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A MODEL FOR APPLYING ARTIFICIAL INTELLIGENCE TO EDUCATIONAL DATA ANALYSIS AND SUPPORTING THE PROFESSIONAL TRAINING OF COMPUTER SCIENCE TEACHERS

Abstract

The integration of artificial intelligence (AI) tools for educational data analysis and visualization in the training of future computer science instructors is investigated in this study. In order to fill in the identified gaps in preservice teachers' AI competencies, the research attempts to create a practice-oriented digital simulator model. Using performance evaluations and a pre- and post-intervention survey, 120 preservice computer science teachers from two pedagogical universities in Kazakhstan participated in an empirical study. Only 28% of participants demonstrated basic proficiency in data analysis prior to the intervention, indicating serious deficiencies in AI literacy and practical skills. In light of these findings, a five-module architecture for a digital simulator is suggested, which includes case situation, practical sandboxes, theoretical underpinnings, visualization tools, and an evaluation system. By strengthening abilities in data interpretation, ethical AI application, and pedagogical decision-making, this model improves educational assessments' objectivity and transparency. In order to promote flexible and knowledgeable teaching methods, the study emphasizes how important it is to incorporate AI technologies into teacher education programs.

Keywords: artificial intelligence, data analysis, computer science, educational analytics, teacher training, visualization, digital simulator.

Introduction. Artificial intelligence (AI) has become a powerful force in education today, changing the way people learn and teach. AI technologies mimic human intelligence to make learning more personalized, give feedback in real time, and help educators make decisions based on data [1]. This integration is especially important in computer science education, where teachers need to teach students not only technical skills but also how to live in a world that is becoming more digital. However, there is still a big problem: many preservice computer science teachers don't get enough training in how to use AI tools for analyzing and visualizing educational data, which makes it hard for them to use these tools in a fair and effective way [2].

The literature on AI in education (AIED) and learning analytics emphasizes AI's capacity to improve educational outcomes. For example, AI systems can change the content to fit the needs of each learner by using machine learning algorithms and natural language processing. This means moving from a one-size-fits-all approach to a more personalized one [3, 4]. Research underscores AI's function as an intelligent assistant, providing immediate feedback and customizable tasks that enhance student engagement and performance [1, p. 2; 3, p. 267]. In Kazakhstan and Uzbekistan, AI applications in geographical education demonstrate benefits in knowledge dissemination but also reveal barriers such as low digital literacy among educators [5]. Even though these improvements have been made, there are still well-known risks like data privacy, algorithmic bias, and digital inequality [6, 7]. Educational analytics, which includes dashboards that show how well students are doing, is of paramount importance for making smart decisions about how to help students, but there are still problems with understanding the data and teachers' workloads [8, 9, 10]. Global surveys, such as HolonIQ's (Holon Intelligence Quotient) 2023 report, show that 25% of educational organizations use AI successfully. However, staff shortages (54%) and lack of resources (50%) make it harder for more organizations to use AI [11]. Motivations include better student outcomes (75%) and saving money (45%), which shows how important AI is for strategy (Figure 1).

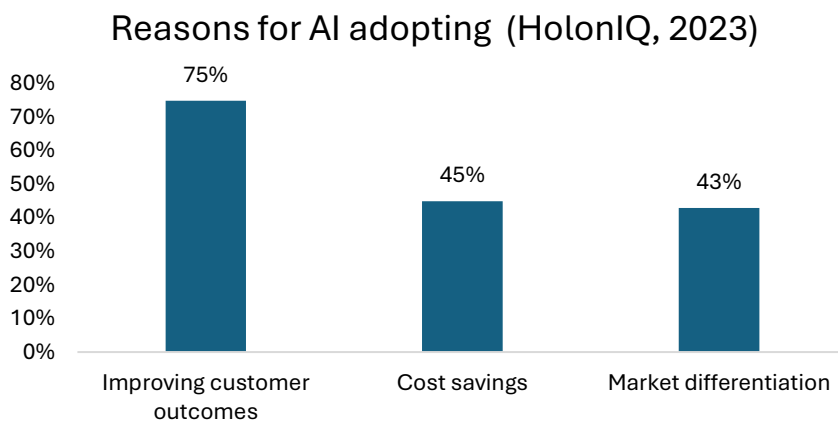


Figure 1. Reasons for implementing AI.

Source: compiled by the authors based on [11, “Enablers and barriers to AI adoption” section, p. 1].

Barriers to adoption are illustrated in Figure 2, highlighting the need for targeted training.

