosystem (Buşu, A., 2024). However, the widespread use of AI-based learning environments also introduces new factors that contribute to the development of students' cognitive and metacognitive abilities.

In this context, students' reflective skills are particularly important. Reflection is considered one of the important cognitive mechanisms that allow students to analyze their learning activities, evaluate learning outcomes, and improve learning strategies in the learning process (Siminto et al., 2023). Studies have shown that reflective and metacognitive skills play an important role in improving learning outcomes and improving the quality of the educational process (Zang et al., 2021). Therefore, identifying the factors that contribute to students' reflective skill development in AI-based learning environments is a current area of pedagogical research. Recent empirical evidence indicates that the integration of artificial intelligence into learning activities can contribute to the development of higher-order cognitive processes, including reflective thinking, particularly when AI is embedded within purposeful instructional designs (Saritepeci, M., & Yildiz Durak, H., 2024). Recently, the number of scientific studies on AI in education has increased significantly. Researchers are considering the impact of AI technologies on the educational process in various directions. In particular, the possibilities of AI in the development of personalized learning systems, its role in the formation of intelligent learning platforms, and its impact on optimizing learning outcomes are being widely studied (Begum, I. 2024).

Research in the field of Artificial Intelligence in Education (AIED) also examines the

adaptive capabilities of learning platforms, the relationship between educational technologies and learning outcomes, and the usability of digital learning environments (Alenezi, F. Y., 2023). These studies suggest that intelligent learning systems can tailor the learning process to individual learners' needs. The role of metacognitive and reflective skills in AI-based learning environments has also been widely discussed in scientific research (Ouyang, Z., 2025). Some studies show that AI platforms can influence the development of students' self-regulation skills and active participation in the learning process (Abgaryan et al., 2023). At the same time, it is well known that the characteristics of digital learning environments affect students' motivation to learn, learning effectiveness, and reflective thinking skills. However, the exact mechanisms by which AI-based learning environments influence students' reflective skills have not yet been fully studied. Some studies suggest that this relationship may be mediated by indirect factors, for example, through mediating variables such as self-regulation, learning motivation, and engagement in the learning process. The development of AI in education is closely related to the international concept of Education 4.0. This concept aims to modernize the education system by integrating digital technologies and intelligent systems into the educational process. Studies show that AI technologies contribute to updating educational content, improving teaching methods, and digitally transforming the learning environment.

Reflective learning and metacognitive skills are considered to be important components of the learning process. Metacognitive skills allow students to monitor their own learning, plan learning strategies, and assess learning outcomes. Research has shown that AI-based learning systems can enhance students' metacognitive skills through learning analytics and feedback mechanisms. At the same time, digital educational technologies are considered one of the factors contributing to the development of students' reflective thinking. Such technologies provide an opportunity to effectively manage students' learning activities through data-based feedback, learning analytics,

and intelligent tools for teachers (Ceylan, M., & Mnzile, J. Y., 2025).

Although the studies reviewed above have examined the impact of AI technologies on the educational process from various angles, the specific factors that influence students' reflective skills in AI-based learning environments have not been fully explored. First, while many studies have focused on learning outcomes and learning effectiveness, the mechanisms underlying the development of reflective skills and their relationship with the structural features of the learning environment have not been sufficiently studied (Ray, S., & Ray, D., 2024). Second, the impact of AI-based learning environments on students' reflective thinking across different cultural and institutional contexts has been relatively underexplored. In this context, factors such as access to educational resources, digital infrastructure, learning culture, and academic ethics are important (Toyokawa, 2023). Third, it is not yet fully understood what the pedagogical impact of AI-based learning tools - chatbots, intelligent learning systems, and learning analytics - has on students' reflective thinking skills. At the same time, issues of data security and academic ethics in the use of such technologies are also important areas of research (Abdelmagid, 2024). In this regard, this study aims to systematically analyze the factors that affect students' reflective skills in AI-based learning environments and identify their interrelationships.

