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Prediktivno modeliranje učinka studenata zasnovano na veštačkoj inteligenciji u Moodle-u: Studija slučaja COLOURS Alliance-a

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Summary in Serbian: Evropski univerzitetski savezi imaju za cilj da poboljšaju studentski uspeh i omoguće personalizovano učenje kroz integraciju digitalnih platformi i inteligentnih alata koji podržavaju procese nastave i učenja. Ovaj rad istražuje primenu veštačke inteligencije (VI) za predviđanje studenata koji su u riziku od akademskog neuspeha analizirajući njihove aktivnosti u okviru Moodle, široko korišćene platforme za e-učenje. Naša studija slučaja je evropski univerzitetski savez COLOURS i njegove Moodle platforme na svakom partnerskom univerzitetu, ali i interoperabilne infrastrukture postavljene na nivou saveza (bilo da je to Moodle ili posebno određeni agregatori i portali). Analiza razmatra više indikatora, uključujući broj završenih zadataka, sati provedenih u učenju, učešće u diskusionim forumima, prisustvo nastavnim aktivnostima i angažovanje sa digitalnim resursima kao što su materijali za učenje, kvizovi i simulacije. Nameravamo da prvo uključimo kvantitativne podatke, ali u kasnijim fazama istraživanja i kvalitativne aspekte, kao i različite kontekste. Za potrebe analize saveza COLOURS, model mašinskog učenja „Slučajna šuma“ implementiran je u Pajtonu koristeći Google Colab za analizu podataka o aktivnostima na Moodle-u i predviđanje studenata u riziku. Podaci o aktivnostima studenata prikupljaju se sa Moodle-a putem Learning Record Store-a (LRS), koji obezbeđuje standardizovane xAPI izjave i pouzdano izdvajanje podataka. Ovaj pristup koristi bogat skup podataka prikupljen u Moodle-u i prediktivne mogućnosti veštačke inteligencije kako bi podržao rano otkrivanje rizika i personalizovane preporuke za učenje. Očekivani ishod je rana identifikacija studenata u riziku, omogućavajući blagovremene intervencije i doprinoseći razvoju efikasnijih, personalizovanih strategija učenja koji poboljšavaju akademska postignuća.

Keywords: Veštačka inteligencija, COLOURS Alliance, Slučajna šuma, Učenici u riziku, Prediktivno modeliranje, Analitika učenja, Interoperabilnost, Moodle

AI-Based Predictive Modeling of Student Performance in Moodle: A Case Study from the COLOURS Alliance

Abstract in English: European university alliances aim to enhance student performance and enable personalized learning through the integration of digital platforms and intelligent tools that support teaching and learning processes. This paper explores the application of Artificial Intelligence (AI) to predict students at risk of academic failure by analyzing their activity within Moodle, a widely used e-learning platform. Our case study is the European university alliance COLOURS and its Moodle platforms across each partner university, but also the interoperable infrastructures set on Alliance level (be it Moodle of Moodles or specially designated aggregators and portals. The analysis considers multiple indicators, including the number of completed assignments, hours spent studying, participation in discussion forums, attendance in learning activities, and engagement with digital resources such as learning materials, quizzes, and simulations. We intend to incorporate quantitative data first, but at later stages of the research, also qualitative aspects, as well as diverse contexts. For the purposes of the COLOURS alliance analysis, a Random Forest machine learning model is implemented in Python using Google Colab to analyze Moodle activity data and predict at-risk students. Student activity data are collected from Moodle through a Learning Record Store (LRS), which ensures standardized xAPI statements and reliable data extraction. This approach leverages the rich dataset collected in Moodle and the predictive capabilities of AI to support early risk detection and personalized learning recommendations. The expected outcome is the early identification of at-risk students, enabling timely interventions and contributing to the development of more effective, personalized learning strategies that enhance academic achievement.

Keywords: Artificial Intelligence, COLOURS Alliance, Random Forest, At-Risk Students, Predictive Modeling, Learning Analytics, Interoperability, Moodle

1. Introduction

The major development for AI-based predictive modeling for student performance within the Learning Management Systems (LMS) and more specifically Moodle, are the shifts toward Learning Analytics (LA) and Educational Data Mining (EDM) and from simple statistical tracking to complex deep learning models that offer early intervention capabilities. Traditional Moodle evaluation relied on "static" rule-based systems (e.g., checking if a student has logged in). Modern literature identifies a transition toward Supervised Machine Learning, where Moodle logs, including quiz submissions, forum interactions, and assignment timelines, serve as features to train predictive models (Abuzinadah et al., 2023). Moodle's own Analytics API now integrates with Python-based backends (TensorFlow) to provide real-time performance insights (MoodleDocs, 2021).

