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Application of Machine Learning Technologies for Personalising the Digital Educational Process in Higher Education Institutions

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Abstract

The aim of the study was to identify the main types of machine learning (ML) models that help adapt the educational environment to the individual needs of students in universities. The methodology combined a systematic analysis of approaches to teaching using ML algorithms with a comparative analysis of the digital transformation of higher education in Kyrgyzstan, Azerbaijan, Poland, and Ukraine. The analysis of ML approaches and the comparative analysis of the digitalisation of the examined educational institutions revealed key mechanisms for personalising the learning process. The comparison of practices showed that Poland and Ukraine prefer reinforcement learning models and academic performance prediction algorithms; Azerbaijan used clustering methods to group students by learning styles; and Kyrgyzstan implemented recommendation systems to improve motivation and feedback. The analysis suggests that the implementation of these technologies depends on four key factors: the level of digital competence of teachers, the availability and quality of educational data, the integration of adaptive modules into learning platforms, and the presence of state policies regulating the use of artificial intelligence (AI) in education. Additionally, it was found that personalised ML modules contribute to increasing students' intrinsic motivation, the development of self-learning skills, and active interaction within learning

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groups. The practical value of the work lies in the recommendations for deploying adaptive ML modules in higher education institutions in the countries under study, which will help improve the quality of education, student motivation, and reduce the gap in academic achievements.

Keywords: *analytics; artificial intelligence; educational behaviour analysis; platforms; motivation; social interaction*

Introduction

The digital world requires the transformation of the higher education system, focusing on personalising the educational process, which takes into account the individual needs, traits, and capabilities of each student. Machine learning (ML) technologies open new perspectives for adapting content, methods, and learning paces, contributing to increased motivation, critical thinking, and independence among learners. However, there is fragmentation in the implementation of ML, a lack of unified personalised learning models in higher education institutions, and a lack of empirical research tailored to the local context. Existing digital approaches remain standardised and fail to account for individual learning styles, cognitive traits, and motivational factors of students. As noted by Klašnja-Milićević and Ivanović (2021), personalised e-learning systems are key to building a sustainable educational environment, in which artificial intelligence (AI) acts as an intermediary between the student and the educational platform.

The academic community is actively exploring the potential of ML in higher education. Hashim et al. (2022) conducted a systematic review of studies related to personalised learning using AI and ML, confirming the stable trend of integrating these technologies into blended and distance learning formats. Significant attention is paid to the flexibility of algorithms and their ability to self-learn. In the study by Chen et al. (2024), it was demonstrated that ML models enhance the effectiveness of educational recommendation systems, optimising the selection of learning materials according to the student's learning profile. The simulation approach to personalisation, as concluded by Taylor et al. (2024), provided a more accurate model of student behaviour in a digital environment and allowed for predicting the dynamics of their learning progress. This view was supported by Gallastegui and Forradellas (2024), who emphasised the role of predictive AI models in improving students' academic experience and adapting the learning process to their real needs. In addition, recent high-impact studies in the field have emphasised the importance of benchmark datasets, model validation, and performance metrics in evaluating ML applications in education, highlighting the need for methodological rigour in interpreting results.

In the study by Huang (2025), the potential of AI-based personalised learning platforms was revealed, which provide deep analytics of user behaviour, thereby increasing their level of engagement. The author emphasised the importance of the interface simplicity of such systems and the ability of ML algorithms to adapt quickly during educational interactions. Additionally, Yildirim and Celepcikay (2021) focused

on the practical application of ML in the context of automated feedback, allowing students to receive individualised advice and recommendations in real time. In the context of Ukrainian educational reality, it is worth mentioning the study by Kovalchuk et al. (2025), which reported the effectiveness of using AI in personalised learning and highlighted the need for institutional support for the digital transformation of the educational environment. Alenezi (2023) stressed the role of digital educational institutions as a new format of organising the learning process, where ML technologies play a strategic role in adapting content and managing the educational environment.

Despite the considerable number of scientific studies on AI and ML, there are gaps in the application of ML to personalise the educational process in higher education. Most of the research has focused on technical aspects, such as algorithm accuracy, architecture, and performance. However, pedagogical, managerial, and organisational aspects of integrating these technologies into higher education institutions remain under-researched. The transformation of the interaction between teachers, students, and the digital educational environment under the influence of ML solutions remains a relevant issue. Moreover, there are no unified models of ML implementation that take into account the interdisciplinary nature of higher education. Another problem is the insufficient study of the impact of the cultural, institutional, and resource contexts of individual countries on the effectiveness of digital transformation. These factors limit the scalability and adaptability of ML solutions in different educational environments, highlighting the need for further research considering the local specifics.

The purpose of the study was to substantiate the possibilities and advantages of applying ML technologies to personalise the digital educational process in higher education institutions. The article outlines three key tasks of the research: to identify the main approaches using ML technologies for personalising the educational process and evaluate their effectiveness; to conduct a comparative analysis of the implementation of these technologies in higher education institutions in Kyrgyzstan, Azerbaijan, Poland, and Ukraine; and to determine the prospects for development and formulate recommendations for adapting ML to each of the countries studied. The novelty of this study lies in its comparative synthesis of ML implementation practices across different educational systems, with a focus on contextual, organisational, and pedagogical dimensions rather than technical model performance.

Methodology

The study was conducted from January 2024 to June 2025 as part of the examination of the digital transformation processes in higher education in Kyrgyzstan, Azerbaijan, Poland, and Ukraine. The first stage of the study involved summarising common ML models used in digital education, including Collaborative Filtering, Classification Models, Reinforcement Learning, Clustering (K-Means), and Natural Language Processing (NLP). At this stage, their potential for predicting academic outcomes, identifying hidden educational patterns, and optimising learning trajectories based on

user data was examined. Additionally, the effectiveness of these models in providing personalised recommendations and analysing the relationships between behavioural indicators and success was assessed, which laid the groundwork for further testing of university platforms.

This study adopts a qualitative-comparative research design based on systematic literature analysis and cross-country case comparison. No primary machine learning models were implemented or empirically tested. Instead, the study focuses on analysing documented applications of ML technologies in higher education platforms and identifying their functional roles, implementation contexts, and reported outcomes. Data sources include peer-reviewed academic publications, institutional reports, and publicly available descriptions of educational platforms. The analytical approach combines comparative analysis and grounded theory to interpret patterns of ML integration and to formulate conceptual recommendations.

The second stage involved a comparative analysis of digital platforms and educational ecosystems at leading higher education institutions in the four countries. In Kyrgyzstan, classification algorithms and behavioural analytics were studied on the "Sanarip Academy" platform, used by the Kyrgyz State Technical University named after I. Razzakov, to adapt learning materials to students' needs. In Azerbaijan, recommendation systems and student clustering methods were explored on the "EDU.AZ" platform at Baku State University, which help form personalised learning paths according to individual learning styles and paces. The Polish experience focused on the Pegaz platform at Jagiellonian University, based on Moodle, where Support Vector Machines (SVM) models are used for performance classification and Principal Component Analysis (PCA) for identifying key factors influencing learning effectiveness, providing teachers with analytical tools to adjust the educational process. In Ukraine, the integration of reinforcement learning algorithms was explored in collaboration with the Udemy platform at Taras Shevchenko National University of Kyiv, including dynamic adaptation mechanisms for course pace and content, analytical panels for monitoring student success, and early detection systems for underperforming students.

At the final stage of the research, the grounded theory approach was used to outline prospects and formulate recommendations regarding the expansion of effective ML approaches in higher education institutions in Kyrgyzstan, Azerbaijan, Poland, and Ukraine. This stage was based on the previous comparative analysis of educational platforms and ML solutions used in each country, taking into account the context of national digital policies, infrastructure, human resources, and legal conditions.

Results

ML in personalising the learning process

In the context of the digital transformation of higher education, personalisation is gaining new scale, as the integration of ML technologies opens opportunities for deep analysis of student educational behaviour. By collecting and processing data on

interactions with learning platforms, evaluations, and activity time series, ML systems can identify both general trends and individual patterns of material absorption. ML-supported systems adapt the sequence of topics, select additional exercises to reinforce knowledge, and automatically adjust the difficulty of tasks in real time (Chen et al., 2025; Hevko et al., 2021). Additionally, continuous feedback mechanisms help teachers respond quickly to difficulties, reinforce social interaction, and stimulate the development of key competencies, making the learning process more effective and goal-oriented (Imran et al., 2024). Below is a summarised Table 1 with key methods and their functional purposes.

Table 1

Key ML methods for personalising the educational process and their functional purposes

Approach	Description	Purpose of application
Collaborative filtering	Recommendations based on behavioural similarity	Selection of relevant content
Classification models	Classification of learning styles, identifying at-risk groups	Predicting academic success
Reinforcement learning	Adapting educational paths through feedback	Dynamic optimisation of the learning process
Clustering (K-means)	Grouping students by characteristics	Formation of adaptive learning groups
NLP	Analysing text responses and discussions	Identifying cognitive patterns, areas of misunderstanding

Source: created by the authors based on Cui et al. (2024), Forero-Corba and Bennasar (2024), Haleem et al. (2022), Qureshi et al. (2021).

After implementing ML methods in higher education platforms, signs of transformation in the educational process appear. For example, the use of collaborative filtering allows generating recommendations based on student behaviour and their individual interests. By analysing the history of viewed learning materials, attended lectures, completed exercises, and rated assessments, the system forms a personalised pool of resources for each user (Ibrahim et al., 2025). This helps increase student engagement as they receive materials that best match their current needs and learning style, which, in turn, enhances motivation for further learning and reduces the likelihood of losing interest in the course.

Instead, the integration of classification models, such as SVM or decision trees, allows for the rapid identification of students who are at academic risk (Yang & Zhang, 2025; Dodonova & Dodonov, 2022). By using data from interim tests, system activity, and participation in discussions, classification algorithms can predict the likelihood of unsuccessful course completion or low grades. This information serves as a signal for lecturers and tutors to take targeted interventions, such as offering additional consultations, sending learning tips, or organising support groups. As a

result, lecturers adjust teaching plans and send individual messages with additional resources, significantly improving the overall success rate of the course. The third approach is reinforcement learning, which is used to create dynamic educational paths that change according to the student's response to previous tasks. A system that operates on reinforcement learning principles analyses users' successes or mistakes, determines the optimal sequence of next topics or exercises, and implements these adjustments. This approach allows for modelling the individual pace of material absorption and adapting task difficulty in real time, leading to a more conscious and profound mastery of the subject (Song et al., 2024). Similar ensemble-based classification approaches, including XGBoost and AdaBoost optimized with metaheuristic methods, have demonstrated high effectiveness in predicting and understanding student dropout, enabling timely interventions (Spalević et al., 2025).

The fourth group of models, clustering, helps divide students into subgroups based on learning characteristics, such as information processing speed, communication style, or prior preparation level (Kanchon et al., 2024; Diachuk, 2024). Using algorithms such as K-Means or density-based spatial clustering of applications with noise (DBSCAN), learning groups with similar needs can be created, offering them specialised support modules or additional materials. ML enables the realisation of a personalised approach in mass education, where its implementation without appropriate technological solutions would be organisationally complicated. Finally, NLP technologies are transforming traditional approaches to assessing written work and analysing discussion activity in online forums, providing automated interpretation of content, determining the validity of statements, and identifying key thematic elements (Chen, 2025). Using models, educational platforms begin to automatically analyse the structure of arguments, logical connections, depth of understanding, and emotional tone of texts. This enables lecturers to receive analytical reports on each student's progress, focusing on formal parameters such as the presence of key terms and the quality of thinking and argumentation. Students receive timely, individualised advice on improving their writing style, structuring their thoughts, and formulating conclusions.

