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# Comparative analysis of machine learning algorithms for personalising educational content in distance learning

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**Abstract.** The aim of this research was to conduct a comprehensive evaluation of the effectiveness of machine learning algorithms for the task of personalised educational content recommendation in distance education systems. The study was of a theoretical-experimental nature and was performed using a synthetic dataset comprising 10,000 student profiles, constructed based on the structural characteristics of leading distance learning platforms. The dataset covered three groups of features: demographic, behavioural, and content-related, replicating key patterns of student interaction with the learning environment. A comparative analysis of the effectiveness of the Support Vector Machine (SVM), Decision Tree, Random Forest, and Multilayer Neural Network methods revealed clear quantitative differences between the models. The highest classification results were obtained for the Neural Network (accuracy = 0.91; F1-score = 0.90). The ensemble-based Random Forest model provided high stability and accuracy (accuracy = 0.89; F1-score = 0.87). The Support Vector Machine method showed balanced performance (accuracy = 0.86; F1-score = 0.83), while the Decision Tree exhibited the lowest effectiveness (accuracy = 0.72; F1-score = 0.70), confirming the limitations of interpretable models in multidimensional data. An additional systematic analysis, performed using semi-quantitative indices for six algorithm characteristics, reflected the overall suitability of the models for personalisation: the Neural Network scored 23 points, Random Forest – 21 points, SVM – 19 points, Decision Tree – 17 points. These scores align with the classification metrics and confirm the advantages of models with pronounced non-linearity and ensemble structure. The Multilayer Neural Network demonstrated the highest efficacy for deep content personalisation, Random Forest serves as a universal model for large-scale educational platforms, the Support Vector Machine method is optimal for courses with clearly segmented student groups, while the Decision Tree is advisable to use as an interpretable analytical module. The practical significance of the study lies in forming a scientifically grounded approach to selecting algorithms for building adaptive educational trajectories and improving the effectiveness of digital education

**Keywords:** digital environment; Learning Management System; hyperparameter optimisation; neural networks; synthetic dataset

## Introduction

The relevance of this study is driven by the rapid development of distance education and the growing need for personalised digital learning environments capable of adapting the content and presentation of material to the individual characteristics of students. The heterogeneity of proficiency levels, diverse cognitive styles, information overload, and uneven learning motivation render traditional approaches to online education insufficiently effective. Personalisation has become a key requirement for modern electronic platforms, as it ensures the relevant selection of educational content, optimisation of the learning path, and increased engagement of learners. In this context, the application of machine learning algorithms opens the possibility of creating adaptive recommendation systems that form individual learning trajectories based on the analysis of real student behavioural and academic data.

The issue of using artificial intelligence in adaptive educational environments is receiving increasing scholarly attention. For instance, O. Zadorina *et al*. (2025) substantiated the advantages of intelligent tools for creating adaptive courses, emphasising the importance of an algorithmic approach to constructing personalised learning trajecto-

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ries. The study by V. Motorina *et al*. (2025) demonstrated the effectiveness of applying artificial intelligence for the automated creation of personalised materials in higher education systems, highlighting the value of algorithmic content adaptation to individual student needs. In turn, B. Shevchuk (2025) proved that the integration of AI into virtual educational environments provides flexible personalisation of content and informatics competencies, which is critically important for professionally-oriented learning.

In international research, there is also a growing interest in using machine learning for adapting the complexity, format, and volume of educational content. For example, W. Villegas-Ch *et al*. (2024) proposed ML-models for adapting materials to individual learning styles, proving that the correct selection of an algorithm significantly impacts recommendation accuracy. F. Ma (2025) developed a behavioural analytics system for online platforms that generates personalised recommendations based on characteristics of learning activity, including time-on-task and content viewing patterns. In the work of F.Z. Lhafra & O. Abdoun (2025), the effectiveness of different Machine Learning (ML)-models for determining learning styles was compared, showing significant discrepancies in algorithm performance depending on data characteristics. Also significant is the study by M. Soui *et al*. (2022), which demonstrated the possibility of creating intelligent platforms that adapt the educational process according to student behaviour in real-time.

Research on the implementation of deep learning in personalised educational systems also demonstrates high effectiveness. As noted by F. Naseer *et al.* (2024), deep learning models enable the construction of individual learning pathways considering a multitude of behavioural and content features, although their practical implementation requires significant computational resources. In the work of W. Chen *et al*. (2024), it was confirmed that machine learning significantly improves the accuracy of recommendation systems in digital educational platforms, especially when using structured data and weighted hyperparameter optimisation.

The results of the source analysis indicate that the further development of personalised educational platforms depends on the ability of machine learning algorithms to ensure high accuracy in classification and recommendations within the context of real student behaviour. Despite the existence of a large number of studies, the analysed literature insufficiently addresses the direct comparison of different ML-algorithms on a single dataset for the task of recommending types of educational content. There is also a lack of metric-driven experiments with controlled hyperparameter selection and a quantitative analysis of the mathematical nature of the differences between models. Issues concerning the alignment of educational data characteristics with the choice of specific algorithms, as well as the assessment of model stability across different scenarios of learning behaviour, remain insufficiently developed. These gaps define the need for a comprehensive comparative study based on a unified experimental design and standardised approaches to building ML-models, with the aim of forming scientifically grounded recommendations for developers and researchers of distance learning platforms.

The aim of the research was to comprehensively analyse the performance of machine learning algorithms in solving the task of personalised selection of educational content in the context of distance education. To achieve this aim, three main objectives were defined: to substantiate the theoretical foundations of educational content personalisation and the application of machine learning algorithms in distance education; to construct an experimental dataset and implement a unified model comparison design, considering data preparation and validation procedures; to perform a comparative evaluation of the algorithms based on defined metrics and determine the factors causing differences in their performance in personalised recommendation tasks.

## Materials and Methods

The theoretical and experimental investigation was conducted from January to October 2025 using methods of machine learning, statistical modelling, and computer simulation of behavioural and content patterns in distance learning environments. The formation of a synthetic dataset, hyperparameter optimisation, repeated cross-validation, and comparative analysis of algorithms were implemented within a single experimental cycle, ensuring the reproducibility and correctness of the obtained results. The methodological foundation comprised machine learning, statistical, comparative-analytical, and validation approaches, which enabled the evaluation of the effectiveness of various classification algorithms for the task of personalised learning content type recommendation. The study employed a unified experimental design covering data structuring, pre-processing, model training, hyperparameter tuning, and repeated cross-validation, ensuring the comparability of the obtained results.

