Personalizing the learning process through data mining in higher education

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Abstract

Relevance. The rapid evolution of the modern labor market necessitates a shift from traditional, standardized career counseling to personalized educational trajectories that account for individual qualities, skills, and preferences, ensuring better professional adaptability and satisfaction.

Purpose. The purpose of the study is to develop and validate a model that will facilitate the selection of a person-centred educational and professional pathway for students.

Methodology. The research methods are comparative, qualitative, and statistical analysis, experimental method, modelling, and prototyping.

Results. The main result of the study was the creation and successful application of an original learning model integrated with modern analytical approaches, including predictive analysis mechanisms for adapting and optimizing individual educational trajectories, which significantly improved the efficiency of the learning process. Experimental implementation showed that students who used the developed model to create their individual educational trajectories achieved a significant improvement in their academic performance and motivation to learn compared to the control group. The hypothesis that personalized guidance influences the choice of more appropriate curricula and courses was confirmed, which in turn has a positive effect on academic performance and satisfaction with learning. The presence of positive feedback from students and teachers also indicates the high adaptability of the model and its potential for scaling up and further implementation in educational practice.

Conclusions. The study validated the positive impact of a personalized approach on students' academic motivation and performance, revealing significant advantages in engagement, strategic career planning, and long-term purposefulness, while also highlighting the need for further research to scale the model, optimize prediction algorithms, and adapt the approach to diverse learning environments and educational standards.

Keywords: adaptive education; statistical modelling; educational modelling; learning technologies; educational motivation; forecasting methodologies; qualification development.

Introduction

The relevance of this topic is due to the rapid development of artificial intelligence technologies, which are thoroughly transforming the educational sphere, opening new opportunities for educational institutions and students to individualize learning processes. Changes in the global economy and employment, accelerated by technological innovation, require a new approach to education capable of providing flexibility, personalization, and continuity in the learning process. In an era of digital transformation of

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work processes, there is a need for professionals with relevant skills, the ability to learn quickly and adapt to constant change.

Modern advances in artificial intelligence open new horizons in the development of educational content and teaching methodologies. Artificial intelligence has the ability to analyse large amounts of data, which allows it to adapt to the individual characteristics of each learner. The application of artificial intelligence in learning involves not only automating processes, but also creating a unique educational experience for each student. Artificial intelligence systems are capable of determining a student’s knowledge level, learning preferences, style, and speed of learning new information [1].

Based on this information, artificial intelligence can shape a personalized learning path by selecting or creating materials that best suit the student. This may include personalized assignments, adaptive tests to check knowledge, and recommendations for learning additional topics and resources comparable to the student’s interests. In this way, a deep customization of content and teaching methods is realized according to each student’s individual development profile. Given the recent advances in artificial intelligence and its broad prospects, it is crucial to create educational systems that effectively implement and optimally utilize these technologies to enhance the intellectual and creative potential of learners. In addition to facilitating traditional forms of learning, intelligent technologies can also greatly enhance the effectiveness of distance and hybrid education. The integration of artificial intelligence tools into online platforms can facilitate the development of personalized educational materials and online courses that actively adapt to the learning dynamics of everyone. In this way, universal access to quality education becomes a reality, opening opportunities for people from different regions and social backgrounds for continuous professional and personal growth.

Researchers I. Assylzhan et al. [2] considered the creation of an artificial intelligence system to analyse the level of personality development and professional readiness of university students. Given the results of surveys based on Paul J. Mayer’s “The Balance Wheel”, they assessed students’ attitudes to key life spheres and the educational process. By applying machine learning techniques, in particular linear regression, support vector machine and random forest, the team developed a system to predict career readiness of graduates with accuracy. The research of the authors S. Dolhopolov et al. [3] focuses on the creation of a method of applying artificial intelligence to determine the professional preferences of university applicants.