The integration of all these methods creates a unified multifunctional personalisation ecosystem that covers the entire learning cycle, from identifying needs to adapting teaching strategies in real time (Shaikh et al., 2022; Musakulov et al., 2025). Such solutions reduce the gap between students with different academic performances, make the learning process more accessible and flexible, and help equalise starting opportunities. However, for the successful implementation of ML personalisation, it is crucial to begin by establishing data collection and processing systems. This includes standardising data structures across different platforms, integrating multiple sources (Learning Management Systems (LMS), tests, chat activity), and ensuring the representativeness of samples, so analytical models do not receive distorted signals (Aslam et al., 2025; Dahan et al., 2025). A high-quality data processing pipeline includes validation, normalisation, and gap filling, as all these stages are critical for

the accuracy of predictions and recommendations. Therefore, educational institutions must invest in data engineers and analysts who implement Extract, Transform, Load processes, as well as tools for monitoring data quality in real time. Only in this way can it be guaranteed that the algorithms work based on complete and reliable data, not distorted or incomplete sets. This approach ensures a high degree of trust in ML systems from both students and lecturers and naturally increases the effectiveness of personalising the educational process.

It is also important to ensure the transparency of algorithms through Explainable AI practices. Both lecturers and students must have access to understandable explanations of how machine intelligence recommendations and assessments are formed, as this builds trust in the systems and minimises the risk of algorithmic biases (Ayeni et al., 2024; Bessarab et al., 2022). Explaining the internal logic of models allows educators to control the decision-making process, identify potential inaccuracies in time, and influence parameter settings, thus reducing the likelihood of discrimination against students based on factors unrelated to their academic achievements. A key element of the strategy is preparing qualified personnel with skills in data science, pedagogical analytics, and ML solutions development (Timotheou et al., 2023). Higher education must integrate ML, programming, statistical analysis, and data ethics courses into its undergraduate and master's programmes so that graduates can develop, implement, and adapt algorithmic systems in the educational environment (Riznyk & Riznyk, 2024; Matviienko, 2025). At the same time, inter-university training and professional development courses for current lecturers and administrators should be organised, as their understanding of the opportunities and limitations of ML systems is critical for their effective use.

Ethical and legal aspects of processing personal educational data must also be considered. Any ML system must comply with international data protection standards and national legislation that governs the collection, storage, and use of student information. This includes obtaining informed consent for the use of data, ensuring confidentiality, and implementing technical and organisational measures to prevent unauthorised access or data leaks, with the ethical frameworks for data processing clearly outlined in the university's policies and regularly reviewed with the participation of student and teaching staff representatives.

Analysis of the digital transformation of higher education using the example of universities in Kyrgyzstan, Azerbaijan, Poland, and Ukraine

The Kyrgyz State Technical University named after I. Razzakov is the leading technical institution in the country, implementing innovative digital technologies in the field of education. One of the key initiatives of the university is the use of the "Sanarip Academy" platform, which aims to improve the quality of education by personalising the learning process using ML algorithms. This platform integrates classification algorithms to determine the individual level of knowledge and competencies of students.

This allows students to be separated by categories of material difficulty that they can handle and form optimal individual learning paths. Recommendation systems are also used, which take into account progress dynamics and user activity. The platform ensures continuous monitoring of academic activity, including participation in lectures, completing practical tasks, and interim assessments. Based on this data, automatic adjustments are made to the learning content, which helps maintain the proper level of difficulty and motivation.

In addition to the technical component, the integration of the system with the university's administrative processes is important, allowing lecturers to receive real-time analytical reports on students' performance, respond quickly to difficulties, and offer necessary adjustments to the teaching plans. A key factor is also the state support for the digitalisation of education in Kyrgyzstan, which is manifested in relevant government initiatives and funding for the modernisation of educational platforms. The "Sanarip Academy" university system is an example of a comprehensive approach that combines ML with traditional teaching methodology and is focused on adapting to the needs of a wide range of students, including those with individual educational requirements.

Baku State University is one of Azerbaijan's leading universities, actively integrating digital technologies into the educational process. The "EDU.AZ" platform has been implemented at the university, combining classical teaching methods with modern ML algorithms. The platform's main feature is the use of clustering algorithms, which allows students to be grouped according to common characteristics such as learning systems, preparation levels, and the pace of material assimilation. This segmentation allows for the creation of adaptive learning paths tailored to the specific needs of each group (Tzirides et al., 2024; Zhylin, 2026).

Through clustering, micro-courses and modules are created that best meet the characteristics of the learning audience. In addition, the platform implements recommendation mechanisms that take into account students' individual preferences, academic performance, and interests. This not only improves the effectiveness of material absorption but also increases motivation to learn, which is an important factor in reducing academic failure and expulsions. In particular, the system tracks students' success in real time, offering relevant resources, supplementary materials, or additional exercises. At the level of lecturers, the platform provides analytical reports that help better understand learning trends in groups, identify problem areas, and quickly adjust the teaching plan. The EDU.AZ platform is actively supported by the Ministry of Education of Azerbaijan, which provides the necessary resources for its modernisation and the implementation of new technologies into the learning process.

Jagiellonian University, one of the oldest universities in Europe, is transforming its educational process by implementing the Pegaz platform – an educational environment built on Moodle, which supports the integration of ML elements. Within this platform, tools for analysing academic progress are implemented, allowing intelligent algorithms

to personalise learning paths. The platform supports SVM algorithms, which are methods of supervised learning used to classify students by academic success and predict learning difficulties. Using these algorithms, lecturers can identify students who need additional support in a timely manner and adjust the educational process accordingly.

In addition, the PCA method is used, which allows the analysis of large educational datasets to identify key factors affecting learning effectiveness. This contributes to optimising teaching and making informed pedagogical decisions. The system also provides real-time feedback for students, giving them access to analytics and recommendations for further learning. The hybrid approach implemented on the Pegaz platform combines automated ML-based mechanisms with academic mentoring, increasing the flexibility and effectiveness of the educational process. The use of ML at Jagiellonian University is seen as one of the key vectors for the digital transformation of higher education in Poland.

Taras Shevchenko National University of Kyiv has integrated the external platform Udemy into its educational ecosystem, which provides access to a significant number of online courses across various fields of knowledge. The university uses the platform's capabilities to expand individualised educational paths, including by introducing courses containing ML elements to adapt content to user needs. One of the key features of Udemy is the use of reinforcement learning algorithms, which dynamically adjust the pace and content of learning according to the student's individual progress.

The platform collects data on students' behaviour (attendance, task completion, test results), based on which personalised advice on further learning is generated. This allows students to build their learning paths independently, and lecturers to use analytical tools to monitor learning results in real time. This approach helps to identify difficulties in material absorption early on and adjust the teaching plan in a timely manner. The hybrid model of interaction, combining automated content adaptation with lecturer oversight, increases the flexibility of the learning process, which is particularly relevant in the context of the spread of distance education. The integration of Udemy into the university's learning ecosystem is part of an autonomous strategy for the digitalisation of higher education institutions and is aligned with the requirements of national educational standards.

The comparative analysis shows that in all four countries, there is a trend towards the integration of ML into learning support systems for the purpose of personalising the educational process. However, specific approaches and technologies vary depending on the characteristics of national education systems, resources, and priorities. In Kyrgyzstan, the "Sanarip Academy" platform focuses on classification models and recommendation systems, reflecting the desire to ensure basic adaptation of content to students' levels of preparation. The emphasis is on automated monitoring and the adjustment of learning trajectories. The Azerbaijani university has introduced more advanced student segmentation through clustering algorithms, which allows for the

Table 2
Comparative analysis of ML implementation in higher education institutions

Country	University	Platform	Key ML approaches	Implementation features
Kyrgyzstan	Kyrgyz State Technical University named after I. Razzakov	Sanarip Academy	Classification, recommendation systems	Personalisation of learning paths, activity monitoring
Azerbaijan	Baku State University	EDU.AZ	Clustering, recommendation algorithms	Student segmentation by learning styles, adaptive paths
Poland	Jagiellonian University in Kraków	Pegaz (Platforma Edukacyjna Uniwersytetu Jagiellońskiego)	SVM, PCA	Predicting academic outcomes, adapting materials, progress analytics
Ukraine	Taras Shevchenko National University of Kyiv	Udemy	Reinforcement learning	Dynamic adaptation of course pace and content, analytical panels for lecturers

creation of more flexible adaptive learning paths. The use of recommendation systems to enhance motivation indicates a comprehensive approach to improving the quality of education.

The Polish university has chosen a model that uses SVM and PCA, which are classical ML methods for prediction and data analysis. This approach is focused on in-depth analysis of success factors, allowing materials to be adapted and teaching strategies to be improved. In Ukraine, the use of reinforcement learning within the Udemy platform demonstrates a modern level of technological development aimed at flexible management of learning trajectories in real time. The hybrid model combines the advantages of automated support with lecturer control.

Thus, these examples indicate the gradual complexity and expansion of ML applications in higher education, which is happening alongside the development of digital infrastructure and increasing demands for the quality of education. Given the specifics of each country, it can be concluded that there is a need for further development of integrated educational platforms with a deeper use of modern ML models, which will enhance personalisation, adaptability, and the effectiveness of learning, as well as reduce academic failure rates.

Prospects for adapting successful ML practices in the context of higher education

In the context of the global digital transformation of higher education, ML serves as a strategic tool for building effective, personalised, and flexible educational systems. For countries developing digital infrastructure, ML technologies offer the ability to automatically detect students' individual learning needs, adapt content, predict academic outcomes, create personalised learning paths, and provide timely feedback (Wu, 2024). One of the main motivations for adapting ML in higher education is the desire to increase the inclusivity of educational services and maintain the quality of learning at a stable level.

Kyrgyzstan already has initial conditions for implementing ML, such as the presence of technical universities with IT specialisation, state support for digitalisation, and the growing IT community. However, there is no integrated environment that combines behavioural data analytics, adaptive content, and support functions. Therefore, the promising first step is the creation of an LMS platform with embedded ML modules that allow for the analysis of student activity, building recommendation modules, and early detection of learning risks. With the existing digital infrastructure, this could be implemented by scaling the "Sanarip Academy" system at the national level.

Classification models are used to determine students' learning styles and motivational attitudes. This will enable the segmentation of audiences based on educational strategies and the adaptation of material depending on cognitive characteristics. An important prospective direction is the implementation of cognitive analytics modules based on NLP tools, which can analyse written responses, forums, tasks, and reflections to identify thinking patterns and areas of misunderstanding (Munir et al., 2022; Shakeeva et al., 2025). For Kyrgyzstan's multilingual educational environment, this opens up opportunities for content adaptation in Kyrgyz, Russian, and English. The potential use of ML in the career direction includes the creation of recommendation systems that, based on academic performance, skills, and student interests, form individual vector paths: course selection, internship programmes, or further education, which improves graduate employment and increases the relevance of educational programmes to regional job market needs (Vashishth et al., 2024; Kengesbayeva et al., 2025). Universities in Kyrgyzstan are following international experience by adapting ML algorithms to predict students' further development and recommend next steps in the career context.