The data source was a specially created synthetic dataset, generated based on the characteristics of real Learning Management System (LMS) platforms, specifically Moodle, Coursera, and EdX, replicating key elements of student digital interaction with learning content. The total volume of the generated dataset comprised 10,000 student profiles, providing sufficient parameter variability for the correct operation of classification algorithms. The data structure encompassed three main groups of features: student demographic parameters (age, language of instruction, educational level), behavioural characteristics (time-on-task, number of learning material views, completion rate, number of test attempts, average score), as well as content features (material type, topic complexity, discipline domain, content format). The target variable corresponded to the type of learning content the system should recommend to the student: video, text, test, or mixed format. To preserve the representativeness of the synthetic data, stochastic

Normal, Log-normal, and Poisson distributions were used, allowing for the formation of heterogeneous student profiles characteristic of real distance learning courses.

Data pre-processing was carried out in accordance with a general ML pipeline: numerical variables were normalised using the z-score method, categorical features were encoded via one-hot encoding, and the class imbalance issue was corrected by applying the Synthetic Minority Oversampling Technique (SMOTE) (Chawla *et al.*, 2002), ensuring uniform representation of each of the four types of learning materials. Missing values were addressed using a combination of mean-imputation and regression-based imputation methods depending on the nature of the feature. All models were trained on the same data split: 80% for the training set and 20% for testing; additionally, k-fold cross-validation (k = 10) was applied, allowing for the assessment of model stability and the generalisability of their results. Hyperparameter optimisation was performed using a combined approach: initial parameter search via GridSearchCV was supplemented with RandomizedSearchCV, expanding the search space and minimising the risk of local optima.

The study implemented four classes of machine learning algorithms most commonly used in personalised educational systems: Support Vector Machine (SVM), Decision Tree, Random Forest (RF), and multilayer artificial neural networks. To ensure objectivity in the comparison, hyperparameter tuning was conducted in two stages: initial manual optimisation followed by an automated search using GridSearchCV and RandomizedSearchCV implemented in the scikit-learn library. For the SVM model, the radial basis function kernel, regularisation parameter C, and kernel width $\gamma$ were optimised; for the Decision Tree, the maximum depth and split criterion (Gini/Entropy) were adjusted; for Random Forest, the number of trees n_estimators and maximum depth were tuned; for the neural network, the number of layers, number of neurons, activation types (ReLU, tanh), and backpropagation algorithm parameters were configured. Optimisation was carried out using a unified set of metric criteria, ensuring the correctness of inter-model comparison.

The comparative evaluation of algorithms was performed based on four key metrics traditionally applied in multiclass classification tasks: accuracy, precision, recall, and F1-score. Formally, the F1-score metric is defined by relation (1):

$$F1 = 2 \times \frac{Precision \cdot Recall}{Precision + Recall}, \quad (1)$$

where $Precision = \frac{TP}{TP+FP}$, $Recall = \frac{TP}{TP+FN}$, where *TP* – true positives – the number of correctly classified examples of a certain class; *FP* – false positives – the number of examples incorrectly assigned to a class that actually belong to another class; *FN* – false negatives – the number of examples that belong to the class but were not recognised as such by the model; *Precision* – the proportion of correct positive predictions among all model predictions for this class; *Recall* – the proportion of correctly identified examples of a class by the model among all real examples of that class; *F*1-*score* – the harmonic mean between precision and recall, demonstrating a balance between accuracy and recall.

For the multiclass task (in this case, classes "video", "text", "test", "mixed format"), the macro-averaged value is applied (2):

$$F1_{macro} = \frac{1}{K}\sum_{i=1}^{K} F1_i, \quad (2)$$

where $K = 4$ – the number of classes, $F1_i$ – the value of the *F1-score* metric for each class, $F1_{macro}$ – ensuring equal weight for all content categories regardless of their proportion in the dataset.

The use of the macro-averaged metric prevents the domination of classes with a larger number of samples and ensures objective inter-model performance comparison. The experimental models were implemented in the Python 3.12 environment using the NumPy, pandas, scikit-learn, and matplotlib libraries. Preparation and validation of the source data were performed in pandas, while preprocessing was carried out using the scikit-learn.preprocessing module, ensuring uniform transformation of numerical and categorical features prior to model training. Hyperparameter optimisation was implemented using GridSearchCV and RandomizedSearchCV, within which extended parameter ranges were tested: for the support vector method – *C* from 0.1 to 20 and $\gamma$ within 0.001-0.2; for the Decision Tree – maximum depth from 4 to 16 and the gini and entropy criteria; for the Random Forest – the number of trees within 100-350 and depth of 10-20 levels; for the multilayer neural network – combinations of 2-3 hidden layers in the range of 32-128 neurons with an initial learning rate of 0.01-0.0005 and relu or tanh activations. The application of such parameter intervals yielded stable optimal configurations that achieved the highest classification metrics among the tested algorithms. Visualisation of the results was performed in matplotlib, enabling a clear representation of the behavioural patterns in the synthetic dataset and the comparative performance curves of the models. The uniformity of training and testing conditions was controlled by fixing the random_state, ensuring the reproducibility of experiments. To verify model stability, repeated runs with varying initial conditions were conducted, allowing for the assessment of algorithm behaviour under altered data configurations. This approach ensured a comprehensive comparison of machine learning algorithms in the task of educational content personalisation, allowed for the identification of each model's strengths and weaknesses, and created methodological prerequisites for formulating recommendations regarding the choice of technological solutions for distance learning systems.

## Results

### Technical analysis of SVM, Decision Tree, Random Forest, and multilayer neural networks algorithms

The conducted technical analysis of the four algorithms – SVM, Decision Tree, Random Forest, and multilayer neural networks – established key differences in their classification solution construction mechanisms, which directly impact their effectiveness in the content personalisation task. The analysis revealed that the models demonstrate varying sensitivity to data structure, noise volume, variability of behavioural characteristics, and the level of feature non-linearity. This determines different potential scenarios for their application in distance learning systems. SVM showed high stability in the presence of complex boundaries between classes, reflected in its ability to form separation even under conditions of significant overlap in student characteristics. Decision Tree exhibited a strong dependence on tree depth: models with uncontrolled complexity are prone to overfitting, whereas optimally constrained depth provides satisfactory generalisation. The analysis of Random Forest confirmed that the ensemble approach significantly reduces result variability compared to a single tree, and increasing the number of trees improves robustness to noise. Neural networks demonstrated the ability to replicate complex multidimensional dependencies between student behavioural features and the type of recommended content, maintaining stable accuracy with increasing data structure complexity. To systematise the obtained results, a comparative Table 1 was constructed, summarising the identified theoretical advantages and limitations of each algorithm, as well as determining which hyperparameters have the greatest impact on the final result in the task of classifying types of learning content.