The architecture of a directly propagating full neural network (FNN) is used. Developed in Python using Keras, Numpy and Pandas libraries, the software is aimed at improving career guidance and helps to improve students’ academic performance, motivation, and career development by providing more accurate individual information. The article by E. Ospankulov et al. [4] deals with digital personalization in studying of students. They describe models of digital transformation of education and stages of transition from analogue to digital culture in educational organizations. The authors present a digital platform for creating individualized learning trajectories by students. The study confirmed the effectiveness of the platform and the high digital literacy of the staff to facilitate progressive change in the university.

The study by B.K. Shayakhmetova et al. [5] aims to study the impact of Big Data on higher education. The study of big data and mathematical modelling reveals patterns that contribute to the improvement and development of educational systems. The results of the study confirm the importance of Big Data for optimizing educational processes and the progress of all participants in the educational process. The authors suggest using Big Data analysis for more accurate and effective management decision-making in educational institutions, which will allow creating personalized educational programmes. The study by A. Makhambetova et al. [6] highlights the use of personalized learning strategy to improve academic performance and motivation of students. The project developed personalized learning techniques to better meet the needs of each student. Survey results indicate the obsolescence of standard methods and the need to personalize learning. However, there is a problem in that the effective implementation of personalized learning requires significant adaptation of educational modules to the individual characteristics of each student, which is a challenging task for universities.

The study by O. Tapalova and N. Zhienbayeva [7] evaluates the contribution of artificial intelligence to the creation of adaptive educational systems. Proposing the integration of social networks, chatbots, expert systems, intelligent assistants and machine learning, the authors consider the advantages of such solutions: accessibility of learning at any time, training in virtual environments, personalization of content, timely feedback, and stimulation of learning progress. The study also addresses the social and ethical aspects associated with the use of artificial intelligence and focuses on its importance in the digitalization of education. The study by R. Zhilmagambetova et al. [8] focuses on the use of adaptive personalized systems to manage the learning process in blended learning environments. Students appreciate the ability to return to materials multiple times and to explore information in different formats. However, there is a lack of personalization in learning materials and the learning process, which limits the effectiveness of knowledge assimilation. The paper proposes a solution in the form of adaptive personalized learning, which allows customization of content, assignments, and methods to meet the individual needs and learning styles of students. The authors emphasize the role of Moodle in customizing educational content according to students’ needs to enhance learning.

While recognizing the significance of tailoring educational structures to the unique characteristics and needs of students, there is a perceived gap in research regarding the impact of individual educational trajectories on predisposition to certain professions. The purpose of this study is to develop and validate a model of a personalized approach to the educational process that considers the characteristics of students’ personal profile, thus ensuring a higher level of their academic motivation and performance. Facilitating strategic career planning for students using analytical tools to predict professional development.
Materials and Methods
To evaluate the effectiveness of the developed prediction model, an experimental study was conducted. Within the framework of this study, an experimental design was applied, which included the implementation of the model for the formation of individual educational paths of students and the consequent comparison of the results with the results obtained when using traditional approaches in the educational process. Modelling and prototyping were used in the context of model development. Primary data was collected through questionnaire surveys that provided unique information regarding the general demographics and personal characteristics of the participants. In addition, standardized psychometric tests were used to explore in-depth personality traits such as emotional intelligence, self-reflective ability, and stress tolerance levels. The academic success of the students was assessed by analysing their academic performance. The referrals from the teachers reflected the real assessment of students’ applied skills and competences.

To develop a personalized learning model, a training sample was assembled, which included 160 students from the Faculty of Information Technologies of one of the Kazakh National University named after Al-Farabi, Karaganda State University and Abai Kazakh National Pedagogical University. The purpose of this phase of the study was to collect comprehensive data on each of the participants to understand their characteristics and preferences in the learning process. The pilot implementation of the new model involved 2-3 year undergraduate students, 80 students from each of the universities, totalling 150 participants. This sample size is large enough to produce statistically significant data, yet manageable enough to allow for individualized questioning and testing. Participants were selected based on the following criteria: full course load, no academic debt, stable internet access, and consent to participate in the study.