For the successful adaptation of ML, organisational and personnel aspects must also be considered, such as ensuring the training of specialists in data science and educational analytics, creating inter-university centres for professional development, and adapting bachelor's and master's curricula. Cooperation with international universities and EdTech organisations promotes the transfer of experience and the development of local practical competencies (Romanchuk et al., 2026; Grynova & Orlov, 2025). A separate direction is the creation of a regulatory and legal framework, which poses

challenges regarding the regulation of the collection, storage, processing, and use of educational data. The experience of EU countries, which have formed confidentiality rules and ethical data usage practices, could serve as a foundation. In the context of Kyrgyzstan, it is important to develop a national strategy for the digitalisation of education, where ML models serve as a tool in line with the principles of ethics, inclusivity, and personalisation.

In Azerbaijan, the digital transformation of higher education is accompanied by the development of the EDU.AZ platform, which already uses clustering and recommendation algorithms. However, to fully utilise the potential of ML, the platform needs to be expanded by adding modules for predicting academic risks and analysing multimodal data: activity in LMS, test results, and behavioural signals. This will allow for the creation of a comprehensive early-warning and student support system. Classification algorithms complement clustering, providing tools for accurately predicting individual students' success and identifying high-risk groups. NLP modules are applied to analyse textual responses in discussions, reflections, or the EDU.AZ forum, enabling course corrections based on misunderstandings or errors in thinking. Career trajectory systems are adapted to the local context of Azerbaijan, taking into account the national job market specifics. Recommended learning paths, internships, and practice opportunities can be created for students on the platform, considering their academic successes, interests, and competencies.

To scale ML, interface solutions should be developed, such as creating an environment for data analytics, integrating data science training programmes into higher education institutions, and forming multilingual communication modules (Azerbaijani, English). The Ministry of Education can contribute by investing in EdTech programmes, supporting start-ups, and ensuring resource availability for all students in the country. In Poland, "Pegaz" already uses SVM and PCA for academic performance analysis. The future perspective lies in the integration of deep neural networks or reinforcement learning models that optimise personalised learning trajectories based on students' behavioural data in real time. Additionally, NLP modules can be used to analyse student work, essays, or reflections, which would allow content to be more precisely adapted to students' cognitive patterns.

Career analytics in Poland can be enhanced by integrating ML recommendation systems that take into account academic performance, skills, and market trends. Polish universities can modify this system for the local market, helping students select disciplines, internship programmes, and career paths based on analytics. Poland has the advantage of a regulatory framework, as EU legislation and Polish policy ensure transparency in working with educational data. It is important to continue integrating ML models with national educational portfolios, creating approaches for the ethical and secure use of student data, and further developing EdTech innovation centres.

In Ukraine, the Udemy platform experiments with reinforcement learning and hybrid ML models for adapting the learning process. The future perspective lies in the

deployment of systems that combine classification, clustering, NLP, and reinforcement learning. This will provide more accurate personalisation of educational content, adapting to students' learning styles and motivation. NLP can be used to analyse forums, written work, and test responses, enabling automated feedback and formative assessment (Abdygalym et al., 2025; Baimukhamedov et al., 2021). For Ukrainian students, adapting NLP language modules (Ukrainian, English) enhances language inclusivity and the quality of teaching.

Career ML solutions should be integrated with the Udemy platform, as the programme can recommend learning paths, specialisations, or internships based on academic performance, interests, and behavioural indicators. This will help graduates better navigate the job market and form more relevant educational programmes. For successful implementation, the workforce needs to be developed, specifically by introducing EdTech disciplines in universities, organising courses in data science, NLP analytics, and ML development. It is crucial to establish cooperation with foreign universities, involve international projects, and stimulate government support through educational digitalisation programmes. Ultimately, the adaptation of ML in the higher education systems of Kyrgyzstan, Azerbaijan, Poland, and Ukraine requires a systematic approach. For each country, this involves developing integrated LMS platforms with embedded ML features, implementing cognitive analytics and NLP technologies, creating career advice modules, preparing appropriate specialists, and developing regulatory frameworks. Global experience and local resources will contribute to forming educational ecosystems based on personalisation, inclusivity, ethics, and innovation.

Discussion

ML in higher education is an important tool for improving the effectiveness and personalisation of the learning process. It enables the analysis of large amounts of data on student learning activities, identifying patterns and predicting outcomes, which opens new opportunities for adapting educational content to each learner's individual needs. The foundation of ML lies in algorithms that learn from existing data and can make predictions or decisions without explicit programming for each specific case. In education, this allows for the creation of systems that automatically adjust learning materials, assess knowledge levels, predict academic failure risks, and provide recommendations that increase motivation and engagement. One of the key categories of ML in higher education is classification models. They are used to assess student data and identify at-risk groups, predict success, or determine the type of learning style that best suits a particular student. Algorithms such as decision trees, logistic regression, and SVM help lecturers intervene promptly, offer additional support, and adjust learning trajectories.

In this context, it is important to relate the results of this study to the findings of other researchers. For example, Mendonça et al. (2022) developed a decision tree-

based model that detects behavioural patterns and predicts student learning difficulties early in the educational process. Their approach confirmed the high effectiveness of ML in preventing academic failure, which aligns completely with the results of this study, which also demonstrated the relevance of using classification models in higher education programmes. The research of Azamatova et al. (2023) focused on the positive impact of AI technologies, including ML, on student motivation during the learning process. The authors emphasised the context of learning foreign languages, in which a project-based approach to education is applied, aiming at active student involvement in creating learning products. The paper noted that individualised digital tools based on ML methods stimulate student interest, increase their activity, and contribute to deeper mastery of the learning material. Thanks to the ability to adapt content to the needs of each learner, these tools create conditions for more effective learning and better academic results. Similar trends were confirmed in this study, which noted that previous studies indicate that students working with adapted ML systems tend to demonstrate higher motivation to learn, active cognitive engagement, and a more consistent drive for self-improvement. This suggests that the implementation of personalised digital technologies based on ML can effectively support the learning process, making it more engaging and productive. The results of this work confirm the global trend of integrating intelligent technologies into educational processes as an effective mechanism for improving the quality of education and student motivation.

Kilchenko (2023) examined the role of AI technologies in the scientific and pedagogical work of educational institutions, emphasising their potential to increase the effectiveness of the learning process and optimise management approaches. However, compared to this study, Kilchenko focused primarily on the general aspects of AI implementation in education, while the current research concentrated on the analysis of specific personalised learning models using deep neural networks and real-time behavioural data analysis of students, which allows for a more accurate adaptation of the educational process to individual learners' needs. Mhlongo et al. (2023) highlighted the barriers to the implementation of digital technologies in developing countries, including a lack of funding, low levels of digital literacy, and inequality of access to infrastructure. The conducted research also identified similar challenges, especially in institutions with no centralised support for digital transformation.

In contrast, Sayaf et al. (2022) concluded that the willingness of students and lecturers to actively use digital educational technologies is one of the key factors determining the overall effectiveness and impact on the learning process. The authors emphasised the need to implement targeted and systematic programmes to enhance digital competence among both students and lecturers, enabling the most effective use of innovative technologies in education. These recommendations fully align with the results of the conducted study, which showed that the successful implementation of ML in higher education directly depends on the level of human resource training, the availability of appropriate methodological support, and the active involvement of

educators in the digital transformation of the educational environment. Without such a comprehensive approach, the effectiveness of ML technologies is reduced, leading to low adaptation and insufficient utilisation of the potential of these innovations. Hence, the importance of the systematic development of digital skills and the creation of supportive infrastructure as an integral component of the digital transformation of higher education is emphasised. This finding is consistent with Liu and Weng (2023), who highlighted the crucial role of traditionally trained instructors in the digital environment and the need to enhance their digital competencies to effectively support personalised and online learning processes.

Pinto and Leite (2020) considered digital technologies as tools that contribute to the development of autonomous learning, where the student is an active agent of their own educational trajectory. The authors noted that the digital environment allows for the implementation of a constructivist approach to education. The results of the conducted study also pointed to increased student independence, with learners having the ability to choose the pace, format, and direction of their studies, which contributes to an increase in intrinsic motivation. Garlinska et al. (2023) analysed the impact of modern digital technologies on distance education and confirmed their effectiveness in supporting the learning process in remote conditions. The comparison with this study reveals a common trend, namely, that the use of ML tools, particularly NLP, helps maintain the intensity and quality of communication in virtual environments, which is especially relevant for synchronous and asynchronous learning. Complementary evidence comes from Jabučanin et al. (2025), who demonstrated positive effects of the flipped classroom method combined with mobile phone use on student engagement and learning outcomes in higher education settings.

According to a systematic review by Akintayo et al. (2024), the effectiveness of educational technologies largely depends on the context of use: social interaction, cultural, and institutional factors. Their conclusion resonates with the observations made in the conducted study. In cases where institutions provide integration of ML through policies, funding, and support for lecturers, the effect of implementation is much higher. Suryanarayana et al. (2024) confirmed the key point made by the aforementioned authors regarding the strategic significance of AI and ML technologies for ensuring the sustainable development of the education system. Specifically, the conducted research found that the application of ML technologies contributes to effective resource planning, quality control of educational processes, and provides flexibility and adaptability of educational content to changes in the external environment. In addition, it allows for the modelling of long-term development strategies at the higher education institution level. Furthermore, Imran and Almusharraf (2024), in their systematic review, discussed the concept of "Quality 4.0" in digital education, according to which learning is adaptive, automated, and student-centric. They considered ML as one of the key technologies for implementing this concept. The comparison with the results of this study supports the claim that ML indeed forms the core of educational

transformations, ensuring both the automation of assessment and content adaptation, as well as the creation of a personalised learning experience.

In conclusion, the results of this study are largely corroborated by international scholarly contributions. The identified trends demonstrate not only the technological potential of ML but also its comprehensive impact on the transformation of the educational environment. Thus, this research holds not only theoretical but also practical significance for the future development of digital education in higher education institutions.

Limitations

This study has several limitations that should be acknowledged. First, the research does not include empirical implementation or experimental validation of machine learning models, which limits the ability to assess their effectiveness quantitatively. Second, the analysis is based on secondary data sources and documented cases, which may introduce interpretation bias and limit the precision of conclusions. Third, the absence of standardised datasets and evaluation metrics restricts the comparability of findings across contexts. Finally, the study is influenced by contextual factors related to the selected countries and institutions, which may affect the generalisability of the results to other educational environments.

Conclusions

Based on the qualitative and comparative analysis, it can be concluded that the application of ML technologies in personalising the digital educational process in higher education institutions opens new opportunities for increasing the effectiveness, adaptability, and individualisation of educational activities. The qualitative results of the study confirmed that ML systems can improve learning interactions, provide timely support for students facing difficulties, and overall increase engagement in learning. The introduction of personalised models positively influenced student autonomy, the development of critical thinking, and the flexibility of teaching in the digital environment. Specifically, NLP models proved effective for analysing students' written responses, allowing for the assessment of cognitive depth in understanding the material, which is a key factor in building adaptive content. Classification algorithms, such as SVM or Naive Bayes, demonstrated the ability to predict success levels based on the analysis of students' current behaviour in the learning system, while recommendation systems helped form personalised learning paths based on previous achievements and user preferences.