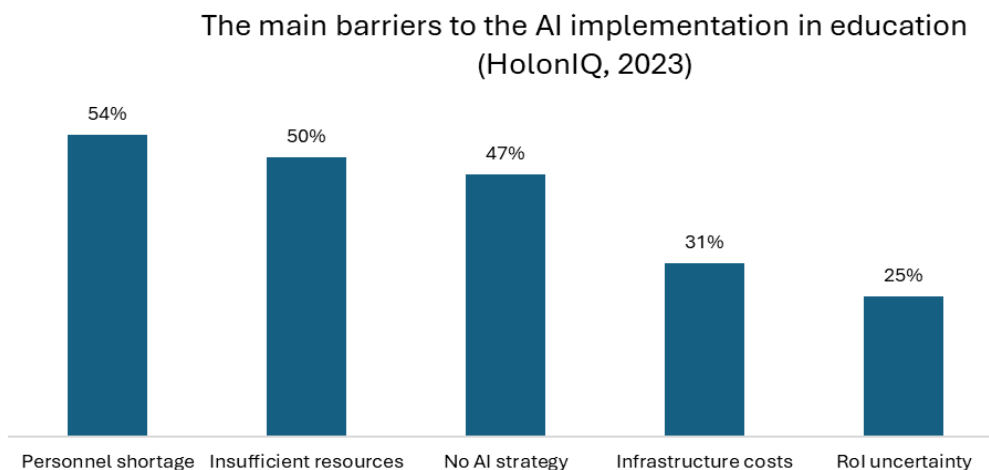


Figure 2. Barriers to the AI introduction in education.

Source: compiled by the authors based on [11, “Enablers and barriers to AI adoption” section, p. 1].

There is a clear lack of AI competencies, according to empirical data from teacher training programs. More than 500 preservice teachers were surveyed, and the results reveal differences in their basic understanding of AI, with many lacking in data handling and ethical application [2, p. 6]. Studies conducted in Kazakhstan have confirmed the benefits of AI in monitoring the quality of education, but they also emphasize the necessity of implementing it in a balanced manner to reduce risks [6, p. 136; 7, p. 169]. AI-PCK (Artificial Intelligence Pedagogical Content Knowledge) incorporates AI into teacher education, following the development of pedagogical models from Shulman's Pedagogical Content Knowledge (PCK) to Technological Pedagogical Content Knowledge (TPACK) and now to AI-PCK (Figure 3) [12].

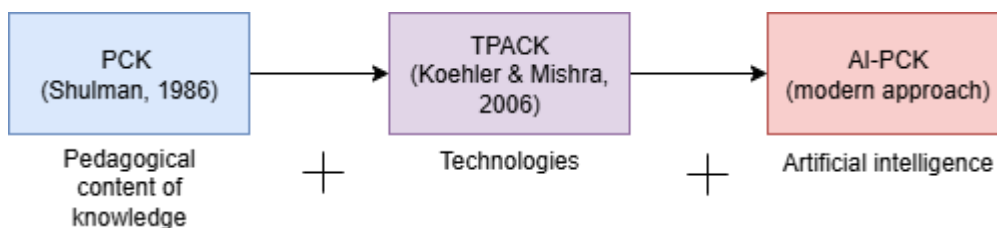


Figure 3. The evolution of Lee Shulman's idea.

Source: compiled by the authors based on [12, pp. 1–31].

This model emphasizes four aspects: AI-PCK, AI teaching ethics, professional knowledge, and a positive attitude toward AI (Figure 4).

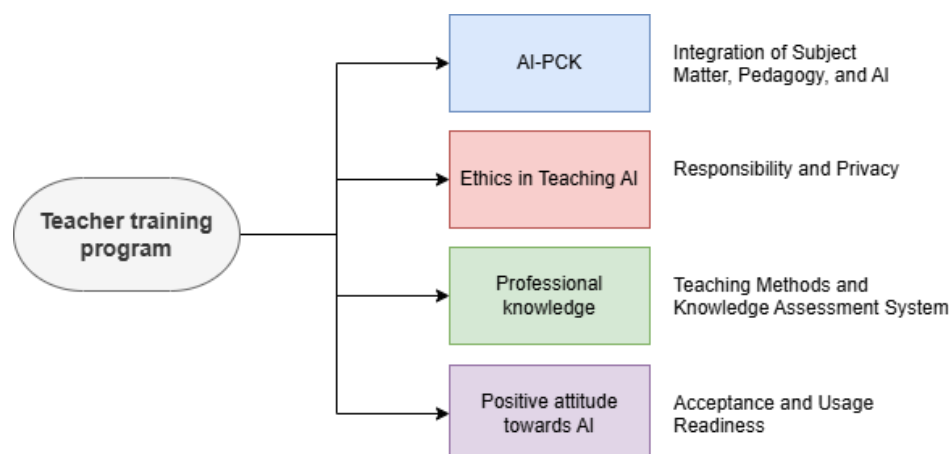


Figure 4. Main aspects of the teacher training program.