For the present study, it was important to create a representative and independent sample of students so that the results of the experiment would be valid and could be generalized. As part of the pilot testing of the new personalized learning model, students were selected from the same university departments whose data had already been used in the development. This choice is due to the desire to ensure full harmonization of the educational context of the experiment with the preliminary training sample, while maintaining the independence of the original and tested data sets. The training sample was generated through stratified random sampling, with each of the three universities serving as a separate stratum. Students from each university were randomly selected based on a predetermined proportion of the total number of students in the faculties.

The number of students from each university for the sample was determined using a proportional approach to ensure equal representation of students from different institutions. The training sample is used to train the model, so it is usually larger so that the model can ‘see’ as many examples as possible and correctly extract patterns from the data. The experimental sample, in turn, is used to test the effectiveness of the model on data that was not used during training to assess how the model would perform in real-world settings.

A software configuration in a 1C system, where all information related to learning activities and personal characteristics of students was efficiently recorded and stored, and custom-built Python scripts were used to collect data as part of the development of the personalized learning model. Python was also used to apply statistical and machine learning techniques to identify patterns, determine correlations and build predictive models. Scripts created included libraries such as pandas for data processing, NumPy for numerical operations, scikit-learn for building and testing machine learning algorithms, and Matplotlib or Seaborn for data visualization.

Results
Formation of students’ profiles
The study collected and analysed a comprehensive dataset including information on students’ vocational interests, learning process, practical activities and characteristics related to vocational skills. The information collected through 1C configuration was used for qualitative analysis. The collected data were organized and systematized to form student profiles. The student profile is compiled based on comprehensive information that includes not only brief personal data such as name, age and educational level. The next set of data concerns academic performance, including information about major courses, academic achievement, and learning interests. Academic performance is assessed according to several criteria, but in the database, they are represented by unified numerical grades – a grade point average that is compiled on the basis of points for each course studied. Each student’s profile includes data on participation in practical classes, projects, laboratory work and is marked with a simple “yes” or “no”.

The student’s field of study is recorded, where instead of a full description, a code is used that unambiguously corresponds to a specific speciality in the institution. These binary values allow the identification of students who demonstrate active practical activity outside theoretical courses. Students’ interests and career aspirations are labelled through a choice system from the options offered. This made it possible to make assumptions about possible academic and professional trajectories based on their personal career aspirations.

Particular attention is paid to the student’s extracurricular activities and hobbies, allowing to trace the breadth of the student’s views and preferences, as hobbies and interests often indicate hidden talents and skills that may also be important in the professional sphere. The profile includes data on belonging to student communities, participation in clubs and projects, where each participation is marked as “yes” or “no”. Individual skills and attributes form an important part of the data, including vocational test scores, level of communication skills and students’ self-assessment of their abilities. Communication skills and teamwork abilities are rated by students on a scale that provides insight into social competencies important in both academic and professional endeavours. The profile also includes information on foreign language proficiency, not in general terms, but with specific language skills, giving us a visualization of the student’s readiness for international communication. Technical
skills, such as programming, are also assessed binary, demonstrating the presence or absence of specific skills. The level of critical thinking is assessed on a scale and is an indicator of the student's ability to approach problem-solving and information processing analytically, which is key to academic growth and professional development.

In the process of forming student profiles, special attention is paid to the measurement of motivation, which is realized through the assessment scale. It makes it possible to assess not only the level of students' inner drive, but also their readiness for an active learning process. Motivation plays a key role in the success of students' academic performance, as it is the driving force that supports students on the way to achieve learning goals [9]. In addition, each student's profile includes information about their individual learning style (Table 1).

Learning style is a characteristic of individual preferences in approaches to learning new information, completing tasks, and interacting with educational materials. This aspect is represented in the profile by a code that indicates a certain type of learning preference, such as visual, auditory, kinaesthetic, and the extent of the gaps. Anomalous and outlier values were detected through visualization methods and statistical analysis and processed accordingly. To ensure a fair contribution of each variable in the model training process, numerical data were scaled. The Chi-square test was applied to detect and assess relationships between different characteristics and satisfaction with education or profession. This ensures that only features with a real, statistically confirmed impact on the outcome of interest are included in the machine learning model, avoiding the use of features that may be uninformative or excessively correlated. Methods were applied to select the most important features that may influence satisfaction with education and the chosen profession.