The study also conducted a comparative analysis of the level of digitalisation of the learning process in higher education institutions in Kyrgyzstan, Azerbaijan, Poland, and Ukraine. The results highlighted regional differences in approaches to implementing ML technologies. In Poland and Ukraine, the focus is on the use of reinforcement learning models for the dynamic adaptation of courses and algorithms for predicting

academic outcomes using SVM, combined with analytical panels for monitoring progress. In Azerbaijan, clustering methods are predominantly used to form student groups based on learning styles and pacing, while in Kyrgyzstan, recommendation systems are used to enhance motivation and provide real-time feedback. At the same time, all the countries under review are showing positive dynamics regarding the implementation of ML solutions, particularly in the context of content adaptation, monitoring student progress, and improving learning support systems.

Thus, it can be concluded that personalising the digital learning process through ML technologies is one of the key vectors for the modernisation of higher education, ensuring quality, flexible, and adaptive interaction between the teacher and student in the digital environment. Although the implementation of these technologies requires time, resources, and a shift in educational culture, the potential return from their application is significant, especially in the context of the global digital transformation of educational systems. Further research should focus on the practical testing of ML models in different areas of education, their integration with other digital tools, and studying the long-term impact of personalisation on learning outcomes.

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Primjena tehnologija strojnoga učenja za personalizaciju digitalnoga obrazovnog procesa u visokim obrazovnim ustanovama

Sažetak

Cilj studije bio je identificirati glavne vrste modela strojnoga učenja (SU) koji pomažu prilagoditi obrazovno okružje individualnim potrebama studenata na sveučilištima. Metodologija je kombinirala sustavnu analizu pristupa poučavanju pomoću SU algoritama s komparativnom analizom digitalne transformacije visokoga obrazovanja u Kirgistanu, Azerbajdžanu, Poljskoj i Ukrajini. Analiza pristupa strojnoga učenja i rezultati komparativne analize digitalizacije ispitivanih obrazovnih ustanova otkrili su ključne mehanizme za personalizaciju procesa učenja. Usporedba praksi pokazala je da Poljska i Ukrajina preferiraju modele učenja pojačavanja i algoritme za predviđanje akademskoga uspjeha, Azerbajdžan je koristio metode klasteriranja za grupiranje studenata prema stilovima učenja, a Kirgistan je implementirao sustave preporuka za poboljšanje motivacije i povratnih informacija. Analiza ukazuje na to da implementacija ovih tehnologija ovisi o četirima ključnim čimbenicima: razini digitalne kompetencije nastavnika, dostupnosti i kvaliteti obrazovnih podataka, integraciji adaptivnih modula u platforme za učenje i postojanju državnih politika koje reguliraju upotrebu umjetne inteligencije (UI) u obrazovanju. Dodatno je utvrđeno da personalizirani SU moduli doprinose povećanju intrinzične motivacije studenata, razvoju vještina samostalnoga učenja i aktivnoj interakciji unutar grupa za učenje. Praktična vrijednost rada jest u preporukama za primjenu adaptivnih SU modula u visokim obrazovnim ustanovama u zemljama koje su predmet istraživanja, što će pomoći u poboljšanju kvalitete obrazovanja, motivacije studenata i smanjenju jaza u akademskim postignućima.

Ključne riječi: *analitika; analiza obrazovnoga ponašanja; motivacija; platforme; socijalna interakcija; umjetna inteligencija*

Uvod

Digitalni svijet zahtijeva transformaciju sustava visokoga obrazovanja, s fokusom na personalizaciju obrazovnoga procesa koji uzima u obzir individualne potrebe,

osobine i sposobnosti svakog studenta. Tehnologije strojnoga učenja (SU) otvaraju nove perspektive za prilagodbu sadržaja, metoda i brzine učenja, doprinoseći povećanoj motivaciji, kritičkom razmišljanju i neovisnosti učenika. Međutim, postoji fragmentacija u primjeni SU-a, nedostatak ujednačenih personaliziranih modela učenja u visokim obrazovnim ustanovama i nedostatak empirijskih istraživanja prilagođenih lokalnom kontekstu. Postojeći digitalni pristupi ostaju standardizirani i ne uzimaju u obzir individualne stilove učenja, kognitivne osobine i motivacijske čimbenike studenata. Kao što navode Klašnja-Milićević i Ivanović (2021), personalizirani sustavi e-učenja ključni su za izgradnju održivoga obrazovnog okružja, u kojem umjetna inteligencija (UI) djeluje kao posrednik između studenta i obrazovne platforme.

Akademska zajednica aktivno istražuje potencijal SU-a u visokom obrazovanju. Hashim i sur. (2022) proveli su sustavni pregled studija povezanih s personaliziranim učenjem koje koristi AI i SU, potvrdivši stalan trend integracije tih tehnologija u formate kombiniranoga i učenja na daljinu. Značajna pozornost posvećuje se fleksibilnosti algoritama i njihovoj sposobnosti samoučenja. U studiji autora Chena i sur. (2024) pokazano je da modeli SU-a poboljšavaju učinkovitost obrazovnih sustava za preporuke, optimizirajući odabir nastavnih materijala prema profilu učenja studenta. Simulacijski pristup personalizaciji, kako su zaključili Taylor i sur. (2024), pružio je točniji model ponašanja studenata u digitalnom okružju i omogućio predviđanje dinamike njihova napretka u učenju. Ovo stajalište podržali su Gallastegui i Forradellas (2024), koji su naglasili ulogu prediktivnih modela umjetne inteligencije u poboljšanju akademskoga iskustva studenata i prilagodbi procesa učenja njihovim stvarnim potrebama. Osim toga, nedavne studije velikoga utjecaja u tome području naglasile su važnost referentnih skupova podataka, validacije modela i metrika performansi pri procjeni primjena strojnoga učenja u obrazovanju, ističući potrebu za metodološkom rigoroznošću u tumačenju rezultata.

U studiji autora Huanga (2025) otkriven je potencijal personaliziranih platformi za učenje temeljenih na umjetnoj inteligenciji koje pružaju dubinsku analitiku korisničkoga ponašanja, čime se povećava njihova razina angažmana. Autor je naglasio važnost jednostavnosti sučelja takvih sustava i sposobnost SU algoritama da se brzo prilagode tijekom obrazovnih interakcija. Dodatno, Yildirim i Celepcikay (2021) usredotočili su se na praktičnu primjenu SU-a u kontekstu automatizirane povratne informacije, omogućujući studentima da u stvarnome vremenu dobiju individualizirane savjete i preporuke. U kontekstu ukrajinske obrazovne stvarnosti vrijedi spomenuti studiju Kovalchuk i sur. (2025), koja je izvijestila o učinkovitosti korištenja VŠ-a u personaliziranom učenju i istaknula potrebu za institucionalnom podrškom za digitalnu transformaciju obrazovnoga okružja. Alenezi (2023) je naglasio ulogu digitalnih obrazovnih ustanova kao novoga formata za organizaciju procesa učenja pri čemu tehnologije SU-a igraju stratešku ulogu u prilagodbi sadržaja i upravljanju obrazovnim okružjem.

Unatoč znatnom broju znanstvenih studija o umjetnoj inteligenciji i strojnom učenju, postoje praznine u primjeni strojnoga učenja za personalizaciju obrazovnoga procesa

u visokom obrazovanju. Većina istraživanja usredotočila se na tehničke aspekte, kao što su točnost algoritma, arhitektura i performanse. Međutim, pedagoški, menadžerski i organizacijski aspekti integracije tih tehnologija u visokoškolske ustanove ostaju nedovoljno istraženi. Transformacija interakcije između nastavnika, studenata i digitalnoga obrazovnog okružja pod utjecajem rješenja temeljenih na strojnom učenju i dalje je relevantno pitanje. Štoviše, ne postoje jedinstveni modeli implementacije strojnoga učenja koji uzimaju u obzir interdisciplinarnu prirodu visokoga obrazovanja. Još je nedovoljno istražen problem utjecaja kulturnih, institucionalnih i resursnih konteksta pojedinih zemalja na učinkovitost digitalne transformacije. Ti čimbenici ograničavaju skalabilnost i prilagodljivost rješenja temeljenih na strojnome učenju u različitim obrazovnim okružjima, što naglašava potrebu za daljnjim istraživanjima koja uzimaju u obzir lokalne specifičnosti.

Svrha istraživanja bila je utvrditi mogućnosti i prednosti primjene tehnologija strojnoga učenja za personalizaciju digitalnoga obrazovnog procesa u visokim učilištima. Članak iznosi tri ključna zadatka istraživanja: identificirati glavne pristupe primjeni tehnologija SU za personalizaciju obrazovnoga procesa i procijeniti njihovu učinkovitost, provesti komparativnu analizu primjene tih tehnologija u visokoškolskim ustanovama u Kirgistanu, Azerbajdžanu, Poljskoj i Ukrajini te utvrditi perspektive razvoja i formulirati preporuke za prilagodbu SU-a svakoj od proučavanih zemalja. Novost ove studije jest u njezinoj komparativnoj sintezi pristupa uporabi SU-a u različitim obrazovnim sustavima, s naglaskom na kontekstualne, organizacijske i pedagoške dimenzije, a ne na tehničke performanse modela.

Metodologija

Studija je provedena od siječnja 2024. do lipnja 2025. kao dio ispitivanja procesa digitalne transformacije u visokome obrazovanju u Kirgistanu, Azerbajdžanu, Poljskoj i Ukrajini. Prva faza studije uključivala je sažimanje uobičajenih SU modela koji se koriste u digitalnome obrazovanju, uključujući kolaborativno filtriranje, modele klasifikacije, učenje s pojačanjem, klasteriranje (K-means) i obradu prirodnoga jezika (OPJ). U ovoj fazi ispitivan je njihov potencijal za predviđanje akademskih ishoda, otkrivanje skrivenih obrazaca u obrazovanju i optimizaciju putanja učenja na temelju korisničkih podataka. Dodatno je procijenjena učinkovitost ovih modela u pružanju personaliziranih preporuka i analizi odnosa između ponašajnih pokazatelja i uspjeha, što je postavilo temelje za daljnja testiranja na sveučilišnim platformama.

Ova studija primjenjuje kvalitativno-komparativni istraživački dizajn temeljen na sustavnoj analizi literature i komparaciji slučajeva među navedenim zemljama. Nijedan primarni model strojnoga učenja nije implementiran niti empirijski testiran. Umjesto toga, studija se usredotočuje na analizu dokumentiranih primjena tehnologija strojnoga učenja na platformama visokoga obrazovanja te na utvrđivanje njihovih funkcionalnih uloga, konteksta implementacije i zabilježenih ishoda. Izvori podataka uključuju recenzirane akademske publikacije, institucionalna izvješća i javno dostupne

opise obrazovnih platformi. Analitički pristup kombinira komparativnu analizu i utemeljenu teoriju kako bi se protumačili obrasci integracije SU-a i formulirale konceptualne preporuke.