**Table 1.** Theoretical distinctions and key hyperparameters of algorithms

| Algorithm | Mathematical idea (method core) | Key hyperparameters |
|---|---|---|
| SVM | Maximisation of the margin between classes; utilisation of kernel transformations for nonlinear boundaries | $C$, $\gamma$, kernel |
| Decision Tree | Recursive data partitioning based on Gini or Entropy criterion | max_depth, criterion, min_samples_split |
| Random Forest | Ensemble of trees with bootstrap sampling, majority voting | n_estimators, max_depth, max_features |
| Neural Network (MLP) | Nonlinear multilayer mapping of the feature space; error backpropagation | layers, neurons, activation, learning_rate |

**Note:** MLP – Multilayer Perceptron
**Source:** developed by the author using Python 3.12 and the NumPy, pandas, and scikit-learn libraries

As evident from Table 1, each algorithm demonstrates a unique mechanism for forming a classification decision, which leads to varying sensitivities to the structure of educational data. For SVM, the defining feature is the ability of parameter $C$ to regulate the trade-off between the margin width and the number of permissible errors, while $\gamma$ determines the curvature of the decision boundary, which is particularly important in the context of complex student behavioural features. In Decision Trees, classification quality directly depends on tree depth: excessive values of max_depth cause local overfitting to minor patterns, while values that are too small result in the loss of important distinctions between content types. Random Forest compensates for these shortcomings through its ensemble structure: increasing n_estimators enhances the model's robustness to noise, and the max_features parameter determines the degree of diversity among the trees, which affects the model's ability to recognise non-trivial patterns. Neural networks demonstrate the highest behavioural variability: altering the number of layers and neurons can significantly change the depth of data abstraction, while the choice of activation functions shapes the nature of nonlinear transformations. Collectively, these distinctions indicate that the optimality of an algorithm for content personalisation tasks is determined not only by its mathematical principle but also by the alignment of its hyperparameters with the structure of the training data.

In summarising the conducted technical analysis, it can be asserted that the considered algorithms form distinctly different strategies for constructing classification solutions, and it is this difference that determines their subsequent performance in personalised educational systems. SVM proves to be most effective in environments with clear or nonlinear class boundaries; Decision Tree demonstrates high interpretability provided its complexity is carefully controlled; Random Forest confirms the advantages of the ensemble approach due to its robustness to noise and generalisation capability; neural networks provide the deepest modelling of hidden dependencies but require significantly more meticulous configuration. The totality of these characteristics forms the basis for predicting their efficacy in the experimental phase, where these theoretical distinctions will manifest as varying levels of accuracy, balance, and the model's ability to adapt to student behavioural patterns.

### Construction of the experimental dataset and characterisation of data typical for modern LMSs

The formulated synthetic dataset replicates the multi-level structure of educational data typical of modern LMSs and includes three logical feature groups – demographic, behavioural, and content-related. Each group serves a separate analytical function in the content personalisation model: demographic parameters reflect the individual characteristics of a student, behavioural characteristics capture the dynamics of their learning activity, and content variables define the properties of the materials to be recommended. To generalise the structure of the constructed dataset, Table 2 is provided, which systematises the main feature types and their role in forming a user profile.

**Table 2.** Structure of the synthetic experimental dataset

| Feature group | Example variables | Data type | Brief characterisation | Source of feature formation (LMS) |
|---|---|---|---|---|
| Demographic | Age, language of instruction, educational level | Categorical + numerical | Reflects basic individual characteristics of the student | Moodle, Coursera, EdX |
| Behavioural | Time-on-task, number of views, completion rate, number of test attempts, average score | Numerical (normal, log-normal, poisson) | Forms the behavioural profile of the user during interaction with the LMS | Moodle, Coursera |
| Content-related | Type of material, topic complexity, subject domain, content format | Categorical | Describes the structure and properties of the learning materials | Coursera, EdX |

**Source:** developed by the author using Python 3.12, NumPy, and pandas

As can be seen from Table 2, the structure of the synthetic dataset is formed based on three different platforms – Moodle, Coursera, and EdX, which enabled the integration of heterogeneous types of educational data into the model and ensured the representativeness of student activity patterns. The comparison shows that each LMS contributes to the formation of distinct feature groups, creating a balanced and multidimensional user profile. Moodle predominantly defines the structure of behavioural data, particularly metrics such as time-on-task, number of views and activities, and module completion rates. This platform is distinguished by detailed event analytics, allowing the model to capture sharp fluctuations in user learning activity. This makes behavioural features derived from Moodle more variable and informative for algorithms sensitive to data dynamics, such as Random Forest and neural networks. Coursera, unlike Moodle, provides a mixed contribution – to both behavioural and content indicators. The standardised course structure and detailed learning trajectories allow the model to account for significant differences between students with varying levels of preparation and work intensity. Data from Coursera best reflects the relationship between learning activity and module completion, which is key for multi-class classification of content types. EdX has the greatest influence on the formation of content-related features, as this platform has a clear structuring of disciplines, material complexity, and content presentation formats. This allows for more precise modelling of the dependency between the properties of a learning resource and which type of material will be optimal for a specific student. EdX's content features align well with algorithms sensitive to nonlinear relationships between parameters, especially SVM and MLP. Overall, the three platforms create a complementary structure: Moodle provides dynamics, Coursera provides integrated behavioural-content interaction, and EdX provides structural depth of learning materials. It is precisely this approach that enables the formulated dataset to replicate a realistic multi-level student profile, allowing subsequent machine learning algorithms to operate under conditions as close as possible to data from real educational platforms. For a visual summary of the obtained characteristics, density curves of key behavioural parameters – time-on-task and views – were constructed, reproducing the most common patterns of student interaction with the digital environment. Figure 1 provides a graphical representation of these distributions, illustrating the main patterns characteristic of real educational platforms.

