

ENHANCING EFFICIENCY IN HIGHER EDUCATION SYSTEMS THROUGH ARTIFICIAL INTELLIGENCE TECHNOLOGIES

Allaberdiyev Bobur

National University of Uzbekistan.

International Islamic Academy of Uzbekistan.

allaberdiyev_91@mail.ru

Abstract:

The rapid development of artificial intelligence (AI) is changing how higher education institutions teach, assess, and manage learning, yet evidence on its efficiency and risks remains dispersed across technical, pedagogical, and policy literature. This article aims to analyze the theoretical and practical possibilities of using AI technologies, including deep learning, neural networks, large language models (LLMs), and adaptive learning systems, to improve the efficiency of higher education and to identify the ethical and regulatory conditions for their use. The study is based on an analytical review of peer-reviewed research and international reports published mainly between 2015 and 2025, a comparative analysis of specialized AI educational platforms, and a document analysis of international and Uzbek regulatory frameworks. The results describe the functions of machine learning in education, the architecture of neural-network models for predicting student performance, and the four-component structure of adaptive learning systems. Evidence from controlled evaluations indicates that intelligent tutoring systems and online formative assessment improve learning outcomes and that predictive learning analytics can help identify students at risk at an early stage, although the reported effects depend strongly on implementation. The analysis also shows that data protection, algorithmic bias, the reliability of AI-text detection, and academic integrity require institutional regulation. The article concludes that AI improves efficiency in higher education when it is combined with transparent governance, the AI literacy of students and faculty, and the development of language resources for national languages such as Uzbek.

Keywords: artificial intelligence; higher education; deep learning; neural networks; large language models; adaptive learning; learning analytics; automated assessment; academic integrity; algorithmic fairness.

Introduction

Digital transformation is bringing profound changes to higher education, and the rapid growth of artificial intelligence (AI) technologies requires a reconsideration of how the educational process, teaching methods, and assessment are organized. A systematic review of AI applications in higher education has shown that research concentrates on profiling and prediction, assessment and evaluation, adaptive systems, and intelligent tutoring, while the pedagogical perspective of educators remains underrepresented [1]. AI is thus becoming not only a technical tool but also a strategic factor in improving educational quality, building individual learning trajectories, and managing institutions.

Uzbekistan pays particular attention to the development of the digital economy and AI technologies. The “Digital Uzbekistan – 2030” Strategy created the legal and organizational basis for the digitalization of the education sector [2], and in 2024 the Strategy for the Development of Artificial Intelligence Technologies until 2030 set national targets for the introduction of AI in public administration, the economy, and the social sphere [3].

International research has addressed the use of generative AI in education and research [4], the conditions under which AI moves from the laboratory into everyday classroom practice [5], and the AI literacy that students and teachers require [6]. In Uzbekistan, research on natural language processing has produced language resources such as a parallel Uzbek–Kazakh corpus for machine translation [7] and ontological models of sentence structure in the Kazakh and Uzbek languages [8], which are preconditions for AI tools that work in national languages. However, an integrated analysis of the pedagogical, ethical, and economic efficiency of machine learning (ML), LLMs, and adaptive systems in higher education that also takes national regulatory conditions into account is still lacking.

The purpose of this research is to analyze the theoretical and practical possibilities of using deep learning, neural networks, LLMs, and adaptive learning systems in higher education and to substantiate their impact on educational efficiency together with the related ethical and legal requirements. To achieve this purpose, the study analyzes the educational functions of ML and neural network architectures, compares the capabilities of LLMs and specialized AI platforms, examines adaptive learning and student performance prediction models, and identifies the ethical, legal, and institutional conditions for the use of AI in education. The results are intended to support higher education institutions in integrating AI tools into learning management systems, adaptive platforms, and assessment, and in developing academic integrity policies.

Materials and Methods

The study is designed as an analytical (narrative) review combined with comparative and document analysis. Peer-reviewed articles, monographs, and reports of international organizations published mainly between 2015 and 2025 were identified in Scopus, Web of Science, and Google Scholar using combinations of the keywords “artificial intelligence”, “higher education”, “learning analytics”, “adaptive learning”, “intelligent tutoring”, and “large language models”. Priority was given to systematic reviews, meta-analyses, and controlled evaluations that report measurable learning or retention outcomes.