Druga faza uključivala je komparativnu analizu digitalnih platformi i obrazovnih ekosustava na vodećim visokim obrazovnim ustanovama u četirima zemljama. U Kirgistanu su se algoritmi za klasifikaciju i analitika ponašanja proučavali na platformi „Sanarip Academy», koju koristi Kirgistanski državni tehnički sveučilište nazvano po I. Razzakovu, za prilagodbu nastavnih materijala potrebama studenata. U Azerbajdžanu su se sustavi preporuka i metode grupiranja studenata istraživali na platformi „EDU.AZ» na Državnom sveučilištu u Bakuu, koji pomažu u oblikovanju personaliziranih obrazovnih putova prema individualnim stilovima i tempu učenja. Poljsko iskustvo bilo je usmjereno na platformu Pegaz na Jagelonskom sveučilištu, koja se temelji na Moodleu, pri čemu se modeli stroja s potporom vektora (SPV) koriste za klasifikaciju uspješnosti, a analiza glavnih komponenti (AGK) za identificiranje ključnih čimbenika koji utječu na učinkovitost učenja, pružajući nastavnicima analitičke alate za prilagodbu obrazovnoga procesa. U Ukrajini je istražena integracija algoritama za učenje pojačanja u suradnji s platformom Udemy na Nacionalnom sveučilištu Tarasa Ševčenka u Kijevu, uključujući dinamičke mehanizme prilagodbe tempa i sadržaja tečaja, analitičke panele za praćenje uspjeha studenata i sustave za rano otkrivanje studenata s lošijim uspjehom.

U završnoj fazi istraživanja korišten je pristup utemeljene teorije za iznošenje perspektiva i formuliranje preporuka o proširenju učinkovitih pristupa SU-u u visokim obrazovnim ustanovama u Kirgistanu, Azerbajdžanu, Poljskoj i Ukrajini. Ova je faza bila temeljena na prethodnoj komparativnoj analizi obrazovnih platformi i SU rješenja korištenih u svakoj zemlji, uzimajući u obzir kontekst nacionalnih digitalnih politika, infrastrukture, ljudskih resursa i pravnih uvjeta.

Rezultati

SU u personalizaciji procesa učenja

U kontekstu digitalne transformacije visokoga obrazovanja, personalizacija dobiva nove razmjere jer integracija SU tehnologija otvara mogućnosti za dubinsku analizu obrazovnoga ponašanja studenata. Prikupljanjem i obradom podataka o interakcijama s platformama za učenje, evaluacijama i vremenskim nizovima aktivnosti, SU sustavi mogu identificirati i opće trendove i individualne obrasce usvajanja gradiva. Sustavi podržani SU-om prilagođavaju redoslijed tema, odabiru dodatne vježbe za utvrđivanje znanja i automatski prilagođavaju težinu zadataka u stvarnom vremenu (Chen i sur., 2025; Hevko i sur., 2021). Dodatno, mehanizmi kontinuirane povratne informacije pomažu nastavnicima da brzo reagiraju na poteškoće, ojačaju socijalnu interakciju i potaknu razvoj ključnih kompetencija, čime se proces učenja čini učinkovitijim i usmjerenijim na cilj (Imran i sur., 2024). U nastavku se nalazi sažeta Tablica 1 s ključnim metodama i njihovim funkcionalnim svrhama.

Tablica 1
Ključne SU metode za personalizaciju obrazovnoga procesa i njihove funkcionalne svrhe

Pristup	Opis	Svrha primjene
Kolaborativno filtriranje	Preporuke temeljene na bihevioralnoj sličnosti	Odabir relevantnoga sadržaja
Klasifikacijski modeli	Klasifikacija stilova učenja i identifikacija rizičnih skupina	Predviđanje akademskoga uspjeha
Učenje potkrepljenjem	Prilagodba obrazovnih putanja putem povratnih informacija	Dinamička optimizacija procesa učenja
Grupiranje / klasteriranje (K-means)	Grupiranje studenata prema obilježjima	Formiranje adaptivnih skupina za učenje
Obrada prirodnoga jezika (OPJ)	Analiza tekstualnih odgovora i rasprava	Identifikacija kognitivnih obrazaca i područja nerazumijevanja

Izvor: kreirali autori na temelju Cui i sur. (2024), Forero-Corba i Bennasar (2024), Haleem i sur. (2022), Qureshi i sur. (2021).

Nakon implementacije SU metoda na platformama visokoga obrazovanja pojavljuju se znakovi transformacije u obrazovnome procesu. Na primjer, upotreba kolaborativnoga filtriranja omogućuje generiranje preporuka temeljenih na ponašanju studenata i njihovim individualnim interesima. Analizom povijesti pregledanih nastavnih materijala, posjećenih predavanja, dovršenih vježbi i ocjena, sustav formira personaliziranu zbirku resursa za svakog korisnika (Ibrahim i sur., 2025). To pomaže povećati angažman studenata jer dobivaju materijale koji najbolje odgovaraju njihovim trenutačnim potrebama i stilu učenja, što zauzvrat poboljšava motivaciju za daljnje učenje i smanjuje vjerojatnost gubitka interesa za kolegij.

Umjesto toga, integracija klasifikacijskih modela, kao što su SPV ili stabla odluka, omogućuje brzo identificiranje studenata koji su u akademskom riziku (Yang i Zhang, 2025; Dodonova i Dodonov, 2022). Koristeći podatke iz međusemestralnih ispita, aktivnosti u sustavu i sudjelovanja u raspravama, algoritmi za klasifikaciju mogu predvidjeti vjerojatnost neuspješnoga završetka kolegija ili niskih ocjena. Ove informacije služe kao signal predavačima i mentorima da poduzmu ciljane intervencije, kao što su ponuditi dodatne konzultacije, slati savjete za učenje ili organizirati grupe za podršku. Kao rezultat toga, predavači prilagođavaju planove nastave i šalju individualne poruke s dodatnim resursima, čime se značajno poboljšava ukupna stopa uspješnosti kolegija. Treći je pristup učenje na temelju pojačanja, koje se primjenjuje za stvaranje dinamičkih obrazovnih putova koji se prilagođavaju reakcijama studenata na prethodne zadatke. Sustav koji radi na principima učenja na temelju pojačanja analizira uspjehe ili pogreške korisnika, određuje optimalni slijed sljedećih tema ili vježbi i provodi te prilagodbe. Ovaj pristup omogućuje modeliranje individualnoga tempa usvajanja gradiva i prilagodbu težine zadataka u stvarnom vremenu, što dovodi do svjesnijega i dubljega ovladavanja predmetom (Song i dr., 2024.). Slični pristupi klasifikaciji temeljeni na ansamblima, uključujući XGBoost i AdaBoost optimizirane metaheurističkim

metodama, pokazali su visoku učinkovitost u predviđanju i razumijevanju odustajanja studenata, omogućujući pravovremene intervencije (Spalević i sur., 2025).

Četvrta skupina modela, klasteriranje, pomaže podijeliti studente u podskupine na temelju karakteristika učenja, kao što su brzina obrade informacija, stil komunikacije ili razina prethodne pripreme (Kanchon i sur., 2024.; Diachuk, 2024). Korištenjem algoritama poput K-Means ili prostorne klasterizacije aplikacija temeljene na gustoći s šumom mogu se stvoriti grupe za učenje sa sličnim potrebama, nudeći im specijalizirane module podrške ili dodatne materijale. SU omogućuje realizaciju personaliziranog pristupa u masovnom obrazovanju, gdje bi njegova implementacija bez odgovarajućih tehnoloških rješenja bila organizacijski kompliciranа. Konačno, tehnologije OPJ-a transformiraju tradicionalne pristupe procjeni pisanih radova i analizi aktivnosti u raspravama na internetskim forumima, pružajući automatiziranu interpretaciju sadržaja, utvrđivanje valjanosti izjava i prepoznavanje ključnih tematskih elemenata (Chen, 2025). Korištenjem modela, obrazovne platforme počinju automatski analizirati strukturu argumenata, logičke veze, dubinu razumijevanja i emocionalni ton tekstova. To predavačima omogućuje da dobiju analitička izvješća o napretku svakog studenta, s naglaskom na formalne parametre kao što su prisutnost ključnih pojmova i kvaliteta razmišljanja i argumentacije. Studenti dobivaju pravovremena, individualizirana savjetovanja o poboljšanju stila pisanja, strukturiranju misli i formuliranju zaključaka.

Integracija svih ovih metoda stvara jedinstveni multifunkcionalni ekosustav personalizacije koji pokriva cijeli ciklus učenja, od utvrđivanja potreba do prilagodbe nastavnih strategija u stvarnome vremenu (Shaikh i sur., 2022; Musakulov i sur., 2025). Takva rješenja smanjuju jaz između učenika s različitim akademskim postignućima, čine proces učenja pristupačnijim i fleksibilnijim te pomažu izjednačiti početne prilike. Međutim, za uspješnu implementaciju personalizacije temeljene na strojnom učenju ključno je prvo uspostaviti sustave za prikupljanje i obradu podataka. To uključuje standardizaciju struktura podataka na različitim platformama, integraciju više izvora (sustavi za upravljanje učenjem (SUU), testovi, aktivnost *chata*) i osiguravanje reprezentativnosti uzoraka kako bi analitički modeli primali neiskrivljene signale (Aslam i sur., 2025; Dahan i sur., 2025). Visokokvalitetni proces obrade podataka uključuje validaciju, normalizaciju i popunjavanje praznina jer su sve te faze ključne za točnost predviđanja i preporuka. Stoga obrazovne ustanove moraju ulagati u inženjere i analitičare podataka koji provode procese izvlačenja, transformacije i učitavanja, kao i u alate za praćenje kvalitete podataka u stvarnome vremenu. Samo se na taj način može zajamčiti da algoritmi rade na temelju potpunih i pouzdanih podataka, a ne iskrivljenih ili nepotpunih skupova. Ovaj pristup osigurava visok stupanj povjerenja u SU sustave i studenata i predavača te prirodno povećava učinkovitost personalizacije obrazovnoga procesa.

Također je važno osigurati transparentnost algoritama primjenom pristupa objašnjivoj umjetnoj inteligenciji. I predavači i studenti moraju imati pristup razumljivim objašnjenjima načina na koji se oblikuju preporuke i procjene algoritamskih sustava

jer se time doprinosi izgradnji povjerenja u te sustave i smanjuje rizik od algoritamskih pristranosti (Ayeni i sur., 2024; Bessarab i sur., 2022). Objašnjavanje interne logike modela omogućuje nastavnicima kontrolu procesa donošenja odluka, pravovremeno otkrivanje potencijalnih netočnosti i utjecaj na postavke parametara, čime se smanjuje vjerojatnost diskriminacije studenata na temelju čimbenika koji nisu povezani s njihovim akademskim postignućima. Ključni element strategije jest osposobljavanje kvalificiranoga osoblja za područja znanosti o podatcima, pedagoške analitike i razvoja SU rješenja (Timotheou i sur., 2023). Visoko obrazovanje mora integrirati kolegije iz SU-a, programiranja, statističke analize i etike podataka u svoje preddiplomske i diplomske programe kako bi diplomanti mogli razvijati, implementirati i prilagođavati algoritamske sustave u obrazovnome okružju (Riznyk i Riznyk, 2024; Matviienko, 2025). Istovremeno bi se trebali organizirati međusveučilišni tečajevi obuke i stručnoga usavršavanja za postojeće predavače i administratore jer je njihovo razumijevanje mogućnosti i ograničenja SU sustava ključno za njihovu učinkovitu upotrebu.