During the study, a predictive model was developed and tested to personalize the educational process of students based on the analysis of their personality traits and academic performance. The model uses a combination of statistical and machine-learning algorithms to identify relationships between students' individual characteristics and their satisfaction with education and profession. Python programming language tools, including specialized libraries for data manipulation (pandas), statistical analysis (SciPy), machine learning (scikit-learn), and visualization of results (Matplotlib and Seaborn) served as the basis for data processing and analysis. Scripts for interaction with 1C database were developed to optimize the process of information export and integration of the model into the information system of the educational institution.

Statistical analysis using the Chi-square criterion is carried out without dividing the data into samples, since its purpose is to investigate the frequencies of various characteristics in the sample as a whole and to determine their relationship with satisfaction with education and profession. This process precedes machine learning and serves as an initial assessment of the significance of the features. As a result of this tool, a set of weights for each characteristic is generated, which allows the most significant factors to be identified. Additionally, the use of Fisher's criterion is envisaged to improve the accuracy of statistical analysis. To develop the machine-learning model, data from the 1C system were selected and formatted, which were then divided into two samples: training and test. The proportional division of the data ensured that the model was trained on the main patterns of the dataset (70%) and its accuracy tested on an independent test set (30%). Training the model on the training sample involved tuning the optimal hyperparameters through grid search and cross-validation, thereby ensuring the accuracy and robustness of the model. The performance of the model was evaluated based on metrics such as accuracy and others applied to the results on the test sample.

The predictive model includes machine learning algorithms that not only evaluate the importance of each attribute for predicting student satisfaction, but also provide a predictive model with accuracy evaluation. Random Forest in conjunction with other machine learning algorithms was used to achieve integrity of representation in the model on personalization of educational process. In addition to it, the Gradient Boosting algorithm could be applied, which consistently improves the models by focusing on areas where previous models made errors and thereby improving the overall accuracy. The machine

### Table 1. Comprehensive dataset

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Data type</th>
<th>Characteristic category</th>
</tr>
</thead>
<tbody>
<tr>
<td>Identifier (ID)</td>
<td>Integer</td>
<td>Identification</td>
</tr>
<tr>
<td>Name</td>
<td>Line of text</td>
<td>Personal data</td>
</tr>
<tr>
<td>Age</td>
<td>Integer (16 to 65)</td>
<td>Personal data</td>
</tr>
<tr>
<td>Grade Point Average (GPA)</td>
<td>Real number (usually from 0 to 100)</td>
<td>Academic progress</td>
</tr>
<tr>
<td>Participation in practical classes</td>
<td>Binary value “Yes/No”</td>
<td>Academic activities</td>
</tr>
<tr>
<td>Direction of study</td>
<td>Code</td>
<td>Academic specialization</td>
</tr>
<tr>
<td>Professional interests and aspirations</td>
<td>Code</td>
<td>Career aspirations</td>
</tr>
<tr>
<td>Extracurricular activities and hobbies</td>
<td>Binary value “Yes/No”</td>
<td>Social activity</td>
</tr>
<tr>
<td>Communication skills</td>
<td>Rating on a scale (1-5)</td>
<td>Skills and competencies</td>
</tr>
<tr>
<td>Teamwork ability</td>
<td>Rating on a scale (1-5)</td>
<td>Skills and competencies</td>
</tr>
<tr>
<td>Foreign language skills</td>
<td>Set of numeric values</td>
<td>Language skills</td>
</tr>
<tr>
<td>Technical skills</td>
<td>Binary value “Yes/No”</td>
<td>Professional skills</td>
</tr>
<tr>
<td>Level of critical thinking</td>
<td>Rating on a scale (1-5)</td>
<td>Cognitive abilities</td>
</tr>
<tr>
<td>Motivation</td>
<td>Rating on a scale (1-5)</td>
<td>Personal qualities</td>
</tr>
<tr>
<td>Learning style</td>
<td>Code</td>
<td>“V” for visual, “A” for auditory, “K” for kinaesthetic</td>
</tr>
</tbody>
</table>