The study's theoretical significance is to explain the mechanisms underlying the development of students' reflective and metacognitive skills in AI-based learning environments. The results provide an opportunity to consider educational theories and the design of digital learning environments from an integrated perspective. The practical significance of the research lies in developing pedagogical recommendations for the effective use of artificial intelligence technologies in higher education institutions. The recommendations will enable curriculum updates, improved teaching methods, and learning environments that foster the systematic development of students' reflective skills. Thus, the results of the

study will help identify pedagogically effective ways to use artificial intelligence technologies in the higher education system and develop scientifically based recommendations aimed at developing students' self-regulation, critical thinking, and reflective skills.

Materials and Methods. *Research design.* This study employed a quantitative, cross-sectional, non-experimental research design aimed at identifying the factors associated with students' reflective skills in artificial intelligence-supported learning in higher education. The relationships among the latent variables were examined using Partial Least Squares Structural Equation Modeling (PLS-SEM).

PLS-SEM was selected for three reasons. First, the study is exploratory and prediction-oriented rather than strictly confirmatory, since the mechanisms linking AI-supported learning to the development of reflective skills have not yet been firmly established in the literature. Second, the research model contains five latent constructs measured reflectively by multiple observed indicators, which corresponds to the type of model for which PLS-SEM is intended. Third, PLS-SEM does not require the assumption of multivariate normality and performs robustly with moderate sample sizes, which makes it one of the most widely applied statistical approaches in social and pedagogical research.

Research model and hypotheses. The research model comprised four exogenous constructs and one endogenous construct. The exogenous constructs were Perceived Usefulness of AI (PU), Perceived Ease of Use of AI (PEOU), AI Usage in Learning (AIU), and AI-based Feedback (AIF). The endogenous construct was students' Reflective Skills (RS).

Perceived usefulness and perceived ease of use represent students' evaluative beliefs about AI as a learning tool, that is, the extent to which AI is seen as effective for completing learning tasks and as easy and clear to operate. AI usage reflects the behavioral dimension of the model, namely the frequency and regularity with which students draw on AI tools in their academic work. AI-based feedback captures the informational support students receive from AI

systems in the form of immediate responses, error identification, and improvement suggestions. Reflective skills, as the outcome construct, refer to students' capacity to critically analyze their own learning activity, evaluate learning outcomes, identify the causes of their errors, and improve their learning strategies.

On this basis, four hypotheses were formulated:

H₁ Perceived usefulness of AI is related to students' reflective skills.

H₂ Perceived ease of use of AI is related to students' reflective skills.

H₃ The intensity of AI usage in learning is related to students' reflective skills.

H₄ AI-based feedback is related to students' reflective skills.

All five constructs were specified as reflective, since within each construct the indicators are conceptually interchangeable manifestations of a single underlying concept and are expected to covary positively.

Participants and sampling procedure. The study was conducted at two higher education institutions in Kazakhstan: Abai Kazakh National Pedagogical University and Kazakh National Women's Teacher Training University. The institutions were selected purposively. Both are pedagogical universities, which means that the respondents are prospective teachers, and reflective competence is a core professional requirement for this group. This setting therefore allows the experience of future teachers with AI technologies to be examined in direct connection with the development of their reflective skills.

Participants were recruited through non-probability convenience sampling among students of the two universities. Participation was open to all students who were willing to complete the online questionnaire, and the final analytical sample consisted of 234 respondents. Respondents took part in the study voluntarily and submitted their answers through the online questionnaire.

The adequacy of the sample size was evaluated against two commonly applied criteria for PLS-SEM. According to the ten-times rule, the minimum sample size should be

at least ten times the largest number of structural paths directed at a single construct in the model; with four paths directed at Reflective Skills, the required minimum is 40 cases. According to the inverse square root method, a sample of 234 cases allows path coefficients of $|\beta| \geq 0.163$ to be detected at the 5% significance level with a statistical power of 80%. The sample obtained therefore satisfies both criteria, although it also implies that path coefficients smaller than this threshold should be interpreted with caution.

Measurement instrument. Data was collected using a structured self-report questionnaire developed for the purposes of this study. The instrument operationalized the five latent constructs of the research model through 21 observed indicators: Perceived Usefulness of AI was measured by four indicators (PU1–PU4), Perceived Ease of Use of AI by four indicators (PEOU1–PEOU4), AI Usage in Learning by four indicators (AIU1–AIU4), AI-based Feedback by four indicators (AIF1–AIF4), and Reflective Skills by five indicators (RS1–RS5). The full wording of the items is presented in Table 1.