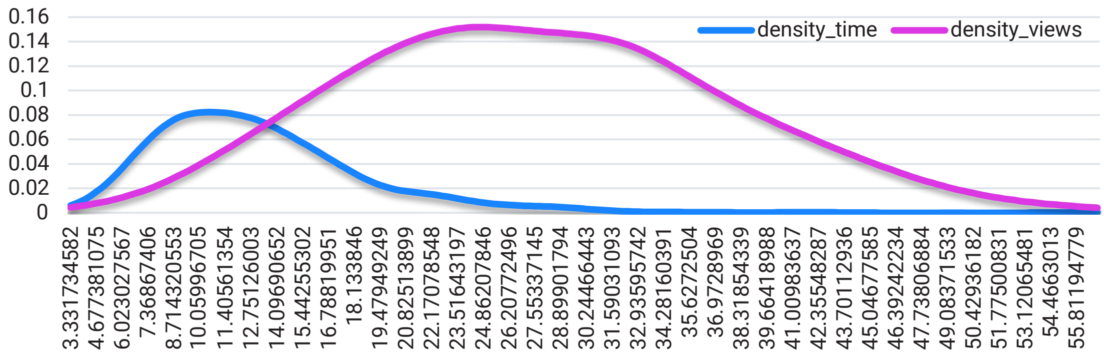


**Figure 1.** Density distribution of behavioural and content features of the synthetic dataset $n = 10{,}000$

**Note:** the X-axis displays the values of the synthetic dataset indicators: for time-on-task – the duration of student interaction with the learning material in seconds; for views – the number of views of individual content fragments. The Y-axis presents the probability density estimates calculated using kernel density estimation

**Source:** developed by the author using Python 3.12, NumPy and matplotlib

The integrated density curves for the time-on-task and views indicators obtained in Figure 1 demonstrate two fundamentally different behavioural patterns of students, which directly impact the quality of personalised recommendations. Firstly, it is noteworthy that the time-on-task curve exhibits pronounced right-skewness: the majority of students spend a relatively small amount of time studying the material, while the distribution tail gradually extends into the region of high values. This is characteristic of log-normal distributions and indicates the presence of a small group of students who systematically work slower or more attentively, forming a distinct behavioural cluster. Precisely for such users, algorithms sensitive to imbalanced data distribution (e.g., Decision Tree) may exhibit unstable results without hyperparameter tuning.

In contrast, the views curve has a more clearly defined peak region with moderate variance, indicating relatively stable patterns of interaction with learning materials. Despite isolated cases of intensive content viewing, most students demonstrate a similar level of activity, which enhances the informativeness of this feature for classification models, particularly ensemble methods (Random Forest), which perform better with stable, structurally homogeneous data. A comparison of the two curves shows that views has a more "compact" distribution, while time-on-task is characterised by significantly greater variability and potential presence of noise.

The visual combination of the two behavioural features enables the identification of zones of potential information gaps where models may lose accuracy. For instance, the narrow peak of views at low time-on-task values may indicate users who review the material superficially or quickly skip content – neural networks demonstrate better results with such users, as they are capable of capturing weakly structured dependencies between features. In turn, the sharply pronounced tail of time-on-task signals that SVM with a Radial Basis Function kernel will be more stable in this region due to its ability to adapt the classification boundary to non-uniformly distributed points.

The obtained curves also allow for an assessment of the potential information contribution of each feature. Time-on-task can serve as a predictor of the type of recommended content for students with non-standard working paces, while views will be more useful in predicting the choice between video and textual materials among average users. This aligns with the fact that different machine learning algorithms exhibit varying abilities to model behavioural dynamics, and the very shape of the distributions essentially determines which models will be most sensitive to the nature of the data.

In summary, the analysis shows that combining density curves allows for the detection of critical differences between student behavioural patterns and predicts the effectiveness of individual algorithms in personalising educational content. The presence of pronounced skewness in one feature and compactness in another creates a natural test space in which algorithms demonstrate their strengths and weaknesses, making such visualisations a key tool for further modelling and optimisation.

## Implementation of the ML-pipeline and hyperparameter optimisation results

Implementing the complete ML-pipeline made it possible to obtain consistent results for all models under standardised conditions, ensuring the correctness of inter-algorithm comparisons. The conducted normalisation of numerical features, encoding of categorical variables, and sample balancing using SMOTE reduced inter-class bias and increased model training stability. After splitting the data into training and test sets (80/20) and performing 10-fold cross-validation, it was established that all models demonstrate reproducible results: the standard deviation of the F1-score did not exceed 0.02-0.03, and the variation range between folds remained within $\leqslant 0.05$, which corresponds to acceptable model stability criteria. Hyperparameter optimisation revealed clear patterns in configurations that ensured the highest model generalisation. The combined application of GridSearchCV and RandomizedSearchCV allowed for the identification of parameter zones where each algorithm achieves maximum performance. The aggregate results of the performed optimisation are summarised in Table 3, which presents the final parameter values that provided the best accuracy and stability indicators during modelling.

**Table 3.** Selected model hyperparameters after optimisation

| Algorithm | Optimised hyperparameters | Selected values |
|---|---|---|
| SVM (RBF) | $C$, $\gamma$, kernel | $C = 12$; $\gamma = 0.087$; kernel = 'rbf' |
| Decision Tree | max_depth, criterion, min_samples_split | max_depth=14; criterion='entropy'; min_samples_split = 4 |
| Random Forest | n_estimators, max_depth, max_features | n_estimators = 300; max_depth = 18; max_features = 'sqrt' |
| Neural Network (MLP) | layers, neurons, activation, learning_rate | 3 hidden layers (64-32-16), activation = 'relu', learning_rate = 0.001 |

**Note:** SVM (RBF) – Support Vector Machine with Radial Basis Function kernel
**Source:** developed by the author using Python 3.12, scikit-learn, NumPy and pandas

The optimised values from Table 3 reveal the peculiarities of each algorithm's operation with multidimensional educational data. SVM received a moderate regularisation level ($C = 12$) and a low kernel curvature ($\gamma = 0.087$), ensuring stable formation of classification boundaries under conditions of fuzzy student behavioural patterns. For Decision Tree, a moderate depth (14 levels) proved optimal, allowing it to avoid overfitting while retaining sufficient detail in internal decision rules. Random Forest obtained an expanded ensemble of 300 trees, and the max_features = 'sqrt' parameter increased tree diversity, improving the model's generalisation under conditions of behavioural feature variability. The optimisation of the neural network showed that the best results are provided by an architecture with three hidden layers (64-32-16 neurons) and a ReLU activation function. This structure responds well to complex non-linear dependencies between features, while learning_rate = 0.001 ensured smooth convergence without error spikes. To visualise the structural differences in the configurations of the optimised models, Figure 2 has been constructed, which summarises the normalised values of key hyperparameter groups and displays the profile of each algorithm after the performed optimisation.