Data cleaning and preparation

The Chi-square test requires the data to be categorical and free of missing values [10]. During the preprocessing, it was necessary to encode all quantitative data into categorical ones. First and foremost, a search and correction of errors in the data were carried out, such as incomplete records, incorrect formats, and missing values. Using 1C software and Python scripts, we identified missing values and incorrect entries. Missing data were either restored or removed, depending on their significance and the extent of the gaps. Anomalous and outlier values were detected through visualization methods and statistical analysis and processed accordingly. To ensure a fair contribution of each variable in the model training process, numerical data were scaled. The Chi-square test was applied to detect and assess relationships between different characteristics and satisfaction with education or profession. This ensures that only features with a real, statistically confirmed impact on the outcome of interest are included in the machine learning model, avoiding the use of features that may be uninformative or excessively correlated. Methods were applied to select the most important features that may influence satisfaction with education and the chosen profession.

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The learning model was trained on a separate benchmark dataset to ensure unbiased results. After the training process was completed, the machine-learning model was evaluated based on its performance on the test sample. The model achieved an accuracy of 85%, indicating that in 85 cases out of 100 the model correctly predicted students’ satisfaction with their educational path or profession. In addition, the F1-measure was 0.82, indicating a good balance between precision and recall. The area under the error curve (AUC) showed a value of 0.90, confirming the high ability of the model to discriminate between classes. These metrics indicate the high predictive ability of the model.

The final product of the research is a system able to analyse the current characteristics of students and provide recommendations regarding the most suitable educational trajectories and professions, considering their personal characteristics and preferences. The model also provides guidance on how to improve certain skills for successful development in the chosen fields, thus contributing to the personal and career development of everyone.

Integration of the model with the 1C system allows automatically generating individual reports for each student, which facilitates the process of counselling and determining the direction of further studies. One report focuses on identifying the most appropriate educational trajectories and professions according to their unique characteristics and preferences. The second report focuses on a list of skills that need to be developed to succeed in their chosen fields. The guidance received supports each student’s personal and career development. This required the output data to be accurately formatted so that the 1C system could interpret it correctly and use it to generate reports, recommendations, and educational trajectories. This will contribute to a more informed choice of educational programme and career path, and in the long term – to an increase in the overall level of satisfaction with the educational environment and professional activity.

**Pilot implementation of the model**

During the experimental implementation of the developed model the work with two groups of students was carried out, where in the experimental group individualized recommendations of the system were used to select educational and professional trajectories. In the control group, students continued to study according to the standard programme without the intervention of the model. By the end of the experiment, a significant increase in the level of motivation and increased satisfaction with the chosen educational pathway was noted among the students in the experimental group using the survey (Figure 1).

Many students expressed positive feedback on how the guidance provided by the model helped them to better understand their strengths and identify potential career paths, confirming the effectiveness of the model in increasing students’ confidence in their academic and professional choices. In contrast, in the control group, although there was some improvement in educational achievement, there was no significant increase in motivation and satisfaction with learning. The increase in motivation and satisfaction in the control group, despite the lack of intervention of the personalized model, may be due to a general improvement in the educational environment or psychological factors such as moral support and engagement, as well as the students’ natural self-development and adaptation to the demands of the educational programme. In addition, the realization that they were involved in the study may have had a stimulating effect on the students because of the desire to look successful in the eyes of the researchers or to compete with the experimental group. The students remained at their initial levels of confidence in choosing a career path.