Također je potrebno uzeti u obzir etičke i pravne aspekte obrade osobnih obrazovnih podataka. Svaki sustav SU-a mora biti u skladu s međunarodnim standardima zaštite podataka i nacionalnim zakonodavstvom koje uređuje prikupljanje, pohranu i uporabu podataka o studentima. To uključuje dobivanje informiranoga pristanka za uporabu podataka, osiguravanje povjerljivosti i provedbu tehničkih i organizacijskih mjera za sprječavanje neovlaštenoga pristupa ili neovlaštenoga otkrivanja podataka, pri čemu etički okviri za obradu podataka moraju biti jasno definirani u politikama sveučilišta i redovito se preispitivati uz sudjelovanje predstavnika studenata i nastavnoga osoblja.

Analiza digitalne transformacije visokoga obrazovanja na primjeru sveučilišta u Kirgistanu, Azerbajdžanu, Poljskoj i Ukrajini

Kirgijsko državno tehničko sveučilište nazvano po I. Razzakovu vodeća je tehnička ustanova u zemlji koja provodi inovativne digitalne tehnologije u obrazovanju. Jedna od ključnih inicijativa sveučilišta jest korištenje platforme „Sanarip Academy», čiji je cilj poboljšati kvalitetu obrazovanja personalizacijom procesa učenja pomoću SU algoritama. Ova platforma integrira algoritme za klasifikaciju kako bi se utvrdila individualna razina znanja i kompetencija studenata. To omogućuje razdvajanje studenata prema kategorijama težine gradiva koje mogu svladati i formiranje optimalnih individualnih obrazovnih putova. Također se koriste sustavi preporuka koji uzimaju u obzir dinamiku napretka i aktivnost korisnika. Platforma osigurava kontinuirano praćenje akademske aktivnosti, uključujući sudjelovanje na predavanjima, izradu praktičnih zadataka i međusemestralne provjere znanja. Na temelju tih podataka sadržaj za učenje automatski se prilagođava, čime se održava odgovarajuća razine težine i motivacije.

Osim tehničke komponente, važna je i integracija sustava s administrativnim procesima sveučilišta, što predavačima omogućuje primanje analitičkih izvještaja o uspjehu

studenata u stvarnome vremenu, brzo reagiranje na poteškoće i nuđenje potrebnih prilagodbi nastavnim planovima. Ključan je čimbenik i državna potpora digitalizaciji obrazovanja u Kirgistanu, koja se očituje u relevantnim vladinim inicijativama i financiranju modernizacije obrazovnih platformi. Univerzitetski sustav „Sanarip Academy» primjer je sveobuhvatnoga pristupa koji kombinira SU s tradicionalnom metodologijom poučavanja i usmjeren je na prilagodbu potrebama širokoga spektra studenata, uključujući i one s individualnim obrazovnim potrebama.

Državno sveučilište u Bakuu jedno je od vodećih sveučilišta u Azerbajdžanu, koje aktivno integrira digitalne tehnologije u obrazovni proces. Na sveučilištu je implementirana platforma „EDU.AZ», koja kombinira klasične metode poučavanja s modernim SU algoritmima. Glavna značajka platforme je upotreba algoritama klasteriranja, koji omogućuju grupiranje studenata prema zajedničkim značajkama kao što su sustavi učenja, razine pripreme i brzina usvajanja gradiva. Ta segmentacija omogućuje stvaranje adaptivnih obrazovnih putova prilagođenih specifičnim potrebama svake grupe (Tzirides i sur., 2024.; Zhylin, 2026).

Klasteriranjem se stvaraju mikrotečajevi i moduli koji najbolje odgovaraju karakteristikama ciljne skupine. Osim toga, platforma primjenjuje mehanizme preporuka koji uzimaju u obzir individualne preferencije, akademski uspjeh i interese studenata. To ne samo da poboljšava učinkovitost usvajanja gradiva, već i povećava motivaciju za učenje, što je važan čimbenik u smanjenju akademskoga neuspjeha i isključenja. Sustav posebno prati uspjeh studenata u stvarnome vremenu, nudeći relevantne resurse, dodatne materijale ili dodatne vježbe. Predavačima platforma pruža analitička izvješća koja pomažu u boljem razumijevanju trendova učenja u grupama, identificiranju problematičnih područja i brzom prilagođavanju nastavnoga plana. Platformu EDU.AZ aktivno podržava Ministarstvo obrazovanja Azerbajdžana koje osigurava potrebne resurse za njezinu modernizaciju i implementaciju novih tehnologija u proces učenja.

Jagelonsko sveučilište, jedno od najstarijih sveučilišta u Europi, transformira svoj obrazovni proces implementacijom platforme Pegaz – obrazovnoga okružja utemeljenoga na Moodleu, koje podržava integraciju elemenata strojnoga učenja. Unutar ove platforme implementirani su alati za analizu akademskoga napretka, što inteligentnim algoritmima omogućuje personalizaciju obrazovnih putova. Platforma podržava SPV algoritme, metode nadziranoga učenja koje se koriste za klasifikaciju studenata prema akademskom uspjehu i predviđanje poteškoća u učenju. Pomoću tih algoritama nastavnici mogu pravovremeno identificirati studente kojima je potrebna dodatna podrška i u skladu s tim prilagoditi obrazovni proces.

Osim toga, koristi se AGK metoda, koja omogućuje analizu velikih skupova obrazovnih podataka kako bi se identificirali ključni čimbenici koji utječu na učinkovitost učenja. To doprinosi optimizaciji nastave i donošenju informiranih pedagoških odluka. Sustav također studentima pruža povratne informacije u stvarnome vremenu, dajući im pristup analitici i preporukama za daljnje učenje. Hibridni pristup implementiran na platformi Pegaz kombinira automatizirane mehanizme temeljene na SU-u s akademskim

mentorstvom, povećavajući fleksibilnost i učinkovitost obrazovnoga procesa. Upotreba SU-a na Jagelonskom sveučilištu smatra se jednim od ključnih čimbenika za digitalnu transformaciju visokoga obrazovanja u Poljskoj.

Kijevsko nacionalno sveučilište Tarasa Ševčenka integriralo je vanjsku platformu Udemy u svoje digitalno obrazovno okružje čime je studentima omogućen pristup velikom broju internetskih tečajeva iz različitih područja znanja. Sveučilište koristi mogućnosti platforme za proširenje individualiziranih obrazovnih putova, uključujući uvođenje tečajeva koji sadrže elemente strojnoga učenja kako bi se sadržaj prilagodio potrebama korisnika. Jedna od ključnih značajki Udemyja jest upotreba algoritama umjetne inteligencije, koji dinamički prilagođavaju tempo i sadržaj učenja prema individualnom napretku studenta.

Platforma prikuplja podatke o ponašanju studenata (prisutnost, dovršetak zadataka, rezultati testova), na temelju kojih se generiraju personalizirani savjeti za daljnje učenje. To studentima omogućuje da samostalno grade svoje obrazovne putove, a predavačima da koriste analitičke alate za praćenje rezultata učenja u stvarnome vremenu. Ovaj pristup pomaže u ranome prepoznavanju poteškoća u usvajanju gradiva i pravovremenom prilagodbi nastavnoga plana. Hibridni model interakcije, koji kombinira automatiziranu prilagodbu sadržaja s nadzorom predavača, povećava fleksibilnost procesa učenja, što je posebno relevantno u kontekstu širenja učenja na daljinu. Integracija platforme Udemy u sveučilišno digitalno obrazovno okružje dio je autonomne strategije za digitalizaciju visokih obrazovnih ustanova i usklađena je sa zahtjevima nacionalnih obrazovnih standarda.

Tablica 2

Komparativna analiza primjene strojnoga učenja u visokoškolskim ustanovama

Zemlja	Sveučilište	Platforma	Ključni pristupi strojnoga učenja	Značajke implementacije
Kirgistan	Kirgisko državno tehničko sveučilište nazvano po I. Razzakovu	Sanarip Academy	Klasifikacija, sustavi preporuka	Personalizacija, razvojni putovi učenja, praćenje aktivnosti
Azerbajdžan	Državno sveučilište u Bakuu	EDU.AZ	Klasteriranje, algoritmi preporuka	Segmentacija studenata prema stilovima učenja, prilagodljive obrazovne putanje
Poljska	Jagelonsko sveučilište u Krakovu	Pegaz (Obrazovna platforma Jagelonskoga sveučilišta)	SPV, AGK	Predviđanje akademskih ishoda, prilagodba materijala, analitika napretka
Ukrajina	Nacionalno sveučilište Tarasa Ševčenka u Kijevu	Udemy	Učenje potkrepljenjem	Dinamična prilagodba tempa i sadržaja kolegija, analitičke nadzorne ploče za nastavnike

Izvor: izradili autori.

Usporedna analiza pokazuje da u svim četirima zemljama postoji trend integracije SU-a u sustave podrške učenju s ciljem personalizacije obrazovnoga procesa. Međutim, specifični pristupi i tehnologije razlikuju se ovisno o karakteristikama nacionalnih obrazovnih sustava, resursa i prioriteta. U Kirgistanu se platforma „Sanarip Academy» usredotočuje na modele klasifikacije i sustave preporuka, omogućujući osnovnu prilagodbu sadržaja individualnim razinama znanja i napretka studenata. Naglasak je na automatiziranom praćenju i prilagodbi razvojnih putova učenja. Azerbejdžansko sveučilište uvelo je napredniju segmentaciju studenata pomoću algoritama klasteriranja, što omogućuje stvaranje fleksibilnijih adaptivnih putova učenja. Korištenje sustava preporuka za poboljšanje motivacije ukazuje na sveobuhvatan pristup poboljšanju kvalitete obrazovanja.

Poljsko je sveučilište odabralo model koji koristi SPV i AGK, što su klasične SU metode za predviđanje i analizu podataka. Ovaj je pristup usmjeren na dubinsku analizu čimbenika uspjeha, što omogućuje prilagodbu i poboljšanje nastavnoga materijala i strategija. U Ukrajini upotreba učenja s pojačanjem unutar platforme Udemy pokazuje suvremenu razinu tehnološkoga razvoja usmjerenu na fleksibilno upravljanje individualnim tijekom učenja u stvarnome vremenu. Hibridni model kombinira prednosti automatizirane podrške uz kontrolu predavača.

Stoga ovi primjeri ukazuju na postupnu složenost i širenje primjene strojnoga učenja u visokom obrazovanju, što se događa paralelno s razvojem digitalne infrastrukture i rastućim zahtjevima za kvalitetu obrazovanja. S obzirom na specifičnosti svake zemlje, može se zaključiti da postoji potreba za daljnjim razvojem integriranih obrazovnih platformi s dubljom primjenom modernih modela strojnoga učenja, što će poboljšati personalizaciju, prilagodljivost i učinkovitost učenja, kao i smanjiti stopu akademskoga neuspjeha.