Source: compiled by the authors based on [12, pp. 55–80].

For AI in education, technical tools like Python with libraries like scikit-learn and TensorFlow are essential [13]. AI bots in language learning dynamically modify content [14], while chatbots such as Python Chat Artificial Intelligence (PyChatAI) improve programming abilities by providing tailored feedback [13, p. 3]. AI integration is further supported by cloud platforms (like Google Colab) and visual environments (like Scratch with AI extensions).

One of the research gaps is the lack of thorough AI literacy programs in educational institutions, which causes training and technology demands to diverge [15]. Research supports real-world experience and ethical guidance. Although there are still ethical and technological issues, AI is acknowledged to improve teacher competency in Kazakhstani contexts [6, p. 136; 7, p. 170].

By examining preservice computer science teachers' AI competencies empirically and developing a digital simulator model based on the results, this study fills in these gaps. The scientific novelty of the research lies in the development of a digital simulator for preparing future computer science teachers in the field of educational data analysis using artificial intelligence. Unlike existing studies, which mainly focus on assessing AI literacy or describing individual AI applications in education, the proposed model integrates theoretical preparation, practical work with educational datasets, case-based pedagogical tasks, data visualization, and automated assessment within a unified learning environment. The architecture of the simulator was developed on the basis of empirically identified deficiencies in AI competencies among preservice computer science teachers, thereby establishing a direct link between diagnostic results and instructional design. The goals of the study are to: (1) evaluate current deficiencies in AI skills and knowledge; (2) create a methodological model for a digital simulator; and (3) assess how it might improve teacher preparation. The research helps modernize computer science teacher training in line with international trends by concentrating on educational data analysis and visualization.

Methods and Materials. In order to assess preservice computer science teachers' AI competencies and provide guidance for the creation of a digital simulator model, this study employed a quasi-experimental design. Convenience sampling was used to select 120 third- and fourth-year students of the educational program 6B01511-Computer Science.

The average age of the sample was 21.4 years (Standard deviation (SD) = 1.2), with 65% of the participants being female and 35% being male. Inclusion criteria required enrollment in computer science education programs and basic familiarity with programming (e.g., Python basics)

The 12-week period from September to December 2025 was used for two phases of data collection. In order to evaluate AI literacy across four domains – technical knowledge (e.g., comprehending machine learning algorithms), ethical application (e.g., bias recognition), data analysis skills (e.g., using Python for datasets), and pedagogical integration (e.g., incorporating AI

into lesson planning) – participants in the pre-intervention phase filled out a validated survey that was adapted from Ayanwale, Adelana, Molefi, Adeeko, and Ishola [2, p. 12]. 32 items on a 5-point Likert scale (1 being strongly disagree and 5 being strongly agree) were used in the survey (Cronbach's $\alpha = 0.89$). Furthermore, as part of a performance evaluation task, participants had to use simple Python scripts to analyze a simulated educational dataset (such as student grades and engagement metrics). The task was graded on a scale of 0 to 100, which assessed the quality of the visualization, modeling accuracy, and data cleaning.

The intervention involved a pilot training module incorporating AI tools, delivered online via a prototype platform. Participants were divided into an experimental group (n=60) receiving structured AI training (e.g., modules on scikit-learn for clustering and matplotlib for visualization) and a control group (n=60) receiving standard curriculum. Training sessions (4 hours weekly) focused on practical exercises, such as predicting student performance using regression models.

During the 12-week intervention, participants completed data analysis tasks under instructor guidance and engaged in learning modules designed to develop their computational and pedagogical understanding of AI. The program incorporated interactive lectures, group discussions, and hands-on exercises using a digital simulation platform.

Post-intervention, the survey and performance task were readministered. Quantitative data were analyzed using Statistical Package for the Social Sciences (SPSS) version 27.0, including paired t-tests for pre-post comparisons ($p < 0.05$) and independent t-tests for group differences. Effect sizes were calculated using Cohen's d. Descriptive statistics summarized competency levels, and thematic analysis of open-ended survey responses identified qualitative insights into perceived barriers.