In recent years, digital learning platforms have transformed higher education by providing flexible, interactive, and personalized learning environments. European university alliances have been built with a concept of global campuses, digital and physical, interrelated across countries, time zones and cultures, with common denominator – technology. Our case study, the COLOURS European university alliance (COLOURS alliance website, 2025), in which the University "St. Kliment Ohridski" – Bitola (UKLO) is a partner, aims to enhance student performance and support personalized learning by leveraging Moodle as its primary e-learning platform. Moodle collects extensive data on student activities, including assignments, forum participation, attendance, and engagement with learning resources. These data provide a valuable opportunity to understand student behavior and identify students who may be at risk of academic failure.

Predictive analytics and Artificial Intelligence (AI) have emerged as powerful tools for improving educational outcomes. By analyzing patterns in student activity, AI models can identify at-risk students early and provide instructors with actionable insights for timely intervention. For the purposes of the COLOURS Project, student activity data will be extracted from Moodle and analyzed externally using a Random Forest machine learning model implemented in Python via Google Colab. This approach combines Moodle's rich dataset with AI-based predictive modeling to detect at-risk students and propose personalized learning strategies.

The main objectives of this planned study are:

1. To explore the potential of AI-based predictive modeling in identifying at-risk students using data from Moodle.
2. To plan the implementation of a Random Forest model for classifying students based on multiple behavioral indicators.
3. To demonstrate how the combination of Moodle data and AI could support early interventions and personalized learning strategies to improve academic success.

By integrating AI analysis with Moodle data, this planned initiative contributes to the growing field of Learning Analytics, offering a framework for educators to enhance student engagement, monitor performance, and proactively address academic risks, in alignment with the goals of the COLOURS project.

2. Theoretical background

Artificial Intelligence (AI) has become a powerful tool in education, enabling the analysis of large volumes of student data to improve learning outcomes. Previous research has applied AI techniques, such as Decision Trees, Random Forest, and Neural Networks, to predict student success, identify at-risk students, and personalize learning experiences. Studies have shown that predictive modeling can help instructors detect early warning signs, such as low engagement, incomplete assignments, and poor attendance, allowing timely interventions that increase academic achievement. Recent literature indicates a significant move from descriptive grading to predictive modeling. Educational Data Mining (EDM) now allows institutions to intervene before a student fails and its model efficacy is significant. By applying Long Short-Term Memory (LSTM) and Multi-Task Learning models to predict final grades with high accuracy with a Mean Absolute Error (MAE) as low as 0.0249 in predicting total scores (Sandeepa & Mohottala, 2025). In terms of behavioral data, we can discuss that evaluation is no longer limited to test scores. Models now incorporate "spatiotemporal" data, such as login frequency on Learning Management Systems (LMS), time spent on resources, and even physiological markers of engagement (Shou et al., 2024), which are aspects our approach is incorporating too. Another important shift in the latest research is that IQ is no longer viewed as the sole or even primary predictor of success. For this, we turn to studies published in Nature Human Behaviour in the past years which find that non-cognitive skills—such as grit, self-regulation, and academic interest—are as predictive of achievement as cognitive ability, and their influence actually doubles in teenage years (Malanchini & Allegrini, 2024). This represents a threshold of age where university student profiles are built and shaped through primary and secondary school, which for the new European universities of the future, envisioned as global campuses of interrelated universities and stakeholders which provide challenge-based, problem-based teaching and learning, microcredentials and personalized study plans, across vast offering. For these new environments, the academic identity and "academic enthusiasm" have been identified as core mediators. As evaluation becomes more automated, the literature has raised red flags regarding the "human element" and algorithmic fairness. The "black box" nature of AI predictive tools poses a risk. There is concern that labeling a student as "at-risk" early on can create a self-fulfilling prophecy or "labelling effect" (Holmes et al., 2022), so these aspects should be handled with great care, with late binding and background logic which is not necessarily visible to the end users.

With regards to the Moodle platform, as technological foundation for the courses in our case study, there is visible move in evaluating student performance from "completion tracking" to high-granularity, multi-platform behavioral analysis. There is technical synergy between Moodle and xAPI, the depth of data captured, and the resulting impact on performance evaluation. Traditional Moodle evaluation relies on internal log stores that track basic web requests (e.g., viewed page, submitted quiz). While these provide a "snapshot" of activity, literature identifies them as insufficient for modern learning analytics. Standard Moodle logs often lack the "verb-object" detail required to understand how a student interacted with a resource. xAPI addresses this by providing over a hundred trackable events, down to individual quiz question attempts and video interactions (Yet Analytics, 2025). Unlike native logs, which are locked within Moodle's database, xAPI statements are interoperable. This allows performance data from external tools (e.g., H5P, mobile apps, or offline simulations) to be centralized in a Learning Record Store (LRS) for a holistic view of the student (Bigler et al., 2025).