Many students indicated that the system’s suggestions played a critical role in their self-esteem and self-understanding and helped them gain a clearer understanding of their strengths and identify areas for professional development (Figure 2). Students expressed that personalized guidance made it easier for them to identify what academic and professional areas they had a natural ability and interest in, which in turn allowed them to think more intentionally about their career paths. This was reflected in increased interest in certain subjects, improved performance in those areas recommended by the system as most relevant to their skills and interests, and increased participation in academic and extracurricular activities, especially those that contribute to the development of key qualities and skills necessary in the future profession. However, students in the control group, who did not have access to personalized advice, did not overall see significant improvements in their understanding of personal academic strengths and career interests (Figure 2). Most continued to follow the standard curriculum and did not show a significant increase in engagement or interest in certain disciplines. This indicated the lack of additional incentive or specific focus that the personalized recommendation system provided, and highlighted the difference in perceptions of their educational and professional development between the two groups of students.

![Figure 1. Chart of changes in motivation and satisfaction](image-url)

**Figure 2. Awareness of one’s strengths and professional interests**

Statistics showed that the differences between the two groups in terms of motivation and satisfaction were...
significant. Students in the experimental group showed better results in these aspects compared to the control group, which suggests a positive impact of the system’s personalized recommendations on the educational process and the growth of students’ self-determination. These findings indicate the potential for integrating the model into educational settings to further improve tailoring of learning to students’ individual needs.

Discussion

A detailed analysis of the results of the experiment provides important insights in the context of current research in educational pedagogy. The synergy between students’ individual educational trajectories and career goals becomes evident when they are provided with tools to identify their strengths and preferences, thus enhancing their academic motivation and professional self-awareness. Numerous earlier studies in this area also show successes.

In their work, A. Alam and A. Mohanty [11] explore the possibilities of using educational data analysis techniques, machine learning and learning analytics to predict students’ academic performance. The main objective of the study is to develop detailed guidelines for teachers seeking to apply the methods of these techniques to predict students’ academic performance. The authors analysed relevant research papers and formed a systematic approach to explain the choice of parameters and methodology. A comparison of this work with the present study shows a general interest in personalizing education and using data to improve learning outcomes. However, while the study by the researchers concentrated on predicting academic performance and teacher instructional methodology, the present project aims to directly improve student learning by developing a personalized educational model.

A study by H. Pallathadka et al. [12] evaluates the impact of artificial intelligence in the educational field by predicting student performance. The authors consider machine learning as a key component of artificial intelligence and its ability to classify existing data to predict outcomes. The developed model for student performance evaluation utilizes three machine learning algorithms: support vector method (SVM), Random Forest and regression analysis. The experimental results of the study demonstrated that the SVM algorithm is the most effective in predicting student performance. The study has similarities with the present study in the aspect of using analytical approaches to personalize the educational process and improve academic performance, but focuses on direct prediction of grades, whereas the present study focuses on students’ personality profile and career development.

In an article by researchers O. Saidani et al. [13], the authors proposed a method to predict students’ employability based on their internship data using gradient boosting algorithms such as XGBoost, CatBoost and LGBM. The results showed that internship information provides the best basis for predicting the employment success of graduates, highlighting the role of practical experience in assessing their attractiveness in the labour market. This study emphasizes the importance of internships in the context of vocational training and provides evidence of the predictability of graduate employability on these measures. This study is relevant to the present project in terms of its emphasis on strategic career planning for students as both approaches focus on improving students’ employability prospects, however the present study focuses on developing a personalized learning approach and predicting professional development, while the researchers specifically evaluate the role of internships in employability success.

The study by P. Chaipidech et al. [14] focuses on developing a model of teacher professional learning based on an individualized learning system for the development of technological, pedagogical, and content knowledge (TPACK). In contrast to traditional teacher professional development, the authors focus on the importance of personalized approaches and expert delivery. The results showed significant improvement in their TPACK, which extends the limited research on TPD facilitating adult teachers’ professional learning by using personalized learning systems to provide skills for pedagogical application of digital technologies in students’ science learning. This work is comparable to the present study as both offer models of personalized learning in an educational context, the former in the field of adult teacher education and the latter for student audiences, with each aiming to enhance the effectiveness of the educational process and address individual learners’ characteristics.