The survey was conducted in accordance with the key ethical principles for data use: participants were informed in advance of the survey's purposes and data processing procedures. Participation in the experiment was voluntary, and the analysis results are presented in anonymized and aggregated form. The collected data was used exclusively for this research and was not shared with third parties.

Results and their discussion. Pre-intervention survey results indicated low AI literacy across domains. Mean scores were: technical knowledge (Mean (M) = 2.70, SD = 0.78), ethical application (M = 2.99, SD = 0.85), data analysis skills (M = 2.52, SD = 0.92), and pedagogical integration (M = 2.48, SD = 0.89). Only 28% of participants scored above 3.0 overall, signifying basic proficiency. Performance assessments yielded a mean score of 42.6 (SD = 15.3), with common errors in data cleaning (e.g., 65% failed to handle missing values) and modeling (e.g., 72% misapplied classification algorithms) (Figure 5).

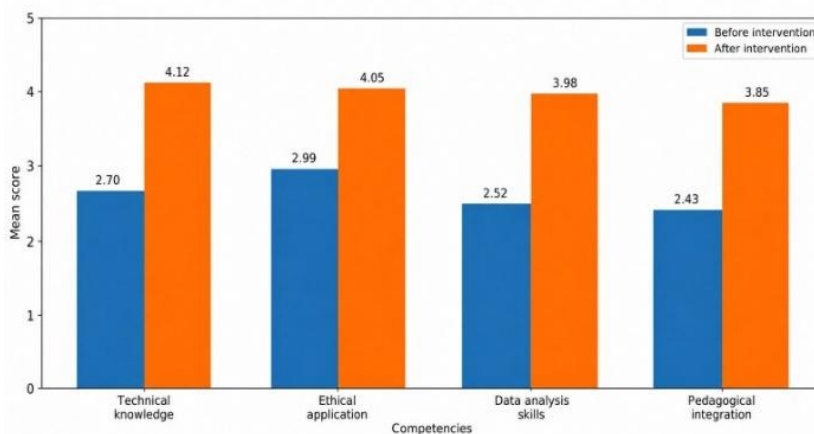


Figure 5. Changes in AI competence in the experimental group.

Source: compiled by the authors.

To verify the comparability of the groups prior to the intervention, independent samples t-tests were conducted using the pre-intervention data. No statistically significant differences were found between the experimental and control groups across any of the measured indicators (Table 1; $p > 0.05$). These findings confirm the baseline equivalence of the groups and support the validity of subsequent comparisons of post-intervention outcomes.

Table 1. Comparison of experimental and control groups at the pre-intervention stage

Indicator	Experimental group (n=60), M±SD	Control group (n=60), M±SD	t	p
Technical knowledge	2.70 ± 0.78	2.71 ± 0.80	-0.07	0.95
Ethical application	2.99 ± 0.85	2.95 ± 0.83	0.26	0.79
Data analysis skills	2.50 ± 0.92	2.48 ± 0.89	0.12	0.90
Pedagogical integration	2.48 ± 0.89	2.53 ± 0.87	-0.31	0.76

Source: compiled by the authors.

Post-intervention, the experimental group showed significant improvements: technical knowledge ($M = 4.12$, $SD = 0.64$; $t(59) = 12.45$, $p < 0.001$, $d = 1.32$), ethical application ($M = 4.05$, $SD = 0.71$; $t(59) = 11.28$, $p < 0.001$, $d = 1.18$), data analysis skills ($M = 3.98$, $SD = 0.68$; $t(59) = 13.02$, $p < 0.001$, $d = 1.45$), and pedagogical integration ($M = 3.85$, $SD = 0.75$; $t(59) = 10.94$, $p < 0.001$, $d = 1.15$). Performance scores rose to 78.4 ($SD = 12.1$; $t(59) = 14.67$, $p < 0.001$, $d = 1.62$). The control group exhibited minimal gains (overall M increase = 0.12, $p > 0.05$) (Figure 6).