The items measuring perceived usefulness and perceived ease of use were formulated in line with the established technology acceptance framework and adapted to the context of AI-supported learning. The items measuring AI usage and AI-based feedback were formulated to reflect the behavioral and informational dimensions of working with AI tools in academic tasks. The items measuring reflective skills were formulated in accordance with conceptualizations of reflective learning as the analysis of one's own learning activity, the evaluation of outcomes, the identification of the causes of errors, and the improvement of learning strategies.

All 21 items were rated on a five-point Likert scale ranging from 1 (completely disagree) to 5 (completely agree). All items were worded in a positive direction; no reverse-worded items were included in the instrument. This is methodologically relevant for the interpretation of the measurement model, since with uniformly positively worded reflective indicators, negative outer loadings are not theoretically expected and require verification of item coding.

Data collection procedure. Data was collected through an online survey. The questionnaire link was distributed among students of the two participating universities, and responses were submitted electronically. The introductory section of the questionnaire presented the aim of the study, explained the structure of the instrument and the response scale, stated that participation was voluntary, and informed respondents that the answers were collected anonymously and that there were no correct or incorrect responses. Completion of the questionnaire followed the respondent's informed consent. The collected responses were exported for statistical processing without any personally identifying information.

Data analysis. The collected data was analyzed using SmartPLS 4 software. Prior to model estimation, the dataset was screened for missing values, out-of-range values, and response patterns indicating inattentive answering. The consistency of item coding and of the direction of the response scale was also verified, since inconsistent coding of a uniformly positively worded scale is one of the known sources of negative indicator loadings in reflective measurement models.

The analysis followed the standard two-stage procedure for PLS-SEM, in which the measurement model is assessed first, and the structural model is interpreted only after the quality of measurement has been established.

Stage one: assessment of the measurement model. Indicator reliability was assessed through the outer loadings of the observed variables. Loadings of approximately 0.708 or higher were considered desirable, since at this level the construct explains more than 50% of the indicator's variance. Indicators with loadings between 0.40 and 0.708 were considered for retention only after examining their contribution to composite reliability, convergent validity, and content validity, while indicators with loadings below 0.40 were treated as candidates for removal or further examination. Internal consistency reliability was assessed using Cronbach's alpha, composite reliability, and rho_A. Convergent validity was assessed through the average variance extracted (AVE),

with values of 0.50 or higher indicating that the construct explains, on average, more than half of the variance of its indicators. Discriminant validity was assessed using the Fornell–Larcker criterion and the heterotrait–monotrait ratio of correlations (HTMT).

Stage two: assessment of the structural model. The structural model was evaluated by computing the path coefficients describing the relationships between the latent variables, corresponding to hypotheses H1–H4. Collinearity among the predictor constructs was examined through variance inflation factor values. The explanatory power of the model was assessed using the coefficient of determination (R^2) for the endogenous construct, which indicates the proportion of variance in students' reflective skills jointly explained by the four AI-related constructs.

Through this sequence of procedures, the study empirically examined the principal factors associated with students' reflective skills in artificial intelligence-supported learning and the interrelationships among them.

Ethical considerations. The study was conducted in accordance with the standard ethical principles governing research involving human participants, including the principles of voluntary participation, informed consent, anonymity, and confidentiality.

Before data collection, all participants were informed about the purpose of the study, the procedures involved, the approximate time required to complete the questionnaire, and the intended use of the collected data. Participation was entirely voluntary. Respondents provided informed consent prior to completing the online questionnaire and were free to decline participation or to discontinue at any stage without providing a reason and without any academic or other consequences.

Responses were collected anonymously. The questionnaire did not request names, contact details, identification numbers, or any other data enabling the identification of individual respondents, and no sensitive personal information was requested at any point of the survey. The confidentiality of the collected data was strictly maintained: the dataset was stored in a

protected form, accessible only to the authors, and was used exclusively for the research purposes described to participants. The results are reported solely in aggregated form, so that no individual response can be traced back to a particular respondent or to a particular group of

students within the participating universities. No incentives or rewards were offered for participation, and no relationship of academic dependence was used to encourage students to take part in the survey.