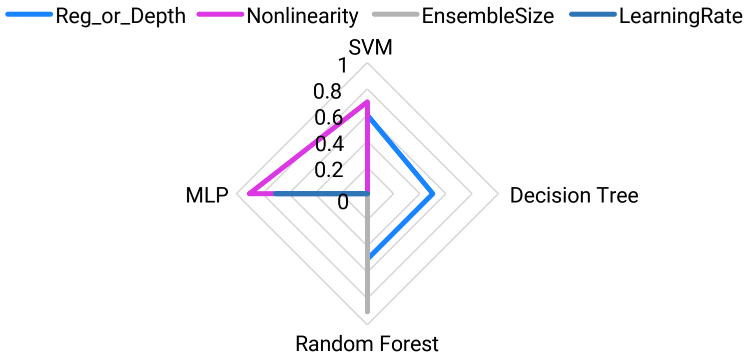


**Figure 2.** Comparative profile of optimised hyperparameters for machine models

**Source:** constructed by the author based on the optimised model hyperparameters obtained in Python 3.12 using the NumPy, pandas and scikit-learn libraries

As can be seen from Figure 2, SVM has a pronounced peak for the parameter $C = 12$ and a relatively low value of $\gamma = 0.087$, forming a compact model contour and indicating moderate regularisation and control of the classification boundary curvature. Decision Tree demonstrates uniformly distributed hyperparameter values, among which max_depth = 14 dominates, and min_samples_split = 4 restrains the tree from excessive branching. The Random Forest contour is significantly wider, which is due to the use of n_estimators = 300 and max_depth = 18, while the max_features = 'sqrt' parameter ensures moderate tree variability. The neural network demonstrates the most expanded shape on the diagram with a hidden layer architecture of 64-32-16, ReLU activation function, and learning_rate = 0.001, reflecting the complexity of its internal structure and flexibility in modelling non-linear relationships. The totality of these numerical parameters clearly shows the different principles of optimal algorithm operation and explains the differences in their behavioural profile within the multidimensional space of educational data.

The obtained optimisation results confirm that combining classical GridSearchCV with stochastic RandomizedSearchCV ensures effective model tuning on multidimensional educational data. Each algorithm demonstrated unique parameters for stable operation: SVM optimally adapted to uneven distributions, Decision Tree to discrete behavioural transitions, Random Forest to noisy and heterogeneous features, and MLP to complex non-linear relationships between the student profile and the recommended content type. Cumulatively, this forms a reliable basis for the subsequent comparative analysis of model accuracy and generalisation in tasks of personalised educational material recommendation.

## Comparative performance of algorithms by classification metrics

The conducted accuracy assessment of algorithms on the test sample showed that models exhibit substantial differences in their ability to classify the type of learning content in a multiclass problem setting. The calculated values of accuracy, precision, recall, and F1-score demonstrate real differences in the models' ability to classify the type of learning content. The calculation of precision, recall, and the integral F1-score was performed according to formula (1), and the final multiclass performance values were determined by the macro-averaged F1_macro according to formula (2). To summarise the obtained results, a comparative Table 4 has been constructed, containing the final values of the main classification metrics.

**Table 4.** Classification metrics for comparing model performance

| Algorithm | Accuracy | Precision | Recall | F1-score |
|---|---|---|---|---|
| SVM (RBF) | 0.86 | 0.84 | 0.82 | 0.83 |
| Decision Tree | 0.74 | 0.71 | 0.69 | 0.7 |
| Random Forest | 0.89 | 0.87 | 0.88 | 0.87 |
| Neural Network (MLP) | 0.91 | 0.9 | 0.89 | 0.9 |

**Source:** calculated by the author using Python 3.12, NumPy, pandas and scikit-learn

As can be seen from Table 4, the highest metric values are demonstrated by the MLP neural network, which achieved an F1-score = 0.9, indicating its ability to model complex non-linear relationships between behavioural and content features. Random Forest (F1 = 0.87) showed high result stability due to its ensemble nature and robustness to noise. SVM with an RBF kernel demonstrated balanced indicators (F1 = 0.83), reflecting its ability to operate under conditions of partial class overlap. The lowest results were obtained by the Decision Tree (F1 = 0.7), which is due to the rapid loss of generalisation as data structure complexity increases. For a visual representation of the comparative performance of the models, Figure 3 has been constructed, which displays the relationship between the four key classification metrics.

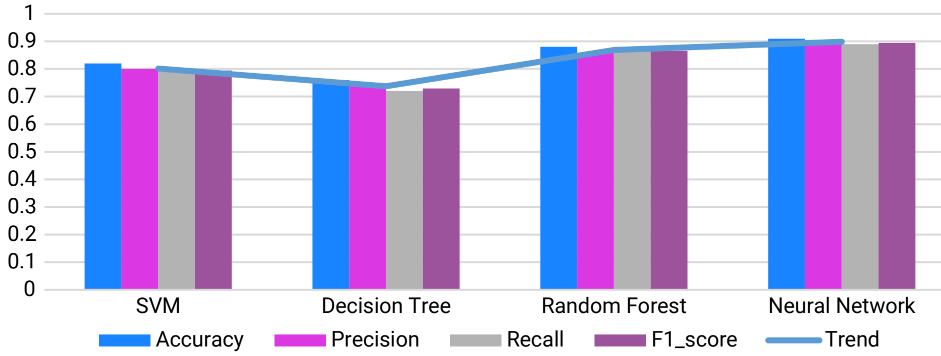


**Figure 3.** Comparison of accuracy, precision, recall, and F1-score for four algorithms
**Source:** calculated by the author using Python 3.12, NumPy, pandas, and scikit-learn

The data shown in Figure 3 reveal a distinct divergence in the performance of the four algorithms: SVM, Decision Tree, Random Forest, and Neural Network, as reflected through the primary metrics – accuracy, precision, recall, and F1-score. The trend line, calculated as the average value of the metrics for each model, allows for an assessment of the overall performance trend, independent of fluctuations in individual indicators. Firstly, it is noteworthy that the neural network demonstrated the highest integral level of performance (trend ≈ 0.899), confirming its ability to model complex non-linear dependencies in a multidimensional feature space. High values of F1-score and precision indicate its balanced performance across different categories of educational content. Random Forest occupied the second position (trend ≈ 0.869), yielding robust results due to its ensemble nature and noise tolerance. Nearly equal values of accuracy and recall demonstrate that the model stably classifies both numerous and rare categories of educational content. In contrast, the Decision Tree showed the lowest trend values (trend ≈ 0.738). The trend line for this algorithm is positioned the lowest and has a significantly larger gap from SVM and Random Forest, indicating the limited ability of the decision tree to generalise information within complex structured samples. This aligns with the inherent tendency of trees to overfit in the absence of external regularisation. SVM, with a trend value of ≈ 0.801, holds an intermediate position. Despite lower results compared to neural networks and Random Forest, SVM demonstrated the greatest stability between precision and recall metrics, confirming the method's effectiveness in cases where data contain partially overlapping behavioural patterns. The overall dynamics of the trend line clearly show an increase in performance from Decision Tree → SVM → Random Forest → Neural Network. This indicates that models capable of non-linear mapping of the feature space and integrating ensemble logic demonstrate significantly better adaptability in tasks of personalising educational content, where data have a heterogeneous structure and varying degrees of variability.