There are several "behavioral indicators" in Moodle that correlate most strongly with academic success:

- *Submission Patterns:* Submission actions are the most crucial predictor of performance, while "delete actions" hold the least predictive value (Ayon et al., 2024).
- *Engagement Logs:* Interaction frequency with Virtual Learning Environment (VLE) resources, such as "clickstream data," is highly effective for identifying students at risk of withdrawal, with some models achieving 99% precision in predicting dropouts (Mahdi-Reza et al., 2024).
- *Time-Series Data:* The timing of interactions (e.g., late-night access or procrastination patterns) is increasingly used in Long Short-Term Memory (LSTM) networks to capture the dynamic nature of learning over a semester (Sandeepa & Mohottala, 2025).

With regards to AI algorithms and their prospective use in the predictive modeling of university student performance, we have analyzed the most applicable ones. The selection of an algorithm depends on the specific "temporal" or "categorical" nature of the student data. Random Forest (RF) and Decision Trees are highly regarded for their interpretability and ability to handle the non-linear relationships often found in socio-economic and demographic data, with RF typically offering higher accuracy by reducing the risk of overfitting (Duch et al., 2024). For high-dimensional datasets involving text-based forum interactions or complex xAPI "verbs," Support Vector Machines (SVM) provide robust classification boundaries (Kaensar & Wongnin, 2023). When the evaluation focuses on the sequence of learning actions over time, such as a student's engagement trajectory across a semester - Long Short-Term Memory (LSTM) networks are superior due to their ability to retain long-term dependencies in time-series data (Sandeepa & Mohottala, 2025). Finally, K-Means Clustering serves as a foundational tool for unsupervised discovery, allowing educators to group students into behavioral profiles (e.g., "procrastinators" vs. "consistent achievers") without prior labeling (Shou et al., 2024).

Table 1 shows the different algorithms considered in the approach along with their strengths and limitations, with regards to their primary use in evaluation.

Table 1. Strengths and limitations of algorithms used in evaluation

Algorithm	Primary use in Evaluation	Strengths	Limitations
Random Forest (RF)	Classifying "Pass/Fail" or "At-Risk" status.	Handles large datasets with many variables (e.g., socio-economic + grades).	Can be a "black box"; hard to explain exactly why a student was flagged.
Support Vector Machines (SVM)	Fine-grained performance categorization.	Effective in high-dimensional spaces (e.g., analyzing sentiment in student essays).	High computational cost for very large datasets.
LSTM (Neural Networks)	Analyzing progress over time (Time-series).	Best for "Early Warning" by tracking how engagement drops over weeks.	Requires massive amounts of data to be accurate.
K-Means Clustering	Grouping students by learning style or behavior.	Helps in personalizing interventions for different "types" of learners.	Results depend heavily on how many groups (k) the researcher chooses.
Decision Trees	Visualizing the path to student success/failure.	High transparency; easy for teachers to understand the logic.	Prone to overfitting (being too specific to one class year).

The typical evaluation of these models is using specific mathematical metrics to ensure they are reliable enough for institutional use:

- *Accuracy:* The percentage of correct predictions.
- *Precision:* Of those predicted to fail, how many actually did? (Reduces "false alarms").
- *Recall:* Of all the students who failed, how many did the model actually catch? (Reduces "missed cases").

$$F_1 = 2 \times \frac{precision \times recall}{precision + recall}$$

The F_1 is the most used metric in recent literature because it balances the need to catch struggling students (Recall) without overwhelming advisors with false alarms (Precision) (Van Rijsbergen, 1979).

These constitute rich foundation for conceptualizing AI-based predictive modeling for assessing university student performance in Moodle.

3. Conceptual Framework

Random Forest (RF) is an ensemble machine learning method that constructs multiple decision trees and aggregates their outputs to produce more accurate and robust predictions. Each decision tree is trained on a random subset of the data and a random subset of features, a process known as *bagging* (bootstrap aggregating). The final prediction is determined by majority voting in classification tasks or by averaging in regression tasks. Random Forest is particularly suitable for educational data analysis because it can handle complex and correlated input variables, is less prone to overfitting than single decision trees, and provides measures of feature importance. These characteristics make it an effective tool for predicting students at risk of academic failure, where multiple behavioral indicators simultaneously influence outcomes.