Table 1

Constructs and indicators used in the research model

Construct	Code	Statement
Perceived Usefulness of AI	PU1	Artificial intelligence makes it easier to complete learning tasks.
	PU2	Artificial intelligence improves my learning efficiency.
	PU3	Artificial intelligence helps me understand complex topics better.
	PU4	Artificial intelligence allows me to save time during the learning process.
Perceived Ease of Use of AI	PEOU1	Artificial intelligence tools are easy for me to use.
	PEOU2	I can quickly learn how to use artificial intelligence platforms.
	PEOU3	I rarely experience difficulties when working with artificial intelligence.
	PEOU4	The interface of artificial intelligence tools is clear and understandable.
AI Usage in Learning	AIU1	I regularly use artificial intelligence tools during my studies.
	AIU2	I frequently use artificial intelligence when completing assignments.
	AIU3	I use artificial intelligence to search for new information.
	AIU4	I use artificial intelligence to improve my academic performance.
AI-based Feedback	AIF1	Artificial intelligence provides immediate feedback on my assignments.
	AIF2	Artificial intelligence helps me identify my mistakes.
	AIF3	Artificial intelligence encourages me to review my work.
	AIF4	Suggestions provided by artificial intelligence help me improve my learning activities.
Reflective Skills	RS1	I critically analyze my own learning activities.
	RS2	I evaluate my results after completing a task.
	RS3	I try to identify the reasons for my mistakes during the learning process.
	RS4	I think about ways to improve my learning strategies.
	RS5	I systematically analyze my strengths and weaknesses in learning.

The indicators in Table 1 are based on assessing students' experiences using artificial intelligence tools in the learning process and their reflective learning abilities. The perceived usefulness of artificial intelligence refers to students' perceptions of these technologies as effective learning tools. The ease of use of artificial intelligence refers to how easily students use these technologies and how clear the interface is. The activity of using artificial intelligence refers to how often students use AI tools during their learning. At the same time, feedback from AI systems highlights the importance of the suggestions and corrections

students receive during learning tasks. Reflective skills assess students' ability to analyze their learning activities, evaluate learning outcomes, and improve learning strategies.

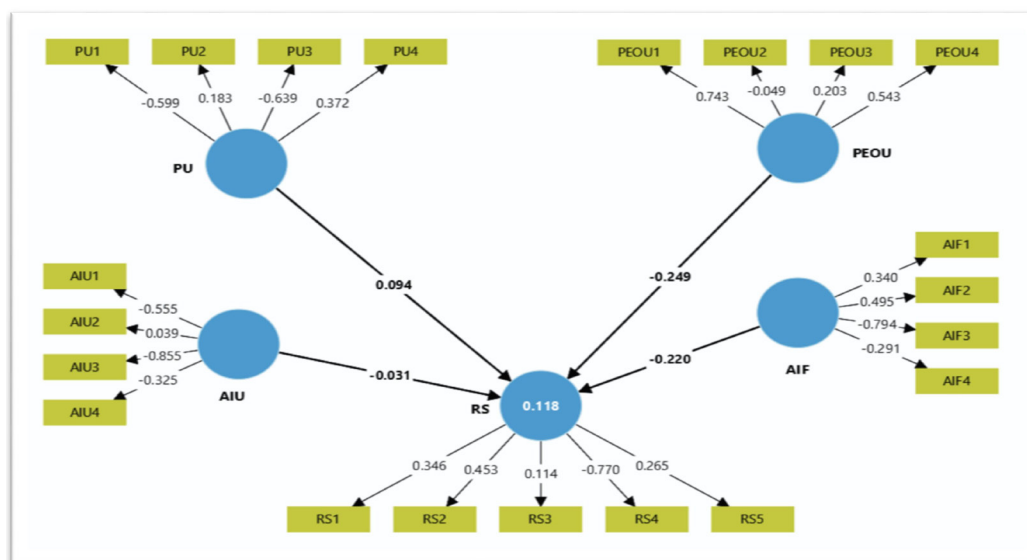
Results. In analyzing the research results, we assessed the relationships between artificial intelligence-based learning factors and students' reflective skills using Partial Least Squares Structural Equation Modeling (PLS-SEM). The research model considered four independent constructs. They were: Perceived Usefulness (PU) of artificial intelligence, Perceived Ease of Use (PEOU), AI Usage (AIU), and AI Feedback (AIF). The dependent variable was students'

reflective skills (RS). During model evaluation, we calculated indicator loadings, path coefficients between constructs, and indicators of the model's

explanatory power. We empirically analyzed the impact of artificial intelligence-based learning factors on students' reflective skills.