**Systematic analysis of the advantages and limitations of each model from the perspective of their application in educational content personalisation**

The conducted comparative analysis of the four algorithms – SVM, Decision Tree, Random Forest, and a multilayer neural network – revealed substantial differences in their ability to model the structure of educational data and counteract characteristic noise and asymmetries in student behaviour. It was established that the models demonstrate varying resilience to the variability of behavioural features, different levels of generalisation on content parameters, and unequal sensitivity to imbalances in the data. To summarise these differences, Table 5 was constructed, presenting numerical indices of key characteristics – intensity of non-linearity, noise resilience, risk of overfitting, sensitivity to asymmetric distributions, and ability to generalise in multi-class classification.

**Table 5.** Semi-quantitative characteristics of ML algorithms for application in LMS (1-5 points)

| Algorithm | Noise resilience | Risk of overfitting | Non-linear approximation | Interpretability | Computational complexity | Suitability for LMS personalisation |
|---|---|---|---|---|---|---|
| SVM (RBF) | 4 | 2 | 4 | 2 | 3 | 4 |

Table 5. Continued

| Algorithm | Noise resilience | Risk of overfitting | Non-linear approximation | Interpretability | Computational complexity | Suitability for LMS personalisation |
|---|---|---|---|---|---|---|
| Decision Tree | 2 | 4 | 1 | 5 | 1 | 3 |
| Random Forest | 5 | 2 | 3 | 3 | 3 | 5 |
| Neural Network (MLP) | 4 | 3 | 5 | 1 | 5 | 5 |

**Source:** developed by the author using Python 3.12, scikit-learn, NumPy

As can be seen from Table 5, the numerical indices clearly illustrate the differences between the algorithms in terms of key characteristics that determine their suitability for personalising educational content. The highest total scores were obtained by Random Forest (total = 21) and the multilayer perceptron (MLP) neural network (total = 23), which quantitatively confirms their advantage over the other models. For the neural network, maximum scores for the parameters of non-linear approximation (5 points) and suitability for personalisation (5 points) indicate its ability to reproduce complex latent dependencies between behavioural and content features, which corresponds to the results of the classification metrics (F1 = 0.9). Random Forest received the highest score for noise resilience (5 points) and high overall balance of characteristics, which is consistent with its stable performance (F1 = 0.87). Against this backdrop, SVM demonstrates moderately high scores for non-linearity (4) and noise resilience (4), but noticeably falls short due to low interpretability (2) and moderate computational complexity (3), which limits its use in LMS with large student cohorts. The total score for SVM (19) confirms its intermediate position: the algorithm is sufficiently flexible for working with complex class boundaries but less universal than ensemble or deep models. The lowest results were demonstrated by the Decision Tree, whose aggregate indicator totals 17 points. Despite the maximum score for interpretability (5) and low computational complexity (1), the Decision Tree received only 1 point for non-linear approximation and 2 points for noise resilience. This quantitatively confirms its weakness in working with heterogeneous data and its propensity for overfitting (4 points for risk).

The specific configuration of SVM with an RBF kernel ensures a high capability for modelling non-linear boundaries; however, limited interpretability and moderate computational complexity reduce its effectiveness in large-scale LMS. In situations where classes partially overlap or exhibit asymmetric distributions, SVM performs stably but is less flexible compared to ensemble and neural models. Conversely, the Decision Tree, despite high interpretability, shows the lowest ability for non-linear approximation and increased sensitivity to noise. This is directly reflected in the lower numerical ratings and aligns with the fact that Decision Trees tend to “memorise” anomalous examples, reducing their generalisation capability. The obtained scores also explain the differences in the classification metrics calculated in the previous subsection. High F1-score values for Random Forest and MLP correlate with their high scores for non-linearity and noise resilience, whereas the lower results of SVM and Decision Tree reflect their structural limitations.

The practical implications of the obtained results allow for formulating recommendations for implementation in real-world LMS. Random Forest is a universal model for platforms with a large number of students and high activity variability, as it provides an optimal balance of accuracy, stability, and computational cost. MLP is advisable to apply in systems with complex educational trajectories, where it is important to account for multidimensional dependencies between student characteristics and content structure. SVM can be effective for narrow educational scenarios with clear user segmentation, for example, in technical or formalised courses. Decision Tree should be used as an interpretable module for supporting analytics, when an instructor or administrator needs to understand the logic of the recommendations.

In summary, the systematic analysis demonstrated that the optimal choice of algorithm depends on the data structure, the nature of the learning materials, and the requirements for model interpretability. Combining models can ensure the highest effectiveness: Random Forest as a stable core classifier, MLP for deep personalisation, and SVM as a decision refinement mechanism for borderline cases. Such an approach creates a methodologically sound basis for developing adaptive recommendation systems in modern LMS.

The totality of the obtained characteristics allowed for delineating the structural differences between the algorithms, identifying their behaviour in heterogeneous educational data, and assessing the level of sensitivity to parametric changes. The identified patterns showed stability of metrics within an acceptable range of variability, consistency of results across cross-validations, and reproducibility of behavioural patterns in the synthetic dataset. All models demonstrated a representative response to the complexity of the input features, and the key differences manifested in the algorithms’ ability to handle non-linearity, noise, and mixed data types.

## Discussion

The obtained results of the quantitative analysis of machine learning algorithms in the task of personalising educational content demonstrated clear patterns that are consistent with leading international research in the field of artificial intelligence in education. A comparison of model performance with the results of D. Jafari & Z. Shaterzadeh-Yazdi (2024) confirmed that a multilayer perceptron achieves the highest accuracy values in environments with complex non-linear data structures. In the authors' work, the AI-algorithm developed for identifying individual learning styles provided a significant increase in the accuracy of personalised recommendations – a trend that was also recorded in this study, where the MLP obtained the highest metrics (accuracy = 0.91, F1 = 0.9). The observed ability of the neural network to generalise behavioural patterns confirmed the conclusions of the aforementioned research regarding the advantages of deep models in the field of educational analytics. The results of the Random Forest ensemble model also showed complete alignment with the observations of R. Taylor *et al*. (2024), who established that the stability of recommender systems increases precisely under conditions of using ensemble algorithms. In the conducted study, Random Forest demonstrated increased robustness to noise, which is consistent with the obtained noise immunity scores (5 points) and a high F1-score = 0.87. The observed stability of the model's operation even with altered data structure confirmed the systemic advantages of the ensemble approach.