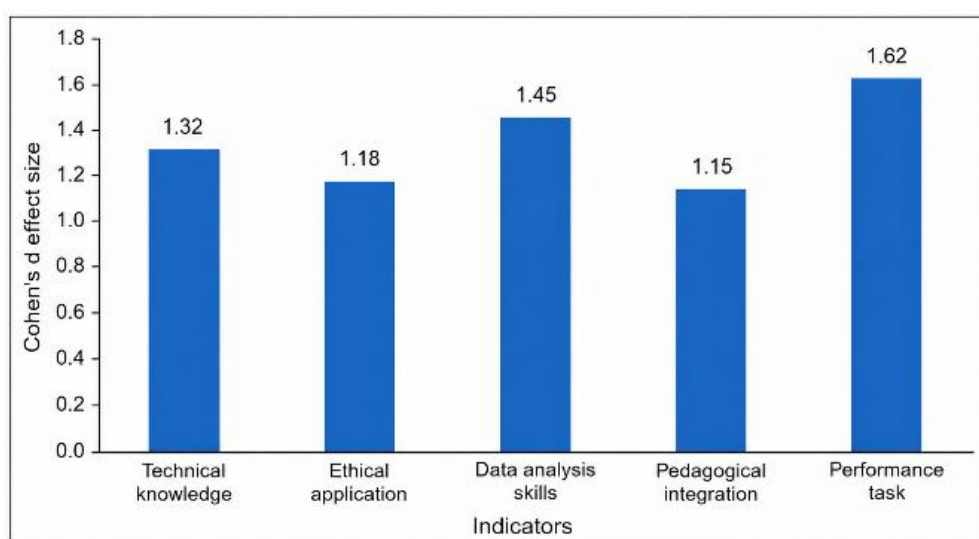


Figure 6. Effect size (Cohen's d) of changes in AI competence in the experimental group.

Source: compiled by the authors.

Note. The statistical indicators are defined as follows: M represents the mean (average score), SD denotes the standard deviation (a measure of variability), t refers to the t-test statistic used to assess differences between groups, p indicates the probability value (statistical significance level), and d (Cohen's d) represents the effect size, reflecting the magnitude of the difference.

Group comparisons post-intervention revealed significant differences: experimental vs. control on survey ($t(118) = 9.87$, $p < 0.001$, $d = 1.05$) and performance ($t(118) = 10.23$, $p < 0.001$, $d = 1.12$). Qualitative responses highlighted barriers like "limited access to AI tools" (45%) and "ethical concerns in data use" (32%), but post-intervention feedback praised practical training for building confidence (78%).

These results highlight a baseline deficit in AI competencies and suggest that structured AI training may contribute to competency development, thereby providing empirical support for the design of a comprehensive digital simulator model.

The empirical findings align with prior research indicating deficits in AI literacy among preservice teachers [2, p. 12; 15, p. 7]. Pre-intervention scores reflect a broader issue: without structured training, future computer science teachers struggle with AI applications, echoing global surveys on implementation barriers [6, p. 123; 11, p. 1]. The significant post-intervention improvements in the experimental group demonstrate that hands-on exposure to AI tools – such as

Python-based analysis – enhances technical and ethical skills, supporting the AI-PCK model [12, p. 31–55].

Quantitative gains (e.g., $d > 1.0$) suggest practical training mitigates knowledge gaps, consistent with studies on AI chatbots like PyChatAI [13, p. 7] and adaptive bots [13, p. 2]. Performance enhancements in data handling and visualization corroborate the value of educational analytics dashboards [8, p. 6; 9, p. 28]. Qualitative insights reinforce the need for ethical focus, addressing biases and privacy concerns [7, p. 165].

The identified deficits in AI competencies are particularly significant in the context of Kazakhstan's ongoing digital transformation of education. The low baseline levels of technical knowledge, data analysis skills, and pedagogical integration observed in this study are consistent with previous findings [2, p. 6; 15, p. 7]. These findings also correlated with studies conducted in Kazakhstan, emphasizing both the growing potential of AI for educational quality monitoring and decision-making and the existing challenges related to digital literacy, ethical risks, and responsible implementation of AI [6, p. 136; 7, pp. 165-170]. The improvements in the experimental group following the intervention are reflected in international literature demonstrating that practice-oriented training and hands-on experience with AI tools facilitate the development of AI-related competencies among preservice teachers [13, p. 7; 15, p. 7]. The large effect sizes obtained in the present study (Cohen's $d > 1.0$) indicate that structured training may address competency gaps and contribute to a comprehensive preparation of future computer science teachers.

Digital simulator development. Based on these results, the architectural model of the digital simulator is proposed. The simulator model consists of five modules. The modules are interconnected, ranging from the theoretical framework to practice, cases, visualization, and the assessment system. The practical and case situation modules directly transmit results to the visualization module and the assessment system (Figure 7).