Figure 1

Structural model describing the impact of AI-based learning on students' reflective skills



In analyzing the research results, the relationship between artificial intelligence-based learning factors and students' reflective skills was assessed using a PLS-SEM structural equation model. The model considered four main independent variables. These were: Perceived Usefulness (PU) of artificial intelligence, Perceived Ease of Use (PEOU), AI Usage (AIU), and AI Feedback (AIF). The dependent variable was students' reflective skills (RS).

According to the structural model results, the explained variance coefficient for reflective skills was $R^2 = 0.118$. This means the factors in the research model explain about 11.8% of the variation in students' reflective skills. In social and pedagogical research, this indicator suggests the complexity of the phenomenon under study and the presence of numerous external factors that affect it. Therefore, the results suggest a role for the learning environment based on artificial intelligence in developing students' reflective thinking skills.

According to the model results, a positive relationship ($\beta = 0.094$) was observed between the perceived usefulness of artificial intelligence and students' reflective skills.

This result suggests that when students perceive artificial intelligence tools as useful for completing learning tasks, they pay closer attention to analyzing their learning activities, evaluating their results, and improving their learning strategies. Therefore, the functional effectiveness of artificial intelligence tools in the educational process may indirectly affect the development of students' reflective skills.

At the same time, the study results indicated that there is a weak or negative relationship between the factors of ease of use of artificial intelligence ($\beta = -0.249$), feedback based on artificial intelligence ($\beta = -0.220$), and activity in using artificial intelligence ($\beta = -0.031$) and students' reflective skills. These results clearly show that using artificial intelligence tools does not automatically increase students' reflective thinking, but in some cases may lead them to rely on ready-made answers. This, in turn, may contribute to underdeveloped skills in self-analysis and reflection on learning activities.

The results obtained during the study demonstrate the importance of pedagogical approaches when introducing artificial intelligence technologies into the educational process.

If artificial intelligence tools are used solely to obtain information or perform tasks, their impact on students' reflective thinking skills may be limited. Therefore, the use of artificial intelligence in the educational process should be combined with reflective tasks, elements of self-analysis, and pedagogical methods that develop critical thinking.

The scientific significance of the study results is closely related to the empirical analysis of the impact of an artificial-intelligence-based educational environment on students' reflective skills. At the same time, the study provides an opportunity to identify pedagogical conditions

for the effective use of artificial intelligence technologies in higher education. These results will inform the development of scientifically sound models for using artificial intelligence tools in training future teachers, as well as strategies to develop students' metacognitive and reflective competencies in a digital educational environment. Overall, the study's results provide important empirical data on the impact of an artificial intelligence-based learning system on students' reflective skills. At the same time, they provide a scientific basis for the effective pedagogical use of artificial intelligence technologies in higher education.

Table 2

Indicators of the research model constructs and indicators

Construct	Description	Indicators
Perceived Usefulness (PU)	Perceived usefulness of artificial intelligence in learning	PU1, PU2, PU3, PU4
Perceived Ease of Use (PEOU)	Ease of using artificial intelligence tools	PEOU1, PEOU2, PEOU3, PEOU4
AI Usage (AIU)	Level of artificial intelligence usage in learning activities	AIU1, AIU2, AIU3, AIU4
AI Feedback (AIF)	Feedback received through artificial intelligence tools	AIF1, AIF2, AIF3, AIF4
Reflective Skills (RS)	Students' reflective learning skills	RS1, RS2, RS3, RS4, RS5

Table 2 presents the latent constructs and their corresponding measurement indicators included in the proposed research model. The model was developed to examine the relationships between AI-related learning factors and students' reflective skills in AI-based learning environments. Each latent construct was operationalized using multiple indicators. Perceived Usefulness (PU) was measured using four indicators (PU1–PU4), Perceived Ease of Use (PEOU) was assessed using four indicators (PEOU1–PEOU4), AI Usage (AIU) was measured using four indicators (AIU1–AIU4), and AI Feedback (AIF) was assessed using four indicators (AIF1–AIF4).