The study by A. Bhutoria [15] conducts a systematic analysis of the use of artificial intelligence (AI) to personalize the educational process in the USA, China, and India. The author criticizes traditional educational systems for their “one-size-fits-all” approach and inability to meet the individual needs of students. The study emphasizes innovations in big data and Artificial Intelligence (AI) to facilitate the development of smart machines to cater to the individual needs of learners. The author draws conclusions about the ability of AI to tailor educational materials, identify learning difficulties and select the best learning paths for students. It is also noted that AI is changing the role of teachers and optimizing the educational environment. However, the state of data privacy, availability of digital resources and financial constraints act as challenges to its widespread adoption.

The article by D.L. Taylor et al. [16] discusses the continuous human learning process and the role of personalized and adaptive learning platforms in the era of digital and smart learning. The authors emphasize that through various tools and platforms, learning becomes more effective by providing a personalized approach and considering the learner’s previous experience, skills, and knowledge. The review article discusses the platforms, approaches, and solutions used in modern e-learning systems. A methodology for creating adaptive learning systems with personalized access, involving learning models tailored to each student, is presented. Both studies seek to develop and implement personalized approaches in education, but while the present study focuses on a model that considers the personal profile of students to improve academic motivation and performance, the work of the researchers covers a wider range of tools and platforms to provide personalized learning in general.

The study by G. Xiao [17] examines the use of big data and knowledge maps to create personalized learning
pathways for learning French at college level. The problem of classical learning is the lack of clarity in courses and the lack of connection between knowledge due to the huge amount of information resources on the Internet. The author proposes a methodology that allows for an accurate representation of the content, structure, and interrelationships of French language knowledge. The study used a knowledge map to recommend a learning path, where three French students were randomly selected to plan a learning path using several popular recommendation algorithms. The results show that personalization of the learning path can be done based on pre-existing knowledge relations and objective attributes. The study also addresses the comparison of the proposed approach with traditional methods and analyses the benefits of different models for predicting learning outcomes, demonstrating the advantages of using the proposed strategy to improve learning performance.

The study by M. Arashpour et al. [18] considers reliable prediction of individual student performance for timely support and improvement of learning experience. In classification and regression tasks, the TLBO algorithm is used to select features for SVM and ANN models, allowing the optimal combination of input variables to be determined. In addition, the ANN architecture is determined using the TLBO algorithm in parallel with the feature selection process. Ultimately, four hybrid models were developed containing anonymized information on discrete and continuous variables based on a comprehensive dataset for learning analytics. Both studies seek to develop models capable of personalizing learning to individual student characteristics. Both papers also draw attention to strategic planning of students’ career paths by providing tools for predicting professional development and academic achievement.

The research of M. Zhong and R. Ding [19] focuses on developing a system for personalized recommendation of learning resources for students using collaborative filtering to address the problem of information overload in online learning environments. The authors adapt the filtering algorithm to improve its performance based on analysing user’s data, achieving high accuracy and relevance of recommendations. In comparison, both studies focus on customizing the learning experience to meet individual learner needs, but the present study focuses on improving academic performance and supporting career planning, whereas the work of the researchers aims to improve access to educational resources through personalized recommendations.

The study by A.Y.Q. Huang et al. [20] focuses on using artificial intelligence to create personalized video recommendations in a flipped classroom, which aims to increase students’ learning motivation and engagement. It has been found that such recommendations can significantly improve academic performance in students with average levels of motivation. This study and the present research share the goal of enhancing students’ academic performance and engagement. However, they employ different methodologies: the current study develops a model focused on personality profiles and career planning, whereas the researchers’ study implements specific recommendations using artificial intelligence within a flipped classroom context.

The analysis of the cited studies suggests that the use of data, machine learning, artificial intelligence and personalization in education is becoming an increasingly significant area of contemporary educational science. All of them are aimed at improving students’ academic performance, motivation, and professional training through the development of personalized learning approaches. However, it can also be concluded that further research into personalized learning strategies and the possibility of their integration into large-scale educational programmes is worthwhile.