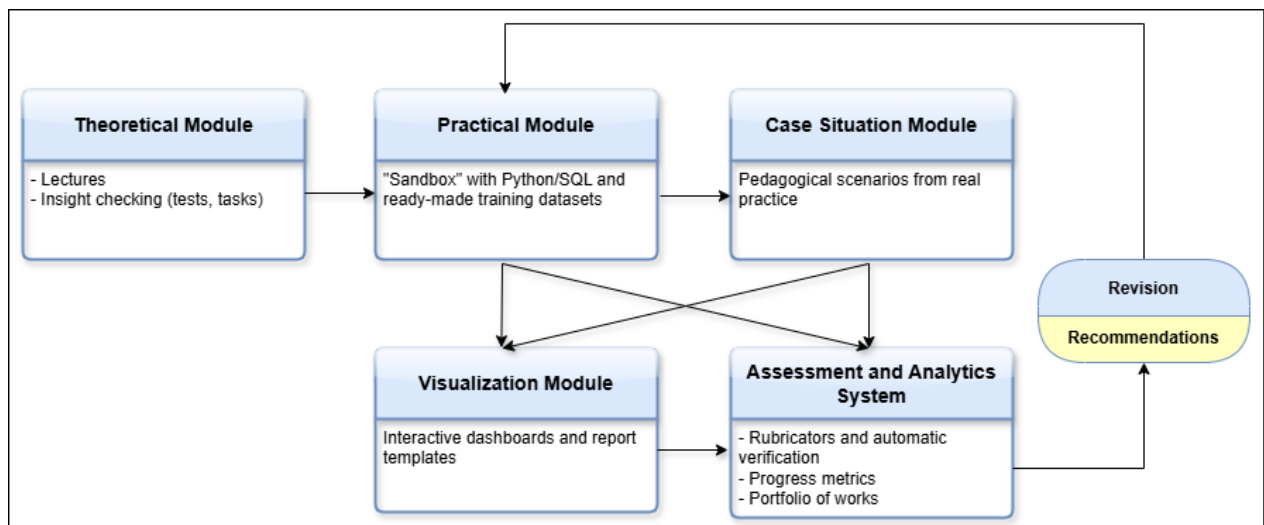


Figure 7. Architecture of the Digital Simulator.

Source: compiled by the authors.

Theoretical Module. The theoretical module comprises lecture materials presented in formats such as slideshows, concise instructional sessions, video recordings, and a comprehensive glossary pertaining to educational analytics and artificial intelligence. This module furnishes foundational concepts, illustrative examples, and structured checklists, enabling students to comprehend the rationale and objectives underlying subsequent practical exercises. This module provides the conceptual foundation for the development of AI-PCK competencies by helping students understand the principles, opportunities, and limitations of applying artificial intelligence in educational contexts [12, pp. 59].

Practical Module. The practical module includes a secure, isolated workspace within the simulator, called a "sandbox", which integrates Python and SQL (Structured Query Language)

environments with pre-prepared training datasets. Students write code directly in the browser interface, ensuring no failures in external systems or tasks. In this module, students learn skills in loading and cleaning data, analyzing training datasets, preparing features, and implementing basic machine learning models, including classification, clustering, and forecasting methods. Installed libraries such as Pandas, Numerical Python (NumPy), Scikit-learn, and Matplotlib/Plotly are provided. Thus, students load and preprocess data in the "sandbox", conduct analytics and visualizations, train basic AI models (including classification, clustering, and prediction), calculate performance metrics, and generate graphical representations with summary reports. The practical module is based on the learning-by-doing approach and supports the transition from theoretical knowledge to the practical application of artificial intelligence methods and educational data analytics in authentic educational contexts.

Case Situation Module. The case situation module includes pedagogical scenarios based on real educational contexts, such as predicting academic performance, identifying at-risk student groups, and analyzing activity patterns in Learning Management System (LMS). Each scenario is accompanied by clearly defined success criteria and limitations. This structure promotes the integration of theoretical knowledge and practical skills through authentic case-based scenarios that contextualize learning activities and enable students to develop targeted solutions while applying AI methods to realistic educational decision-making challenges.

Visualization Module. The visualization module is designed for teaching data storytelling: how to accurately and clearly present results, compare them to a "benchmark" – previous measurements and target indicators, and document the impact of interventions (e.g., pre- and post-intervention analyses). The module includes ready-made templates for presentations and informational bulletins, as well as exports to Portable Network Graphics (PNG) for integration into LMS and reports, Portable Document Format (PDF) for formal documentation and archiving, and PowerPoint Presentation – Open XML (PPTX) for public presenting reports. This module helps develop the visual literacy of future computer science teachers and makes course and student decisions transparent, verifiable, and scalable. As a result, given module supports the development of data literacy and evidence-based decision-making skills through the interpretation and communication of analytical results [8, p. 6; 9, p. 28].