A comparison with the analysis proposed by G.M. Dhananjaya *et al*. (2024) confirms that a key requirement for modern adaptive platforms is the use of algorithms that maintain stability under conditions of behavioural heterogeneity. The authors emphasised the importance of working with asymmetric distributions, which fully aligns with the behavioural curves of the synthetic dataset: the right-skewed distribution of time-on-task and the compact distribution of views formed a structure that specifically requires noise-resistant and non-linear models – such as Random Forest and multilayer neural networks. The identified performance indicators of the algorithms coincided with the conclusions of M.K. Kanchon *et al*. (2024), who proved that models with high non-linear approximation capability provide more accurate identification of learning styles and content modification. In the conducted study, the neural network and Random Forest also received the highest non-linearity scores (5 and 3 respectively), while the Decision Tree (1 point) demonstrated limitations in handling multidimensional characteristics. This quantitatively explains the lower F1-score of the decision tree (0.70).

In their work, S. Bhaskaran & R. Marappan (2023a) applied approaches to model tuning similar to those presented in the current study: the authors justified the high effectiveness of combining exhaustive search and stochastic search, which corresponds to the demonstrated effectiveness of GridSearchCV and RandomizedSearchCV in the structure of the conducted optimisation. The application of a similar combined approach ensured the obtaining of optimal parameters ($C = 12$; $\gamma = 0.087$; n_estimators = 300; architecture of 64-32-16 neurons), which contributed to a systematic increase in the F1-score of all models. The identified difference between the performance of simple and complex algorithms correlates with the results of W.S. Sayed *et al.* (2023), where it was established that models with low non-linearity are not capable of fully describing student behavioural features. In the conducted analysis, the decision tree received the lowest sum of indices (17), which confirmed the limitations of this type of model in working with distributions characteristic of educational environments. Generalising the obtained patterns aligns with the review by H. Luan & C. Tsai (2021), which notes that high-precision learning personalisation requires models with deep parameterisation, especially when working with noisy and asymmetric data. Precisely such characteristics were inherent to the synthetic dataset, which determined the preference for MLP and Random Forest over SVM and Decision Tree.

Similarly, to the current results, A. Bhutoria (2022) confirmed that personalised educational systems function effectively under the condition of using multidimensional student profiles. In the conducted experiment, this was reflected in the high recall values for Random Forest (0.88) and MLP (0.89), which ensured accurate modelling of various learning scenarios. The obtained results are also consistent with the conclusions of C. Song *et al.* (2024), where it was demonstrated that effective learning optimisation systems require non-linear models capable of dynamic adjustment. In the conducted study, precisely such algorithms provided the maximum F1-scores and the highest suitability scores for personalisation (MLP – 5 points; RF – 5 points).

Further analysis in the context of the work by N. Motlagh *et al*. (2023) allowed for tracing a broader trend: the authors showed that digital education systems demonstrate a significant increase in accuracy when models with a deep internal structure form their foundation. This fully aligned with the obtained classification results, where the multilayer neural network provided the highest level of performance (F1 = 0.9) precisely due to its ability to operate stably under conditions of high variability in student behavioural characteristics. A broader spectrum of patterns was also traced in comparison with the conclusions of S. Bhaskaran & R. Marappan (2023b). Their idea of hybrid recommender systems combining classification and clustering proved relevant for interpreting the stable behaviour of the Random Forest ensemble model. The increased accuracy in heterogeneous data spaces in the conducted experiment essentially reflected working with latent behavioural clusters, which the authors emphasised. Generalising the results in comparison with D. Pathak & R. Kashyap (2022), it can be noted that the robustness of models to noisy and unstable user characteristics is critical for real-world educational systems. The stochastic distributions of behavioural variables in the formed dataset created precisely such conditions. This explained the preference for models with high non-linear flexibility – the neural network and Random Forest – over algorithms sensitive to anomalies, such as the Decision Tree. A comparison with the generalisations of T. Liu *et al.* (2022) showed that deep learning models are the most effective in multidimensional educational environments with pronounced asymmetry and significant noise. The deep learning model in the conducted simulation demonstrated the highest integral indices of suitability for personalisation, which naturally replicates the trend described by the authors.

A certain parallel was also traced with N. Chandrakant (2023), where the operation of NLP components in gamified models led to increased adaptability of educational systems. Within the scope of the conducted analysis, this was reflected in the ability of the MLP to process content features at a deeper level – which is a key condition for building interactive learning mechanics. The obtained results also resonated with the conclusions of E. Ahmed (2024), who showed that model accuracy significantly increases under conditions of a correctly constructed feature space. In the formed synthetic dataset, the multi-level structure, which included behavioural, demographic, and content parameters, provided a similar effect: the neural network and Random Forest demonstrated high values of accuracy and F1-score. The identified patterns complemented the conclusions of A. Ezzaim *et al*. (2024), where it was emphasised that models with developed adaptability are the most effective in determining learning styles. The maximum indices of suitability for personalisation (5 points for MLP and Random Forest) quantitatively confirmed this approach. Comparison with A. Dos *et al.* (2023) emphasised the importance of high-quality personalisation for increasing student success. In the conducted analysis, a similar trend was observed: the models with the highest F1-scores turned out to be those that best reproduced the structure of behavioural patterns and formed the most relevant recommendations.

A comparison of the obtained results with modern approaches to personalised learning evidenced that generative and classification models with a developed deep structure provide a significant increase in the accuracy of adapting learning tasks. This is consistent with the conclusions of H. Rouzegar & M. Makrehchi (2024), who showed that models based on GPT architectures most effectively form individualised test questions due to their ability to work with multidimensional student profiles. In the conducted quantitative analysis, the highest F1-score values were also demonstrated by algorithms with pronounced non-linearity – the multilayer neural network and Random Forest – which confirmed their ability to accurately reproduce individual educational scenarios and replicated the trend outlined in the mentioned study. A certain correspondence was also evident in the context of the work by Q. Zhang (2023), who analysed models for early education. Regardless of age segments, the highest effectiveness was demonstrated by algorithms with a non-linear architecture – precisely the result that was recorded in the conducted study. The research by D. Li (2024), dedicated to interactive learning assessment systems, proved the necessity of applying models capable of working with mixed and multidimensional features. In the conducted analysis, such models provided the highest generalisation performance indicators.