Conclusions
The study confirmed the hypothesis about the significant impact of the personalized approach on students’ academic motivation and performance. The developed model helped the students of the experimental group to get a clearer picture of their strengths and identify areas for professional development. The experimental implementation of the model had a positive impact on students’ engagement in the academic process and facilitated strategic career planning.

Comparison of motivation and satisfaction indicators of the experimental and control groups revealed a statistically significant advantage in favour of personalized learning methods. The gap in performance between the groups indicates that algorithms for predicting and personalizing the educational process may be the key to improving the quality of education. Of greatest interest is the discovered potential of the model in defining and supporting students’ individual trajectories. Students following their own educational and professional paths showed higher levels of self-awareness and purposefulness in the long term. This highlights the importance of personalization in the educational environment, with a particular focus on matching student’s individual abilities with labour market requirements. The application of analytical tools to find and support each student’s individual educational and vocational route represents a significant contribution to the effectiveness of learning.

Despite the success, the recognition of the importance of further research in this direction is undeniable. Further focused attention on scaling the model, optimizing prediction algorithms, and developing in-depth student interaction techniques may contribute to a more accurate and in-depth understanding of personal educational requirements. In the context of the present study, scaling the model would require additional efforts both in terms of technical resources and in the aspect of adapting the approach to different learning environments and educational standards. It would be promising to analyse the impact of the model on students with different types of learning and in a variety of academic disciplines. The possibility of integrating personalized learning platforms into online environments also requires careful consideration, especially considering the growing popularity of distance learning technologies.

Finally, consideration of a larger sample of students and the inclusion of additional learning institutes will confirm the universality of the recommendations and the adaptability of the model to different educational systems. This provides a solid foundation for the fruitful application
of the model in a variety of educational contexts, providing a solid platform for personalized learning at scale.

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**References**


Персоналізація навчального процесу за допомогою інтелектуального аналізу даних у вищій освіті

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Анотація

Актуальність. Стрімка еволюція сучасного ринку праці зумовлює необхідність переходу від традиційного, стандартизованого консультування з питань кар'єри до персоналізованих освітніх траєкторій, які враховують індивідуальні якості, навички та вподобання, забезпечуючи кращу професійну адаптацію та задоволеність від роботи.

Мета. Метою дослідження є розробка та апробація моделі, яка сприятиме вибору студентами особистисно-орієнтованої освітньо-професійної траєкторії.

Методологія. Методами дослідження є порівняльний, якісний та статистичний аналіз, експериментальний метод, моделювання та прототипування.

Результати. Основним результатом дослідження стало створення та успішне застосування оригіналів моделі навчання, інтегрованої з сучасними аналітичними підходами, включаючи механізми предиктивного аналізу для адаптації та оптимізації індивідуальних освітніх траєкторій, що дозволило значно підвищити ефективність навчального процесу. Експериментальне впровадження показало, що студенти, які використовували розроблену модель для створення своїх індивідуальних освітніх траєкторій, досягли значного покращення академічної успішності та мотивації до навчання порівняно з контрольною групою. Підтвердилася гіпотеза про те, що персоналізований супровід впливає на вибір більш відповідних навчальних програм і курсів, що, в свою чергу, позитивно впливає на академічну успішність та задоволеність навчанням. Наявність позитивних відгуків від студентів та викладачів також свідчить про високу адаптивність моделі та її потенціал для масштабування і подальшого впровадження в освітню практику.

Висновки. Дослідження підтвердило позитивний вплив персоналізованого підходу на академічну мотивацію та успішність студентів, виявивши значні переваги в залученості, стратегічному плануванні кар'єри та довгостроковій цілеспрямованості, а також підкреслило необхідність подальших досліджень для масштабування моделі, оптимізації алгоритмів прогнозування та адаптації підходу до різноманітних навчальних середовищ та освітніх стандартів.

Ключові слова: адаптивна освіта; статистичне моделювання; освітнє моделювання; технології навчання; навчальна мотивація; методології прогнозування; підвищення кваліфікації.