Assessment and Analytics Module. The assessment and analytics module sets clear and transparent rules for assessing and accumulating learning outcomes. The module uses rubrics aligned with key competencies: data processing, artificial intelligence modeling, visualization, interpretation, and compliance with ethical standards. Task completions are evaluated automatically, assessing code functionality and model accuracy. For visualizations, checks encompass axis labeling and unit specification, scale appropriateness, accessibility features (e.g., contrast and readability), and the avoidance of deceptive practices (e.g., truncated axes or unnecessary three-dimensional effects). The system monitors progress indicators, such as task completion rates, attempt frequencies, and elapsed time. An analytical component compiles portfolios of student artifacts (e.g., dashboards and reports). Students access a competency map delineating gaps and progress trajectories across topics, while instructors benefit from risk/success dashboards, cohort comparisons, and one-click reporting tools. Drawing on these metrics, the module generates personalized recommendations, such as revisiting specific micro-lessons, repeating exercises, or experimenting with alternative visualization or modeling approaches; it also activates early alerts in cases of performance decline. This mechanism establishes a closed feedback loop-comprising attempt, automated evaluation, analytics, recommendation, and refinement-thereby expediting the mastery of AI applications in educational analytics, augmenting assessment objectivity, and upholding standards of data privacy and academic integrity. The module supports continuous feedback, progress monitoring, and competency development through automated assessment, analytics, and personalized recommendations.

Collectively, these five modules provide an integrated learning environment that combines theoretical instruction, hands-on data analysis, pedagogical problem-solving, data storytelling, and continuous assessment. Through this structure, future computer science teachers develop competencies in educational analytics, AI applications, and evidence-based decision-making.

Despite the potential benefits of the proposed model, several limitations of the present study design and empirical evaluation should be acknowledged. The relatively small and non-representative sample (N = 120), consisting solely of third- and fourth-year students, limits the generalizability of the findings. Additionally, the absence of longitudinal follow-up prevents assessment of the long-term effects of the intervention. The study relied exclusively on quantitative methods, which may restrict the breadth of evidence regarding intervention effectiveness. Furthermore, external factors, including the remote learning format and potential technical issues such as internet connectivity and access to equipment, may have influenced participant experiences and outcomes. Finally, the findings may not be directly transferable to other educational institutions, systems, or national contexts due to differences in pedagogical, technological, and cultural conditions.

Taken together, the limitations do not undermine the interpretive value of the findings. The proposed model is intended to address the identified competency gaps by supporting the development of skills in analysis, interpretation, and ethics. Implementation recommendations include curriculum integration (e.g., 20-hour modules in syllabi), faculty training workshops, and iterative evaluations using pre-post metrics. Future research should validate the simulator in larger, randomized trials to assess long-term impacts on teaching efficacy.

Conclusions. This study identified pronounced deficiencies in artificial intelligence (AI) competencies among preservice computer science teachers, as evidenced by baseline survey and performance data revealing low proficiency levels across technical, ethical, analytical, and pedagogical domains. Based on the identified deficiencies and the results of the pilot intervention, a comprehensive digital simulator model is proposed. In particular, targeted training that includes practical AI tools such as machine learning algorithms for data analysis and visualization libraries for graphical presentation, resulted in statistically significant improvements, with effect sizes exceeding 1.0 in key areas. These achievements highlight the transformative potential of AI to improve the work with educational data, enabling the creation of more adaptive, personalized learning environments that respond to individual student needs and foster deeper engagement.

The proposed five-module architecture, including theoretical foundations, practical "sandboxes", case situation, visualization tools, and an integrated assessment system, provides a scalable, practice-oriented framework for teacher training. The proposed simulator has the potential to support both technical skills acquisition and the ethical use of AI. This model aligns with evolving pedagogical paradigms, such as AI-PCK, and removes barriers identified in global surveys, including a lack of resources and a digital literacy deficit. Integrating such technologies into teacher training curricula is crucial, as it gives teachers the opportunity to effectively navigate an AI-based educational environment. Educators will also be able to use analytics to make informed decisions and ensure equitable learning.