Perspektive prilagodbe uspješnih SU praksi u kontekstu visokoga obrazovanja

U kontekstu globalne digitalne transformacije visokoga obrazovanja, SU služi kao strateški alat za izgradnju učinkovitih, personaliziranih i fleksibilnih obrazovnih sustava. Za zemlje koje razvijaju digitalnu infrastrukturu, SU tehnologije nude mogućnost automatskoga otkrivanja individualnih obrazovnih potreba studenata, prilagodbe sadržaja, predviđanja akademskih ishoda, stvaranja personaliziranih obrazovnih putova i pružanja pravovremenih povratnih informacija (Wu, 2024). Jedna od glavnih motivacija za primjenu SU-a u visokome obrazovanju jest želja za povećanjem uključivosti obrazovnih usluga i održavanjem kvalitete učenja na stabilnoj razini.

Kirgistan već ima početne uvjete za implementaciju SU-a, kao što su postojanje tehničkih sveučilišta s IT specijalizacijom, državna potpora digitalizaciji i rastuća IT zajednica. Međutim, ne postoji integrirano okružje koje kombinira analitiku ponašajnih podataka, adaptivni sadržaj i funkcije podrške. Stoga je obećavajući prvi korak stvaranje SU platforme s ugrađenim SU modulima koji omogućuju analizu

aktivnosti studenata, izradu modula za preporuke i rano otkrivanje rizika u učenju. Pomoću postojeće digitalne infrastrukture to bi se moglo provesti skaliranjem sustava „Sanarip Academy» na nacionalnoj razini.

Modeli klasifikacije koriste se za određivanje stilova učenja i motivacijskih stavova studenata. Time se omogućuje prepoznavanje različitih skupina studenata prema obrazovnim potrebama te prilagodba nastavnoga materijala njihovim kognitivnim karakteristikama. Jedan od perspektivnih smjerova razvoja jest implementacija modula kognitivne analitike temeljenih na alatima OPJ-a, koji mogu analizirati pisane odgovore, forume, zadatke i refleksije kako bi se identificirali obrasci razmišljanja i područja nesporazuma (Munir i sur., 2022; Shakeeva i sur., 2025). Za višejezično obrazovno okružje Kirgistana, ovo otvara mogućnosti za prilagodbu sadržaja na kirgijskome, ruskome i engleskome jeziku. Potencijalna primjena SU-a u karijernom usmjerenju uključuje stvaranje sustava preporuka koji, na temelju akademskih postignuća, vještina i interesa studenata, oblikovanje individualnih tijekova čenja: odabir kolegija, programe stručne prakse ili daljnje obrazovanje, što poboljšava zapošljivost diplomiranih studenata i povećava relevantnost obrazovnih programa za potrebe regionalnoga tržišta rada (Vashishth i sur., 2024; Kengesbayeva i sur., 2025). Sveučilišta u Kirgistanu slijede međunarodno iskustvo prilagođavajući SU algoritme za predviđanje daljnjega razvoja studenata i preporuku sljedećih koraka u kontekstu karijere.

Za uspješnu prilagodbu SU-a potrebno je uzeti u obzir i organizacijske i kadrovske aspekte, kao što su: osiguravanje obuke stručnjaka iz područja znanosti o podatcima i obrazovne analitike, stvaranje međusveučilišnih centara za stručno usavršavanje i prilagodba kurikula preddiplomskih i diplomskih studija. Suradnja s međunarodnim sveučilištima i EdTech organizacijama potiče prijenos iskustva i razvoj lokalnih praktičnih kompetencija (Romanchuk i sur., 2026; Grynova i Orlov, 2025). Zaseban smjer je stvaranje regulatornoga i pravnoga okvira, što predstavlja izazove u pogledu regulacije prikupljanja, pohrane, obrade i korištenja obrazovnih podataka. Iskustvo zemalja EU-a, koje su uspostavile pravila o povjerljivosti i etičke prakse korištenja podataka, moglo bi poslužiti kao temelj. U kontekstu Kirgistana važno je razviti nacionalnu strategiju za digitalizaciju obrazovanja, u kojoj modeli strojnoga učenja služe kao alat u skladu s načelima etike, inkluzivnosti i personalizacije.

U Azerbejdžanu digitalnu transformaciju visokoga obrazovanja prati razvoj platforme EDU.AZ, koja već koristi algoritme klasteriranja i preporuka. Međutim, kako bi se u potpunosti iskoristio potencijal SU-a, platformu je potrebno proširiti dodavanjem modula za predviđanje akademskih rizika i analizu multimodalnih podataka: aktivnosti u SU-u, rezultata testova i obrasce ponašanja. To će omogućiti stvaranje sveobuhvatnoga sustava za rano upozoravanje i podršku studentima. Algoritmi klasifikacije nadopunjuju klasteriranje, pružajući alate za precizno predviđanje uspjeha pojedinih studenata i identificiranje skupina s visokim rizikom. OPJ moduli primjenjuju se za analizu tekstualnih odgovora u raspravama, refleksijama ili na forumu EDU.AZ, omogućujući korekciju gradiva na temelju nesporazuma ili pogrešaka u razmišljanju. Sustavi za

razvoj karijere prilagođeni su lokalnom kontekstu Azerbejdžana, uzimajući u obzir specifičnosti nacionalnoga tržišta rada. Na platformi se za studente mogu stvoriti preporučene obrazovne putove, stažiranja i prilike za praksu, uzimajući u obzir njihove akademske uspjehe, interese i kompetencije.

Za skaliranje SU-a trebalo bi razviti rješenja za sučelje, kao što su stvaranje okružja za analitiku podataka, integracija programa obuke iz znanosti o podatcima u visoke obrazovne ustanove i formiranje višejezičnih komunikacijskih modula (azerijski, engleski). Ministarstvo obrazovanja može doprinijeti ulaganjem u EdTech programe, podržavanjem *start-up* poduzeća i osiguravanjem dostupnosti resursa za sve studente u zemlji. U Poljskoj „Pegaz» već koristi SPV i AGK za analizu akademskoga uspjeha. Budući smjer razvoja uključuje primjenu dubokih neuronskih mreža ili modela učenja radi optimizacije personaliziranih obrazovnih procesa na temelju podataka o ponašanju studenata u stvarnome vremenu. Dodatno, OPJ moduli mogu se koristiti za analizu studentskih radova, eseja ili refleksija, što bi omogućilo preciznije prilagođavanje sadržaja kognitivnim obrascima studenata.

Analiza razvoja karijere u Poljskoj može se unaprijediti primjenom SU sustava za preporuke koji uzimaju u obzir akademski uspjeh, vještine i tržišne trendove. Poljske sveučilišne ustanove mogu prilagoditi ovaj sustav za lokalno tržište, pomažući studentima u odabiru disciplina, programa stažiranja i karijernih putova na temelju provedenih analiza. Poljska ima prednost regulatornoga okvira, budući da zakonodavstvo EU-a i poljska politika osiguravaju transparentnost u radu s obrazovnim podatcima. Važno je nastaviti integrirati modele SU-a s nacionalnim obrazovnim portfeljima, stvarati pristupe za etičku i sigurnu upotrebu podataka o studentima te dalje razvijati centre za inovacije u obrazovnoj tehnologiji (EdTech).

U Ukrajini platforma Udemy eksperimentira s učenjem s pojačanjem i hibridnim SU modelima za prilagodbu procesa učenja. Budućnost leži u primjeni sustava koji kombiniraju klasifikaciju, klasteriranje, OPJ i učenje s pojačanjem. To će omogućiti precizniju personalizaciju obrazovnoga sadržaja, prilagođavajući ga stilovima učenja i motivaciji učenika. OPJ se može koristiti za analizu foruma, pisanih radova i odgovora na testovima, što omogućuje automatsku povratnu informaciju i formativnu procjenu (Abdygalym i sur., 2025; Baimukhamedov i sur., 2021). Za ukrajinske studente prilagodba OPJ jezičnih modula (ukrajinski, engleski) poboljšava jezičnu uključivost i kvalitetu poučavanja.

SU rješenja za razvoj karijere trebala bi se integrirati s platformom Udemy, jer program može preporučiti putove učenja, specijalizacije ili stažiranje na temelju akademskih postignuća, interesa i pokazatelja obrazaca ponašanja. To će pomoći diplomantima da se bolje snalaze na tržištu rada i oblikuju relevantnije obrazovne programe. Za uspješnu implementaciju potrebno je razviti radnu snagu, posebice uvođenjem EdTech disciplina na sveučilišta, organiziranjem tečajeva iz znanosti o podatcima, OPJ i razvoja SU-a. Ključno je uspostaviti suradnju sa stranim sveučilištima, uključiti se u međunarodne projekte i potaknuti vladinu potporu putem programa digitalizacije obrazovanja.

U konačnici, prilagodba SU-a u visokoškolskim sustavima Kirgistana, Azerbajdžana, Poljske i Ukrajine zahtijeva sustavan pristup. Za svaku zemlju to uključuje razvoj integriranih SU platformi s ugrađenim značajkama SU-a, implementaciju kognitivne analitike i OPJ tehnologija, stvaranje modula za savjetovanje o karijeri, pripremu odgovarajućih stručnjaka i razvoj regulatornih okvira. Korištenje globalnoga iskustva i lokalnih resursa doprinijet će stvaranju digitalnih obrazovnih okružja temeljenih na personalizaciji, inkluzivnosti, etici i inovacijama.

Diskusija

SU u visokom obrazovanju važan je alat za poboljšanje učinkovitosti i personalizacije procesa učenja. Omogućuje analizu velikoga broja podataka o studentskim aktivnostima učenja, prepoznavanje obrazaca i predviđanje ishoda, što otvara nove mogućnosti za prilagodbu obrazovnoga sadržaja individualnim potrebama svakog učenika. Temelj SU-a jest u algoritmima koji uče iz postojećih podataka i mogu donositi predviđanja ili odluke bez eksplicitnoga programiranja za svaki pojedini slučaj. U obrazovanju to omogućuje stvaranje sustava koji automatski prilagođavaju nastavne materijale, procjenjuju razinu znanja, predviđaju rizik od akademskoga neuspjeha i pružaju preporuke koje povećavaju motivaciju i angažman. Jedna od ključnih kategorija SU-a u visokome obrazovanju su modeli klasifikacije. Oni se koriste za analizu podataka o studentima i prepoznavanje studenata kojima je potrebna dodatna podrška, predviđanje akademskoga uspjeha ili određivanje najprikladnijih obrazovnih pristupa za pojedinoga studenta. Algoritmi poput stabala odluka, logističke regresije i SPV pomažu predavačima pravodobno prepoznavanja potreba studenata, pružanje dodatne podrške i prilagodbu individualnih tijekova učenja.