Three groups of materials were analyzed. The first comprises research on deep learning and other ML methods that are applied to educational data [9]. The second includes the official descriptions of specialized AI educational platforms and published evaluations of their effectiveness. The third consists of the regulatory and policy documents of Uzbekistan, international organizations, and universities. The methods used include theoretical analysis and synthesis, comparative analysis of platforms and policies, and conceptual modeling, which was used to describe the architecture of neural-network prediction models and adaptive learning systems (Figures 1–3). Because the review is not a systematic review in the PRISMA sense, its conclusions rest on the most representative

rather than on exhaustive evidence.

Results

Deep learning and neural network architecture. Deep learning is a branch of ML that automatically extracts hierarchical features from raw data using multi-layer neural networks [10]. Many AI solutions in educational practice are based on deep learning. The multilayer perceptron (MLP), the most basic type of neural network, consists of an input layer, one or more hidden layers, and an output layer. In a student performance model, the input layer receives indicators such as attendance, previous grades, assignment completion, and activity in the learning management system (LMS), and the output layer classifies the student as successful or at risk (Figure 1).

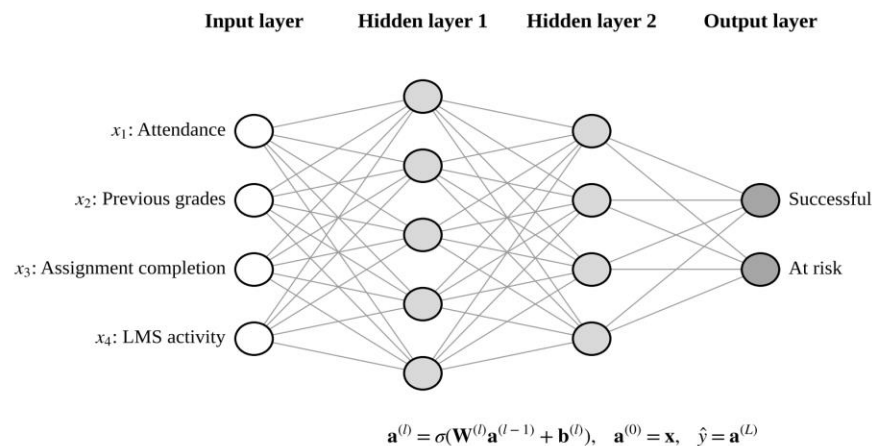


Figure 1. MLP neural network architecture for predicting student performance

Types of ML and their applications in education. Machine learning is applied in education in three main directions: supervised learning (classification and regression), unsupervised learning (clustering and dimensionality reduction), and reinforcement learning, which underlies adaptive learning systems (Figure 2). Educational data mining and learning analytics use these methods to predict performance, detect undesirable learning behavior, group students, and provide feedback to instructors [11].

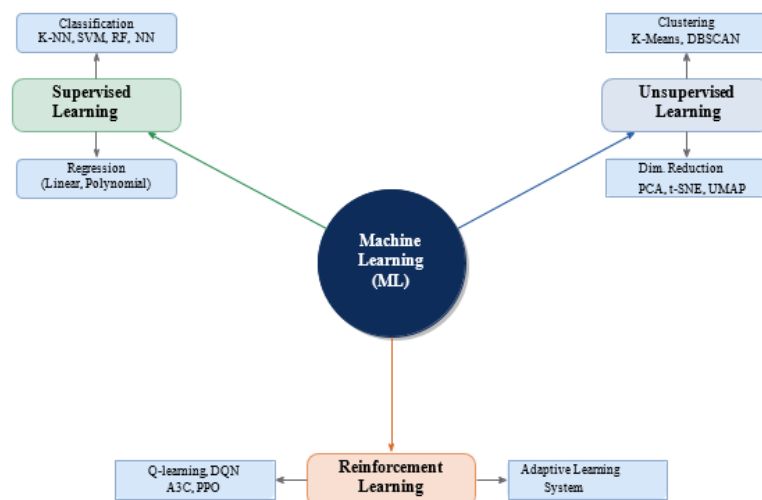


Figure 2. Types of ML and their applications in education

Architecture of the adaptive learning system. Adaptive learning is a software-pedagogical approach that personalizes the learning experience by adapting to each student's knowledge level,