Students' Reflective Skills (RS) were measured using five indicators (RS1–RS5).

The selected indicators represent students' perceptions and experiences of using AI technologies in the learning process, as well as aspects of their reflective learning. In particular, the model considers students' perceptions of the usefulness and ease of use of AI, their use of AI tools, the feedback they receive through AI technologies, and their reflective learning skills. These constructs and indicators provide the measurement basis for examining the relationships between AI-related learning factors and students' reflective skills.

Table 3

Measurement model: Indicator loadings

Construct	Indicator	Outer Loading
PU	PU1	-0.599
PU	PU2	0.183
PU	PU3	-0.639
PU	PU4	0.372

PEOU	PEOU1	0.743
PEOU	PEOU2	-0.049
PEOU	PEOU3	0.203
PEOU	PEOU4	0.543
AIU	AIU1	-0.555
AIU	AIU2	0.039
AIU	AIU3	-0.855
AIU	AIU4	-0.325
AIF	AIF1	0.340
AIF	AIF2	-0.495
AIF	AIF3	-0.794
AIF	AIF4	-0.291
RS	RS1	0.346
RS	RS2	0.453
RS	RS3	0.114
RS	RS4	-0.770
RS	RS5	0.265

Table 3 presents the outer loadings of the observed indicators on their corresponding latent constructs. In PLS-SEM, outer loadings are used to assess the extent to which individual indicators represent their respective constructs and provide an important basis for evaluating the measurement model. Indicator loadings of approximately 0.708 or higher are generally considered desirable because they indicate that the construct explains more than 50% of the indicator's variance. However, indicators with loadings between 0.40 and 0.708 may be retained after considering their contribution to composite reliability, convergent validity, and content validity. Indicators with loadings below 0.40 generally require removal or further examination.

The results presented in Table 3 demonstrate substantial variation in the outer loadings across the constructs. PEOU1 demonstrated the highest positive loading (0.743), indicating a relatively strong association with the Perceived Ease of Use construct. However, PEOU4 had a lower loading of 0.543, while RS2 demonstrated a loading of 0.453. These values indicate weaker indicator-level associations and therefore require further assessment within the measurement model. Several indicators demonstrated negative loadings, including PU1 (−0.599), PU3 (−0.639), AIU1 (−0.555), AIU3

(−0.855), AIF2 (−0.495), AIF3 (−0.794), and RS4 (−0.770). Other indicators demonstrated very low positive or negative loadings, including PU2 (0.183), PU4 (0.372), PEOU2 (−0.049), PEOU3 (0.203), AIU2 (0.039), AIU4 (−0.325), AIF1 (0.340), AIF4 (−0.291), RS1 (0.346), RS3 (0.114), and RS5 (0.265).

The prevalence of low and negative loadings indicates that the measurement properties of several indicators require careful examination before substantive conclusions are drawn from the structural model. In particular, negative loadings may result from reverse-worded indicators, inconsistent coding, or differences in the direction of the response scales. Therefore, the coding and wording of the indicators should be verified before interpreting these results. The measurement model should also be evaluated using internal consistency reliability and convergent and discriminant validity criteria, including Cronbach's alpha, composite reliability, rho_A, AVE, and HTMT. Overall, the results of the initial measurement model indicate that not all indicators demonstrate satisfactory relationships with their respective constructs. Consequently, the structural model findings should be interpreted with appropriate caution until the reliability and validity of the measurement model have been established.

Table 4*Structural model results indicators.*

Hypothesis	Path	Path Coefficient (β)
H ₁	PU $\rightarrow$ RS	0.094
H ₂	PEOU $\rightarrow$ RS	-0.249
H ₃	AIU $\rightarrow$ RS	-0.031
H ₄	AIF $\rightarrow$ RS	-0.220

Table 4 presents the results of the structural model, including the path coefficients associated with the hypothesized relationships between the latent constructs. The structural model was used to examine the relationships between AI-based learning factors and students' reflective skills.