Finally, this integration has broader implications for educational equity, as tools based on artificial intelligence have the potential to make access to high-quality, data-informed teaching methods wider, reducing disparities in learning outcomes across diverse conditions. Future research should explore longitudinal effects of the simulator in varied institutional settings, potentially through randomized controlled trials, to refine its efficacy and scalability. By prioritizing AI literacy in preservice programs, educational systems can cultivate a generation of computer science teachers poised to innovate and excel, thereby advancing student success and societal progress in an increasingly digitized world.

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БІЛІМ БЕРУ ДЕРЕКТЕРІН ТАЛДАУ ЖӘНЕ ИНФОРМАТИКА МҰҒАЛІМДЕРІНІҢ КӘСІБИ ДАЙЫНДЫҒЫН ҚОЛДАУ ҮШІН ЖАСАНДЫ ИНТЕЛЛЕКТІНІ ҚОЛДАНУ МОДЕЛІ

Аңдатпа

Бұл зерттеуде болашақ информатика педагогтерін даярлау барысында жасанды интеллект құралдарын білім беру деректерін талдау және визуализациялау мақсатында интеграциялау мәселесі қарастырылады. Болашақ педагогтердің жасанды интеллект бойынша құзыреттіліктеріндегі анықталған олқылықтарды толтыру мақсатында практикаға бағытталған цифрлық тренажер моделі әзірленді. Эмпирикалық зерттеуге Қазақстанның екі педагогикалық университетінің 120 информатика пәнінің болашақ мұғалімі қатысты; нәтижелерді бағалау және араласуға дейінгі және кейінгі сауалнама қолданылды. Араласуға дейін қатысушылардың тек 28 %-ы ғана деректерді талдаудың базалық деңгейін көрсетті, бұл жасанды интеллект сауаттылығы мен практикалық дағдылардың елеулі кемшіліктерін айғақтайды. Алынған нәтижелер негізінде бес модульді цифрлық тренажер архитектурасы ұсынылды, ол кейс- жағдайларды, практикалық құм жәшіктерін (сандбокстарды), теориялық негіздерді, визуализация құралдарын және бағалау жүйесін қамтиды. Ұсынылған модельді информатика мұғалімдерін даярлау процесінде қолдану анықталған олқылықтарды жоюға, деректерді жүйелі талдау мен интерпретациялау дағдыларын қалыптастыруға, сондай-ақ бағалаудың объективтілігі мен ашықтығын арттыруға ықпал етеді. Алынған нәтижелер жасанды интеллект технологияларын информатика мұғалімдерін даярлау жүйесіне интеграциялаудың қажеттілігін айқындайды.

Түйінді сөздер: жасанды интеллект, деректерді талдау, информатика, білім беру аналитикасы, педагогтерді даярлау, визуализация, цифрлық тренажер.

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МОДЕЛЬ ПРИМЕНЕНИЯ ИСКУССТВЕННОГО ИНТЕЛЛЕКТА ДЛЯ АНАЛИЗА ОБРАЗОВАТЕЛЬНЫХ ДАННЫХ И ПОДДЕРЖКИ ПРОФЕССИОНАЛЬНОЙ ПОДГОТОВКИ УЧИТЕЛЕЙ ИНФОРМАТИКИ

Аннотация

В статье исследуется интеграция инструментов искусственного интеллекта для анализа и визуализации образовательных данных в подготовке будущих педагогов информатики. С целью устранения выявленных пробелов в компетенциях будущих учителей в области ИИ разработана модель практико-ориентированного цифрового тренажера. В эмпирическом исследовании приняли участие 120 студентов – будущих преподавателей информатики двух педагогических университетов Казахстана; использовались оценка результатов деятельности и пред- и пост-опрос. До вмешательства лишь 28 % участников демонстрировали базовый уровень владения анализом данных, что свидетельствует о серьезных недостатках в ИИ-грамотности и практических навыках. На основе полученных результатов предложена пятимодульная архитектура цифрового тренажера, включающая кейс-ситуации, практические песочницы, теоретические основы, инструменты визуализации и систему оценивания. Использование данной модели при подготовке учителей информатики позволяет устранить выявленные пробелы, способствует формированию практических навыков системного анализа и интерпретации данных, повышая объективность и прозрачность оценивания. Полученные результаты подчеркивают необходимость интеграции технологий искусственного интеллекта в систему подготовки учителей информатики.

Ключевые слова: искусственный интеллект, анализ данных, информатика, образовательная аналитика, подготовка педагогов, визуализация, цифровой тренажер.

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