pace, strengths, and weaknesses. Modern adaptive learning systems consist of four main components (Figure 3): the domain knowledge model, which defines the content structure and learning sequence of a course in the form of a knowledge graph or ontology; the student model, which tracks the learner's current knowledge, learning history, and error patterns, often by means of Bayesian knowledge tracing [12]; the pedagogical module, which determines teaching strategies and instructional decisions; and the interface module, which provides presentation and feedback.

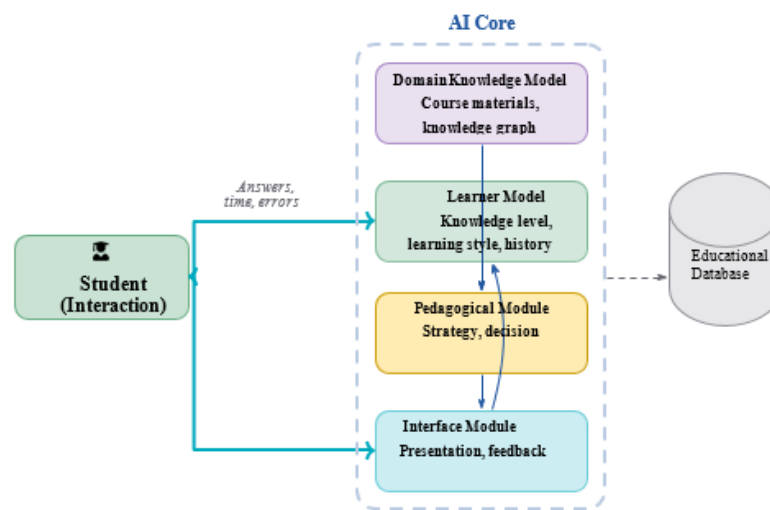


Figure 3. Four-component architecture of an adaptive learning system

LLMs and specialized AI platforms. Large language models are neural networks with billions of parameters trained on large text corpora that can perform text comprehension, generation, and translation tasks, often from only a few examples [13]. In education, they are used for conversational tutoring, content generation, feedback and assessment, and the design of personalized learning pathways, while their limitations include factual errors, bias, and the risk of over-reliance by students [14]. Conversational tutoring builds on the long tradition of intelligent tutoring systems, which, according to a meta-analysis of 50 controlled evaluations, improved students' test performance with a median effect size of 0.66 standard deviations [15]. Table 1 summarizes specialized AI platforms that are widely used in education.

Table 1. Specialized AI educational platforms

Platform	Main functions	Developer
Khanmigo	AI tutor based on GPT-4; Socratic dialogue; support in mathematics and other subjects	Khan Academy (USA)
Duolingo Max	Language learning; AI conversation practice; explanation of answers	Duolingo (USA)
Coursera Coach	Answers to course questions; practice quizzes; goal setting	Coursera (USA)
Gradescope	AI-assisted grading; grouping of similar answers; rubric-based assessment	Turnitin (USA)
Turnitin AI writing detection	Detection of AI-generated text; similarity checking	Turnitin (USA)
Wolfram Alpha Pro	Step-by-step solutions in mathematics, physics, and chemistry	Wolfram Research (USA)
Squirrel AI	Adaptive learning based on fine-grained knowledge points; real-time adaptation	Squirrel AI Learning (China)

Source: compiled by the author from the developers' official descriptions.

Predicting student performance and learning analytics. The prediction of student performance is modeled in ML either as a classification task (successful or at risk) or as a regression task (predicted grade). Table 2 lists the input features most frequently used in such models. Learning-style categories such as VARK, which are sometimes added to these models, were not included, because experimental evidence does not support adapting instruction to learning styles [16].