The first hypothesis (H₁) examined the relationship between Perceived Usefulness (PU) of artificial intelligence and Students' Reflective Skills (RS). The path coefficient for PU $\rightarrow$ RS was $\beta = 0.094$, indicating a weak positive relationship. This finding suggests that students who perceive AI tools as useful for supporting their learning activities may demonstrate somewhat higher levels of engagement in analyzing their learning processes and evaluating learning outcomes. The second hypothesis (H₂) examined the relationship between Perceived Ease of Use (PEOU) and Students' Reflective Skills. The path coefficient for PEOU $\rightarrow$ RS was $\beta = -0.249$, indicating a weak negative relationship. This finding suggests that greater perceived ease of use was associated with lower levels of reflective skills in the present sample. However, this result should be interpreted cautiously, as the observed association does not by itself establish a causal relationship between ease of use and students' reflective skills. The third hypothesis (H₃) examined the relationship between AI Usage (AIU) and Students' Reflective Skills. The path coefficient for AIU

$\rightarrow$ RS was $\beta = -0.031$, indicating a very weak negative relationship. This finding suggests that the level or frequency of AI use was only weakly associated with students' reflective skills in the present research model. Thus, the frequency of AI use alone may not be sufficient to support the development of reflective learning processes. The fourth hypothesis (H₄) examined the relationship between AI Feedback (AIF) and Students' Reflective Skills. The path coefficient for AIF $\rightarrow$ RS was $\beta = -0.220$, indicating a weak negative relationship. This finding suggests that greater reliance on AI-based feedback was associated with lower levels of reflective skills in the present sample. However, the result should not be interpreted as evidence that AI feedback directly reduces students' reflective skills without considering the pedagogical context in which such feedback is used. Overall, the structural model results indicate that the relationships between AI-based learning factors and students' reflective skills are complex and multifaceted. The findings suggest that the presence or frequency of AI use alone may not be sufficient to support the development of reflective skills. Instead, the educational value of AI technologies may depend on how they are incorporated into pedagogical activities, particularly those involving reflection, self-assessment, critical evaluation, and independent reasoning.

Table 5*Coefficient of determination (R^2) indicator*

Endogenous Variable	R^2
Reflective Skills (RS)	0.118

Table 5 presents the coefficient of determination (R^2), which describes the variance explained by the endogenous variable

in the structural model. The R^2 indicator allows us to assess the degree of influence of the independent variables in the research model on

the endogenous variable, as well as the model's explanatory power. According to the PLS-SEM methodology, the R^2 value is considered an important indicator of the model's predictive and explanatory power.

The results showed that the R^2 value for Students' Reflective Skills (RS) was 0.118. This indicates that Perceived Usefulness (PU), Perceived Ease of Use (PEOU), AI Usage (AIU), and AI Feedback (AIF) jointly explained 11.8% of the variance in students' reflective skills. The remaining 88.2% of the variance

may be associated with other factors that were not included in the present research model. The relatively modest level of explained variance indicates that the AI-related constructs examined in this study represent only a part of the factors associated with students' reflective skills. This finding is consistent with the multidimensional nature of reflective learning, which may involve a broader range of cognitive, motivational, behavioral, and pedagogical factors beyond the AI-related variables included in the current model.

Table 6

Sample characteristics

Characteristic	Description
Sample size	234 respondents
Universities	Abai Kazakh National Pedagogical University; Kazakh National Women's Teacher Training University
Data collection method	Online questionnaire
Measurement scale	Five-point Likert scale
Analysis method	Partial Least Squares Structural Equation Modeling (PLS-SEM)
Software	SmartPLS 4

Table 6 presents the main characteristics of the study sample and the procedures used for data collection and analysis. The study included 234 students from Abai Kazakh National Pedagogical University and Kazakh National Women's Teacher Training University. The data were collected through an online questionnaire using a five-point Likert scale. The collected data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS 4.

The participating universities specialize in teacher education and therefore provide a relevant context for examining students' experiences with artificial intelligence technologies in learning and their reflective skills. The sample consisted of students who participated in the study voluntarily and provided responses through the online questionnaire.

The quantitative design and PLS-SEM approach enabled the examination of the relationships between AI-related learning factors and students' reflective skills within the proposed research model. The structural model

included Perceived Usefulness (PU), Perceived Ease of Use (PEOU), AI Usage (AIU), and AI Feedback (AIF) as predictor constructs, while Students' Reflective Skills (RS) served as the endogenous construct.