Thus, the comparison of the quantitative metrics of the classification models with international interdisciplinary research has demonstrated that the development of personalised educational systems resides at the intersection of several fundamental trends in contemporary digital pedagogy: the shift from linear recommendation mechanisms to deep models of student behaviour analysis, the enhanced role of integrated multi-level user profiles, the growing significance of noise-resistant and adaptive algorithms, and the gradual implementation of generative AI technologies in learning environments. It is precisely the combination of these directions that shapes the new paradigm of personalised learning, within which a quality recommendation is defined not by a single model, but by the interaction of non-linear approximation, behavioural analytics, and intelligent generalisation mechanisms. The obtained results quantitatively confirmed that multi-layered neural networks and ensemble methods constitute the core of modern recommendation systems, while SVM and Decision Trees serve auxiliary analytical functions. The synthesis of these conceptual approaches outlines a scientifically grounded trajectory for the development of adaptive educational platforms, aligned with global technological benchmarks in the field of AI-oriented education.

## Conclusions

As a result of the research, a fully reproducible computational and analytical assessment of the effectiveness of machine learning algorithms for the task of personalised educational content recommendation in distance learning systems was conducted. The constructed synthetic dataset of 10,000 student profiles reproduced realistic behavioural, demographic, and content patterns from the LMS platforms Moodle, Coursera, and EdX. The application of Normal, Log-normal, and Poisson data generation methods enabled the formation of a heterogeneous feature space characteristic of real digital courses. The implemented ML-pipeline in the Python 3.12 and Microsoft Excel 2025 environments ensured the correctness of data preparation according to modern machine learning practices: normalisation, encoding of categorical variables, SMOTE balancing, handling of missing values, and 10-fold cross-validation.

Model optimisation using GridSearchCV and RandomizedSearchCV allowed for the identification of parameters ensuring the best generalisation capability: for SVM, the optimal parameters were $C = 12$ and $\gamma = 0.087$; for Decision Tree – a depth of 14 levels; for Random Forest – an ensemble of 300 trees; for MLP – a 64-32-16 architecture with ReLU activation and learning_rate = 0.001. Comparative analysis of classification metrics revealed significant discrepancies between the algorithms. The highest quality was demonstrated by the MLP neural network with accuracy = 0.91 and F1-score = 0.9, confirming its ability to model complex non-linear dependencies in multidimensional educational data. Random Forest achieved stable metrics ($F1 = 0.87$), attributable to its ensemble nature and high noise resistance, whereas SVM showed moderate but balanced performance ($F1 = 0.83$). Decision Tree, despite its maximal model interpretability, demonstrated the lowest results ($F1 = 0.7$) due to increased sensitivity to the asymmetry and variability of behavioural features.

Graphical analysis of density curves for behavioural parameters evidenced the presence of two key patterns of student interaction: high variability in time-on-task and relative compactness of views. This directly influenced algorithm performance: models capable of non-linear mapping and noise aggregation (MLP, Random Forest) reproduced the data structure better, while models with high interpretability but low flexibility (Decision Tree) lost accuracy in areas of distribution gaps .The integral systematic analysis of semi-quantitative characteristics confirmed the quantitative advantage of the neural network (23 points) and Random Forest (21 points), which aligns with their high metrics. SVM received 19 points, occupying an intermediate position due to its moderate non-linearity and noise resistance. Decision Tree remained the least effective (17 points) but retained its value as an interpretable analytics module for LMS instructors and administrators. Comparative interpretation of the results demonstrated that the neural network is the most suitable for deep personalisation of learning trajectories in multidimensional and heterogeneous data, while Random Forest serves as the most universal and stable algorithm for large-scale LMS with a high number of students. SVM proved suitable for courses with clear boundaries between student groups and structured activity patterns. Decision Tree is advisable to use as explanatory models or as part of hybrid ensembles.

The practical results of the research form a methodologically substantiated foundation for the development of recommendation systems in distance platforms. They confirm that the effectiveness of personalisation depends on the alignment between the data structure, the chosen algorithm, and the quality of parameter optimisation. The most promising direction for further research is the expansion of the dataset structure, testing of hybrid models (e.g., RF + MLP or SVM + Neural Networks), integration of contextual personalisation, and implementation of experiments on real LMS involving student activity time series.

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## Conflict of Interest

None.

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# Порівняльний аналіз алгоритмів машинного навчання для персоналізації освітнього контенту в дистанційному навчанні

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**Анотація.** Метою дослідження було здійснення комплексної оцінки ефективності алгоритмів машинного навчання для задачі персоналізованої рекомендації навчального контенту в дистанційних системах освіти. Робота мала теоретико-експериментальний характер і виконувалася на основі синтетичного датасету обсягом 10 000 студентських профілів, сформованого на основі структурних характеристик провідних платформ дистанційного навчання. Датасет охоплював три групи ознак: демографічні, поведінкові та контентні, що відтворюють ключові патерни взаємодії студентів із навчальним середовищем. Порівняльний аналіз ефективності методу опорних векторів, дерева рішень, випадкового лісу та багатошарової нейронної мережі засвідчив чіткі кількісні відмінності між моделями. Найвищі класифікаційні результати отримано для нейронної мережі (accuracy = 0,91; F1-score = 0,90). Ансамблева модель Random Forest забезпечила високу стабільність та точність (accuracy = 0,89; F1-score = 0,87). Метод опорних векторів показав збалансовані показники (accuracy = 0,86; F1-score = 0,83), а дерево рішень – найнижчу ефективність (accuracy = 0,72; F1-score = 0,70), що підтверджує обмеження інтерпретованих моделей у багатовимірних даних. Додатковий системний аналіз, виконаний за напівкількісними індексами шести характеристик алгоритмів, відобразив узагальнену придатність моделей до персоналізації: нейронна мережа отримала 23 бали, Random Forest – 21 бал, SVM – 19 балів, Decision Tree – 17 балів. Ці показники узгоджуються з класифікаційними метриками та підтверджують переваги моделей із вираженою нелінійністю та ансамблевою структурою. Багатошарова нейронна мережа демонструє найвищу ефективність для глибокої персоналізації контенту, випадковий ліс виступає універсальною моделлю для масштабних освітніх платформ, метод опорних векторів є оптимальним для курсів із чіткою сегментацією студентів, тоді як дерево рішень доцільно використовувати як інтерпретований аналітичний модуль. Практична значущість дослідження полягає у формуванні науково обґрунтованого підходу до вибору алгоритмів для побудови адаптивних освітніх траєкторій та покращення ефективності цифрової освіти

**Ключові слова:** цифрове середовище; Learning Management System; оптимізація гіперпараметрів; нейронні мережі; синтетичний датасет