Table 2. Input features of the student performance model

Feature	Description	Type
Attendance	Percentage of classes attended	Numerical
Midterm assessment	Midterm examination score (0–100)	Numerical
Assignment completion	Number of submitted assignments / total number of assignments	Numerical
LMS activity	Daily logins and time spent viewing materials	Numerical
Previous course performance	Scores in previous courses	Numerical
Forum activity	Number of questions, answers, and posts	Numerical
Socio-economic indicators	Scholarship status, employment status	Categorical

Source: compiled by the author.

Published evaluations show both the potential and the limits of these tools. At Purdue University, the Course Signals early-warning system was associated with higher retention and better grades among students in courses that used it [17], although later analyses questioned whether these effects were causal. At the Open University (UK), the predictive learning analytics system OU Analyse was implemented on a large scale to help teachers identify students at risk of failing, and its benefits depended on how actively teachers used the predictions [18]. In a randomized controlled trial, the ASSISTments online homework platform improved students' mathematics achievement with an effect size of 0.18 standard deviations [19]. An evaluation commissioned by Duolingo estimated that about 34 hours of study on the platform were equivalent to one university semester of Spanish [20]; this result, however, has not been replicated in independent peer-reviewed research.

Discussion

The results show that the efficiency of AI in higher education depends less on the algorithms themselves than on the conditions under which they are used. The ethics of AI in education can be summarized in six principles (Figure 4): transparency, achieved through explainable AI; accountability, meaning clear responsibility for errors; fairness, meaning the prevention of algorithmic bias and discrimination; safety, including protection against pedagogical manipulation; privacy, meaning the protection of student data; and inclusivity, meaning the reduction of the digital divide. These principles are consistent with the community-wide framework for the ethics of AI in education proposed by Holmes et al. [21]. Algorithmic bias is a particular risk for prediction models, because historical educational data may encode inequalities related to gender, ethnicity, or socio-economic status and reproduce them in at-risk classifications [22].



Figure 4. Six principles of AI ethics in education

In Uzbekistan, the use of AI in higher education is governed mainly by general digitalization and data protection legislation (Table 3). The Law “On Education” provides for the use of information technologies in the educational process [23], and the Law “On Personal Data” regulates the processing of personal data, including student data [24]. Internationally, the Artificial Intelligence Act of the European Union classifies AI systems used for admission, the evaluation of learning outcomes, and the monitoring of students during tests as high-risk and subjects them to strict requirements [25], which offers a useful reference point for national regulation.

Table 3. Regulatory legal framework relevant to AI in higher education in Uzbekistan

Legal or regulatory act	Main provisions relevant to AI in higher education
“Digital Uzbekistan – 2030” Strategy (2020)	National program of digital transformation, including the education sector
Law “On Personal Data” (2019)	Protection and lawful processing of personal data, including student data
Law “On Education” (2020)	Integration of information technologies into the educational process
Government resolutions on the Higher Education Management Information System (HEMIS)	Digital management of the educational process and student records
Strategy for the Development of AI Technologies until 2030 (2024)	Development of the AI ecosystem, infrastructure, and human resources

Source: compiled by the author.

Generative AI has also changed the conditions of academic integrity. ChatGPT-type tools can produce essays that are difficult to distinguish from student work, which requires changes in the design of assessment [26]. At the same time, testing of AI-text detection tools has shown that none of them is fully accurate or reliable, so their results should not serve as the sole evidence of misconduct [27]. Leading universities and policy bodies, such as the Russell Group universities in the United Kingdom [28] and the U.S. Department of Education [29], therefore favor regulated use and AI literacy rather than prohibition (Table 4).

Table 4. International approaches to the use of AI in higher education

Organization	Approach
UNESCO (2023)	Human-centered use of generative AI; protection of data privacy; capacity building for teachers and researchers
Russell Group universities, UK (2023)	AI literacy of students and staff; adaptation of teaching and assessment; appropriate use consistent with academic integrity

Organization	Approach
U.S. Department of Education (2023)	“Humans in the loop”; alignment of AI with educational goals; trustworthy and evidence-based tools
European Union, AI Act (2024)	AI systems for admission, assessment, and student monitoring classified as high-risk
Uzbekistan, AI Strategy until 2030 (2024)	National framework for AI development, including the training of human resources

Source: compiled by the author.