Discussion. The structural model demonstrated a weak positive relationship between Perceived Usefulness (PU) and students' Reflective Skills (RS) ($\beta = 0.094$). This finding suggests that perceiving AI as useful may support students' engagement in learning activities, although its contribution to reflective skills is limited. Previous studies have also highlighted the role of perceived usefulness in the educational use of AI (Alenezi, 2023; Begum, 2024).

Perceived Ease of Use (PEOU) showed a negative relationship with Reflective Skills ($\beta = -0.249$). This result may indicate that highly convenient AI tools can reduce opportunities for independent analysis when students primarily use them to obtain information or complete learning tasks. Thus, technological convenience does not necessarily lead to deeper learning and reflection (Ayeni, 2024; Buşu, 2024).

AI Usage (AIU) demonstrated a negligible negative relationship with Reflective Skills ($\beta = -0.031$), indicating that the frequency of AI use alone does not automatically contribute to the development of reflective skills. Similarly, AI Feedback (AIF) showed a weak negative relationship with Reflective Skills ($\beta = -0.220$). The negative associations observed for perceived ease of use and AI-based feedback may indicate that technological convenience and automated support do not necessarily generate reflective engagement. This interpretation is consistent with recent experimental work showing that AI-supported learning can benefit students when it is accompanied by explicit self-regulation scaffolding and collaborative reflection (Tsai et al., 2025). Thus, the pedagogical value of AI may depend less on the mere availability of technology than on how learning activities require students to interpret, evaluate, and reflect on AI-supported outputs.

This may suggest that AI-generated feedback is more likely to support reflection when students critically evaluate and apply it rather than simply accept the provided responses (Ouyang, 2025; Toyokawa, 2023). The coefficient of determination ($R^2 = 0.118$) indicates that the four AI-related factors explain 11.8% of the variance in students' reflective skills. This relatively low explanatory value suggests that reflective skills are influenced by additional pedagogical, cognitive, and individual factors that were not included in the present model.

Overall, the findings indicate that AI technologies do not automatically develop students' reflective skills. Their educational value depends largely on how they are integrated into learning activities. Therefore, AI-supported learning should be accompanied by reflective

tasks, critical thinking, self-assessment, and metacognitive activities that encourage students to evaluate information and consciously reflect on their learning processes.

Conclusion. This study examined the relationship between AI-based learning factors and students' reflective skills in higher education. The findings indicate that the role of artificial intelligence in developing reflective skills depends not only on the use of technological tools but also on the way they are integrated into the learning process. The results demonstrate that perceived usefulness has a weak positive relationship with reflective skills, while perceived ease of use and AI-based feedback show negative relationships. AI usage demonstrates a negligible relationship with reflective skills. The relatively low explanatory power of the model ($R^2 = 0.118$) suggests that reflective skills are influenced by a broader combination of pedagogical, cognitive, and individual factors.

The practical implication is that higher education institutions should focus on the purposeful pedagogical integration of AI rather than on technology use alone. AI-supported learning should provide students with opportunities for critical evaluation, self-assessment, reflection, and metacognitive monitoring. Future research should examine additional factors, including students' metacognitive awareness, critical thinking, motivation, digital competence, and teacher support, using larger and more diverse samples. Overall, this study contributes to a better understanding of the relationships between AI-based learning factors and students' reflective skills. It provides a scientific basis for the purposeful and pedagogically informed integration of artificial intelligence technologies into higher education.

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Information about authors:

Németh Nóra Veronika, University of Debrecen, Debrecen, Hungary, ORCID ID: 0000-0002-9556-4778, email: nemeth.nora@ped.unideb.hu

Zhubandykova Akgul, Kazakh National Women's Teacher Training University, Almaty, Kazakhstan, ORCID ID: 0000-0003-4545-2599, email: akgul71@mail.ru

Tukenova Kapiza, Kazakh National Women's Teacher Training University, Almaty, Kazakhstan, ORCID ID: 0000-0002-4559-0708, email: hafiza_1965@mail.ru

Assilbayeva Fatima, Abai Kazakh National Pedagogical University, Almaty, Kazakhstan, ORCID ID: 0000-0002-0965-8314, email: assilbayeva.fatima@gmail.com