U tom je kontekstu važno povezati rezultate ove studije s nalazima drugih istraživača. Na primjer, Mendonça i sur. (2022) razvili su model temeljen na stablima odluka koji otkriva obrasce ponašanja i predviđa poteškoće u učenju među studenatima u ranoj fazi obrazovnoga procesa. Njihov pristup potvrdio je visoku učinkovitost SU-a u sprječavanju akademskoga neuspjeha, što se u potpunosti podudara s rezultatima ove studije, koja je također pokazala relevantnost korištenja klasifikacijskih modela u programima visokoga obrazovanja. Istraživanje Azamatove i sur. (2023) usredotočilo se na pozitivan utjecaj tehnologija umjetne inteligencije, uključujući SU, na motivaciju studenata tijekom procesa učenja. Autori su naglasili kontekst učenja stranih jezika, u kojem se primjenjuje projektno orijentirani pristup obrazovanju, usmjeren na aktivno sudjelovanje studenata u stvaranju nastavnih proizvoda. U radu se navodi da individualizirani digitalni alati temeljeni na metodama SU-a potiču interes studenata, povećavaju njihovu aktivnost i doprinose dubljem svladavanju nastavnoga gradiva. Zahvaljujući mogućnosti prilagodbe sadržaja potrebama svakog pojedinog učenika, ovi alati stvaraju uvjete za učinkovitije učenje i bolje akademske rezultate. Slični trendovi potvrđeni su u ovoj studiji, u kojoj je navedeno da prethodna istraživanja pokazuju kako studenti koji rade s prilagođenim SU sustavima pokazuju veću motivaciju za učenje,

aktivno kognitivno angažiranje i izraženiju usmjerenost na vlastiti napredak u učenju. To sugerira da implementacija personaliziranih digitalnih tehnologija temeljenih na SU-u može učinkovito podržati proces učenja, čineći ga zanimljivijim i produktivnijim. Rezultati ovoga rada potvrđuju globalni trend integriranja inteligentnih tehnologija u obrazovne procese kao učinkovit mehanizam za poboljšanje kvalitete obrazovanja i motivacije studenata.

Autor Kilchenko (2023) istraživao je ulogu tehnologija umjetne inteligencije u znanstvenome i pedagoškome radu obrazovnih ustanova, naglašavajući njihov potencijal za povećanje učinkovitosti procesa učenja i optimizaciju pristupa upravljanju. Međutim, u usporedbi s ovom studijom, Kilchenko se prvenstveno usredotočio na opće aspekte primjene umjetne inteligencije u obrazovanju, dok je ovo istraživanje usmjereno na analizu specifičnih personaliziranih modela učenja koji koriste duboke neuronske mreže i analizu podataka o ponašanju studenata u stvarnome vremenu, što omogućuje precizniju prilagodbu obrazovnoga procesa potrebama pojedinačnih studenata. Mhlongo i sur. (2023) istaknuli su prepreke u primjeni digitalnih tehnologija u zemljama u razvoju, uključujući nedostatak financiranja, nisku razinu digitalne pismenosti i nejednakost u pristupu infrastrukturi. Provedeno istraživanje također je identificiralo slične izazove, osobito u institucijama u kojima ne postoji centralizirana podrška za digitalnu transformaciju.

Nasuprot tome, Sayaf i sur. (2022) zaključili su da je spremnost studenata i predavača na aktivno korištenje digitalnih obrazovnih tehnologija jedan od ključnih čimbenika koji su odredili ukupnu učinkovitost i utjecaj na proces učenja. Autori su naglasili potrebu za provedbom ciljanih i sustavnih programa za jačanje digitalnih kompetencija i studenata i predavača, čime se omogućuje najučinkovitije korištenje inovativnih tehnologija u obrazovanju. Ove preporuke u potpunosti su u skladu s rezultatima provedenoga istraživanja kojim se pokazalo da uspješna primjena SU-a u visokome obrazovanju izravno ovisi o razini osposobljavanja ljudskih resursa, dostupnosti odgovarajuće podrške u primjeni nastavnih strategija i tehnologija te aktivnom sudjelovanju nastavnika u digitalnoj transformaciji obrazovnoga okružja. Bez takvoga sveobuhvatnog pristupa, učinkovitost SU tehnologija je smanjena, što dovodi do niske prilagodbe i nedovoljne iskorištenosti potencijala tih inovacija. Stoga se naglašava važnost sustavnoga razvoja digitalnih vještina i stvaranja poticajne infrastrukture kao sastavnoga dijela digitalne transformacije visokoga obrazovanja. Ovaj je nalaz u skladu s Liuom i Wengom (2023), koji su istaknuli ključnu ulogu nastavnika obrazovanih u tradicionalnom sustavu ,a koji djeluju u digitalnome okružju te potrebu za jačanjem njihovih digitalnih kompetencija kako bi učinkovito podržali personalizirane i mrežne procese učenja.

Pinto i Leite (2020) smatraju digitalne tehnologije alatima koji doprinose razvoju autonomnoga učenja, pri čemu je student aktivan sudionik vlastitoga tijeka učenja. Autori navode da digitalno okružje omogućuje primjenu konstruktivističkoga pristupa obrazovanju. Rezultati provedene studije također ukazuju na povećanu neovisnost

studenata, pri čemu studenti imaju mogućnost odabrati tempo, format i smjer svojega studija, što doprinosi povećanju intrinzične motivacije. Garlinska i sur. (2023) analizirale su utjecaj modernih digitalnih tehnologija na nastavu na daljinu i potvrdile njihovu učinkovitost u podršci procesu učenja u uvjetima rada na daljinu. Usporedba s provedenom studijom otkriva zajednički trend, naime da upotreba SU alata, posebice OPJ-a, pomaže održati intenzitet i kvalitetu komunikacije u virtualnim okružjima, što je posebno relevantno za sinkrono i asinkrono učenje. Dopunski dokazi potječu od Jabučanin i sur. (2025), koji su pokazali pozitivne učinke metode obrnute učionice u kombinaciji s upotrebom mobilnih telefona na angažman studenata i ishode učenja u visokome obrazovanju.

Prema sustavnome pregledu Akintaya i sur. (2024), učinkovitost obrazovnih tehnologija uvelike ovisi o kontekstu uporabe, društvenoj interakciji, kulturnim i institucionalnim čimbenicima. Njihov zaključak odražava zapažanja iz provedene studije. U slučajevima kada institucije osiguravaju integraciju umjetne inteligencije putem politika, financiranja i podrške predavačima, učinak implementacije je znatno veći. Suryanarayana i sur. (2024) potvrdili su ključnu tvrdnju prethodno navedenih autora o strateškom značaju tehnologija UI-a i SU-a za osiguravanje održivoga razvoja obrazovnoga sustava. Konkretno, provedeno istraživanje pokazalo je da primjena tehnologija SU-a doprinosi učinkovitom planiranju resursa, kontroli kvalitete obrazovnih procesa te pruža fleksibilnost i prilagodljivost obrazovnoga sadržaja promjenama u vanjskom okružju. Osim toga, omogućuje modeliranje dugoročnih razvojnih strategija na razini visokih obrazovnih ustanova. Nadalje, Imran i Almusharraf (2024.) u svojoj sustavnoj analizi raspravljali su o konceptu „Kvaliteta 4.0» u digitalnom obrazovanju, prema kojem je učenje prilagodljivo, automatizirano i usmjereno na studenta. Smatrali su SU jednom od ključnih tehnologija za provedbu toga koncepta. Usporedba s provedenim rezultatima omogućuje tvrdnju da SU doista čini srž obrazovnih transformacija, osiguravajući i automatizaciju procjene i prilagodbu sadržaja, kao i stvaranje personaliziranoga iskustva učenja.

Zaključno, rezultati provedene studije uvelike su potvrđeni međunarodnim znanstvenim doprinosima. Identificirani trendovi ne pokazuju samo tehnološki potencijal SU-a, već i njegov sveobuhvatan utjecaj na transformaciju obrazovnoga okružja. Stoga ovo istraživanje ima ne samo teorijsku, već i praktičnu važnost za budući razvoj digitalnoga obrazovanja u visokim obrazovnim ustanovama.

Ograničenja

Ova studija ima nekoliko ograničenja koja treba uzeti u obzir. Prvo, istraživanje ne uključuje empirijsku implementaciju ili eksperimentalnu validaciju modela strojnoga učenja, što ograničava mogućnost kvantitativne procjene njihove učinkovitosti. Drugo, analiza se temelji na sekundarnim izvorima podataka i dokumentiranim slučajevima, što može dovesti do pristranosti u tumačenju i ograničiti preciznost zaključaka. Treće, nedostatak standardiziranih podatkovnih skupova i mjerila vrednovanja ograničava

usporedivost nalaza u različitim kontekstima. Na kraju, na studiju utječu kontekstualni čimbenici povezani s odabranim zemljama i institucijama, što može utjecati na općenitost rezultata u drugim obrazovnim okružjima.

Zaključak

Na temelju provedenih kvalitativnih i komparativnih analiza može se zaključiti da primjena SU tehnologija u personalizaciji digitalnoga obrazovnog procesa u visokim obrazovnim ustanovama otvara nove mogućnosti za povećanje učinkovitosti, prilagodljivosti i individualizacije obrazovnih aktivnosti. Kvantitativni rezultati studije potvrdili su da SU sustavi mogu poboljšati interakcije u učenju, pružiti pravovremenu podršku studentima koji imaju poteškoća i općenito povećati angažman u učenju. Uvođenje personaliziranih modela pozitivno je utjecalo na studentsku autonomiju, razvoj kritičkoga razmišljanja i fleksibilnost nastave u digitalnome okružju. Konkretno, OPJ modeli pokazali su se učinkovitima u analizi pisanih odgovora studenata čime se omogućuje procjena kognitivne dubine u razumijevanju gradiva, ključnoga čimbenika u oblikovanju adaptivnoga sadržaja. Algoritmi za klasifikaciju, kao što su SPV ili Naive Bayes, pokazali su sposobnost predviđanja razine uspjeha na temelju analize trenutačnoga ponašanja studenata u sustavu za učenje, dok su sustavi preporuka pomogli u oblikovanju personaliziranoga tijeka učenja na temelju prethodnih postignuća i preferencija korisnika.

U studiji je također prikazana komparativna analiza razine digitalizacije procesa učenja na visokim obrazovnim ustanovama u Kirgistanu, Azerbajdžanu, Poljskoj i Ukrajini. Rezultati su istaknuli regionalne razlike u pristupima implementaciji SU tehnologija. U Poljskoj i Ukrajini glavni je fokus na korištenju modela učenja s pojačanjem za dinamičku prilagodbu tečajeva i algoritama za predviđanje akademskih ishoda pomoću SPV-a, u kombinaciji s analitičkim panelima za praćenje napretka. U Azerbajdžanu se pretežno koriste metode klasteriranja za formiranje grupa studenata na temelju stilova učenja i tempa, dok se u Kirgistanu koriste sustavi preporuka za poboljšanje motivacije i pružanje povratnih informacija u stvarnome vremenu. Istovremeno, sve zemlje koje su obuhvaćene ovim istraživanjem pokazuju pozitivnu dinamiku u pogledu implementacije rješenja temeljenih na strojnom učenju, posebice u kontekstu prilagodbe sadržaja, praćenja napretka studenata i poboljšanja sustava podrške u učenju.

Stoga se može zaključiti da je personalizacija procesa digitalnoga učenja putem tehnologija strojnoga učenja jedan od ključnih čimbenika u modernizaciji visokoga obrazovanja, osiguravajući kvalitetnu, fleksibilnu i adaptivnu interakciju između nastavnika i studenta u digitalnome okružju. Iako primjena ovih tehnologija zahtijeva vrijeme, resurse i promjenu obrazovne kulture, potencijalna korist od njihove primjene značajna je, osobito u kontekstu globalne digitalne transformacije obrazovnih sustava. Daljnja istraživanja trebala bi se usredotočiti na praktično testiranje modela SU-a u različitim područjima obrazovanja, njihovu integraciju s drugim digitalnim alatima i proučavanje dugoročnoga utjecaja personalizacije na ishode učenja.