The study has limitations. As an analytical review, it relies on published evaluations, many of which were conducted in high-income countries and before the spread of generative AI, and the effects of LLM-based tutoring on learning outcomes in Uzbek universities have not yet been tested empirically. Future research should therefore evaluate AI tools in national higher education institutions using controlled designs and Uzbek-language resources.

Conclusion

The study shows that deep learning neural networks, LLMs, and adaptive learning platforms can transform traditional educational processes in higher education by personalizing learning trajectories, providing immediate feedback, and reducing the routine workload of teachers. Evidence from controlled evaluations confirms that intelligent tutoring and online formative assessment improve learning outcomes and that predictive learning analytics can identify students at risk of failure at an early stage, although the size of these effects depends on how the tools are implemented and used by teachers. At the same time, the widespread use of AI raises ethical, legal, and institutional challenges, including the protection of student data, the prevention of algorithmic bias, the limited reliability of AI-text detection, and the need to redefine academic integrity. The experience of leading universities and international organizations indicates that an open, regulated approach based on academic integrity and the systematic development of AI literacy among students and faculty is more effective than prohibition. For Uzbekistan, further improvement of the regulatory framework, the development of Uzbek-language AI resources, and empirical testing of AI tools in national universities are the key conditions for using AI to increase the efficiency of higher education.

References

- [1] O. Zawacki-Richter, V. I. Marín, M. Bond, and F. Gouverneur, “Systematic review of research on artificial intelligence applications in higher education – where are the educators?,” *Int. J. Educ. Technol. High. Educ.*, vol. 16, Art. no. 39, 2019, doi: 10.1186/s41239-019-0171-0.
- [2] Decree of the President of the Republic of Uzbekistan “On approval of the ‘Digital Uzbekistan – 2030’ Strategy and measures for its effective implementation,” No. UP-6079, Oct. 5, 2020. [Online]. Available: <https://lex.uz/docs/5031048>
- [3] Resolution of the President of the Republic of Uzbekistan “On approval of the Strategy for the development of artificial intelligence technologies until 2030,” No. PP-358, Oct. 14, 2024. [Online]. Available: <https://lex.uz/docs/7159258>
- [4] F. Miao and W. Holmes, *Guidance for Generative AI in Education and Research*. Paris, France: UNESCO, 2023.
- [5] D. Schiff, “Out of the laboratory and into the classroom: The future of artificial intelligence in education,” *AI Soc.*, vol. 36, no. 1, pp. 331–348, 2021, doi: 10.1007/s00146-020-01033-8.
- [6] D. T. K. Ng, J. K. L. Leung, S. K. W. Chu, and M. S. Qiao, “Conceptualizing AI literacy: An exploratory review,” *Comput. Educ.: Artif. Intell.*, vol. 2, Art. no. 100041, 2021, doi: 10.1016/j.caeai.2021.100041.
- [7] B. Allaberdiev, G. Matlatipov, E. Kuriyozov, and Z. Rakhmonov, “Parallel texts dataset for Uzbek-Kazakh machine translation,” *Data Brief*, vol. 53, Art. no. 110194, 2024, doi:

- 10.1016/j.dib.2024.110194.
- [8] B. Allaberdiyev and Z. Raxmonov, "Qozoq va o'zbek tillarida gaplarning tuzilishini ontologik modeli [Ontological model of sentence structure in the Kazakh and Uzbek languages]," *Muhammad al-Xorazmiy avlodlari*, no. 3(25), pp. 12–14, 2023. (in Uzbek)
 - [9] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," *Nature*, vol. 521, no. 7553, pp. 436–444, 2015, doi: 10.1038/nature14539.
 - [10] I. Goodfellow, Y. Bengio, and A. Courville, *Deep Learning*. Cambridge, MA, USA: MIT Press, 2016.
 - [11] C. Romero and S. Ventura, "Educational data mining and learning analytics: An updated survey," *WIREs Data Min. Knowl. Discov.*, vol. 10, no. 3, Art. no. e1355, 2020, doi: 10.1002/widm.1355.
 - [12] A. T. Corbett and J. R. Anderson, "Knowledge tracing: Modeling the acquisition of procedural knowledge," *User Model. User-Adapt. Interact.*, vol. 4, no. 4, pp. 253–278, 1994, doi: 10.1007/BF01099821.
 - [13] T. B. Brown et al., "Language models are few-shot learners," in *Adv. Neural Inf. Process. Syst.*, vol. 33, 2020, pp. 1877–1901.
 - [14] E. Kasneci et al., "ChatGPT for good? On opportunities and challenges of large language models for education," *Learn. Individ. Differ.*, vol. 103, Art. no. 102274, 2023, doi: 10.1016/j.lindif.2023.102274.
 - [15] J. A. Kulik and J. D. Fletcher, "Effectiveness of intelligent tutoring systems: A meta-analytic review," *Rev. Educ. Res.*, vol. 86, no. 1, pp. 42–78, 2016, doi: 10.3102/0034654315581420.
 - [16] H. Pashler, M. McDaniel, D. Rohrer, and R. Bjork, "Learning styles: Concepts and evidence," *Psychol. Sci. Public Interest*, vol. 9, no. 3, pp. 105–119, 2008, doi: 10.1111/j.1539-6053.2009.01038.x.
 - [17] K. E. Arnold and M. D. Pistilli, "Course signals at Purdue: Using learning analytics to increase student success," in *Proc. 2nd Int. Conf. Learn. Analytics Knowl. (LAK '12)*, Vancouver, BC, Canada, 2012, pp. 267–270, doi: 10.1145/2330601.2330666.
 - [18] C. Herodotou, B. Rienties, A. Boroowa, Z. Zdrahal, and M. Hlosta, "A large-scale implementation of predictive learning analytics in higher education: The teachers' role and perspective," *Educ. Technol. Res. Dev.*, vol. 67, no. 5, pp. 1273–1306, 2019, doi: 10.1007/s11423-019-09685-0.
 - [19] J. Roschelle, M. Feng, R. F. Murphy, and C. A. Mason, "Online mathematics homework increases student achievement," *AERA Open*, vol. 2, no. 4, pp. 1–12, 2016, doi: 10.1177/2332858416673968.
 - [20] R. Vesselinov and J. Grego, "Duolingo effectiveness study," City Univ. of New York, New York, NY, USA, Final Rep., 2012.
 - [21] W. Holmes et al., "Ethics of AI in education: Towards a community-wide framework," *Int. J. Artif. Intell. Educ.*, vol. 32, no. 3, pp. 504–526, 2022, doi: 10.1007/s40593-021-00239-1.
 - [22] R. S. Baker and A. Hawn, "Algorithmic bias in education," *Int. J. Artif. Intell. Educ.*, vol. 32, no. 4, pp. 1052–1092, 2022, doi: 10.1007/s40593-021-00285-9.
 - [23] Law of the Republic of Uzbekistan "On Education," No. ZRU-637, Sep. 23, 2020.
 - [24] Law of the Republic of Uzbekistan "On Personal Data," No. ZRU-547, Jul. 2, 2019.
 - [25] Regulation (EU) 2024/1689 of the European Parliament and of the Council of 13 June 2024 laying down harmonised rules on artificial intelligence (Artificial Intelligence Act), *Off. J. Eur. Union*, L series, Jul. 12, 2024.
 - [26] D. R. E. Cotton, P. A. Cotton, and J. R. Shipway, "Chatting and cheating: Ensuring academic integrity in the era of ChatGPT," *Innov. Educ. Teach. Int.*, vol. 61, no. 2, pp. 228–239, 2024, doi: 10.1080/14703297.2023.2190148.
 - [27] D. Weber-Wulff et al., "Testing of detection tools for AI-generated text," *Int. J. Educ. Integr.*, vol. 19, Art. no. 26, 2023, doi: 10.1007/s40979-023-00146-z.
 - [28] Russell Group, "Russell Group principles on the use of generative AI tools in education," London, U.K., Jul. 2023.
 - [29] U.S. Department of Education, Office of Educational Technology, "Artificial intelligence and

the future of teaching and learning: Insights and recommendations,” Washington, DC, USA, May 2023.