Learning Analytics (LA) refers to the systematic collection, measurement, analysis, and reporting of data about learners and their contexts, with the goal of understanding and optimizing learning processes. In the context of e-learning, LA helps instructors monitor student engagement, track progress, detect early signs of low performance, and provide timely interventions. Learning Analytics typically leverages three types of data:

1. **Behavioral data** – student actions such as assignment submissions, forum participation, and quiz interactions;
2. **Performance data** – grades, scores, and completion rates;
3. **Contextual data** – attendance, access to learning resources, and time spent on tasks.

By combining these data types, LA supports personalized learning strategies and evidence-based interventions.

4. Methodology

This study presents a proof-of-concept demonstrating how AI-based predictive modeling can be applied to Moodle activity data to identify students at risk. The primary objective is to establish a scalable workflow for data preprocessing, model training, evaluation, and visualization using trial data. While the current implementation relies on simulated data for demonstration purposes, the methodology is designed to be directly applicable to real student activity records collected within the COLOURS alliance project, enabling timely interventions and personalized learning strategies.

4.1. Data Collection and Description

To illustrate the predictive modeling workflow, a trial dataset of 1000 simulated students was generated to reflect typical Moodle usage patterns. The dataset includes features representing key learning behaviors, such as the number of assignments completed, hours spent studying, forum participation, attendance, and engagement with digital resources, including quizzes and learning materials. Each student is uniquely identified, and in addition to the activity metrics, two outcome variables were defined: **Passed**, a binary indicator of course success, and **Risk_Score**, a continuous measure estimating the likelihood of academic failure. Passed was calculated based on a weighted combination of key activity indicators, while Risk_Score was normalized between 0 and 1 to provide a continuous risk assessment. The simulated dataset ensures sufficient variability to demonstrate the model's capabilities and visualize differences in student risk levels, while serving as a conceptual proof-of-concept.

Table 2. Key Learning Behaviors in the Trial Dataset

Variable	**Description**
Student_ID	Unique identifier for each student
Assignments_Completed	Number of assignments submitted
Hours_Studied	Hours spent on learning activities
Forum_Posts	Number of posts in discussion forums
Attendance	Recorded attendance in classes or online sessions
Digital_Resource_Usage	Engagement with learning materials, quizzes, and simulations
Passed	Binary outcome indicating course success (1) or failure (0)
Risk_Score	Continuous measure estimating the probability of academic failure (0–1)

4.2. Data Preprocessing

The trial dataset was prepared to ensure compatibility with the Random Forest algorithms. All values in the simulated dataset are numeric and complete, so no missing data handling was required. Numeric variables are structured for direct input into the models, and categorical encoding is applied when necessary. This preprocessing ensures that the dataset is ready for machine learning analysis. When real Moodle data are used in the next phase of the project, additional steps will address missing values, inconsistencies, and anomalies inherent in real-world datasets. The current workflow establishes the preprocessing steps required for larger datasets, ensuring that the methodology is scalable and adaptable.

4.3. Model Training

The predictive modeling was performed using a Random Forest approach on the trial dataset. A Random Forest Classifier was used to predict whether a student is at risk of failing or successfully passing the course, while a Random Forest Regressor estimated the continuous Risk_Score for each student, representing the probability of academic failure. The dataset was split into a training set (70%) and a testing set (30%) to train the models and evaluate their performance on unseen data. This approach allows both the binary outcome and the continuous risk measure to be predicted from the same set of student activity indicators. For real Moodle data, the same methodology will be applied after proper data extraction, cleaning, and preprocessing.

4.4. Model Evaluation and Visualization

The performance of the predictive models was evaluated using standard statistical metrics and visualization techniques. For the classification task, accuracy, precision, recall, and F1-score were computed to assess how effectively the Random Forest Classifier distinguished between successful and at-risk students. The accuracy of the classifier was approximately 0.80, indicating that 80% of the predictions matched the actual outcomes. A confusion matrix was generated to visualize correct and incorrect predictions, providing insight into the balance between false positives and false negatives. The F1-score, reflecting the balance between precision and recall, was also computed and found to be around 0.80, demonstrating a reliable classification performance for identifying at-risk students.

For the regression task, the Random Forest Regressor was assessed using the Mean Squared Error (MSE) to measure the deviation between predicted and actual Risk_Score values. Lower MSE values indicate a better model fit and higher predictive reliability. Feature importance analysis was conducted for both models to identify which behavioral indicators had the greatest influence on prediction accuracy. This analysis revealed that variables such as assignments completed, hours studied, and attendance contributed most significantly to predicting student outcomes.

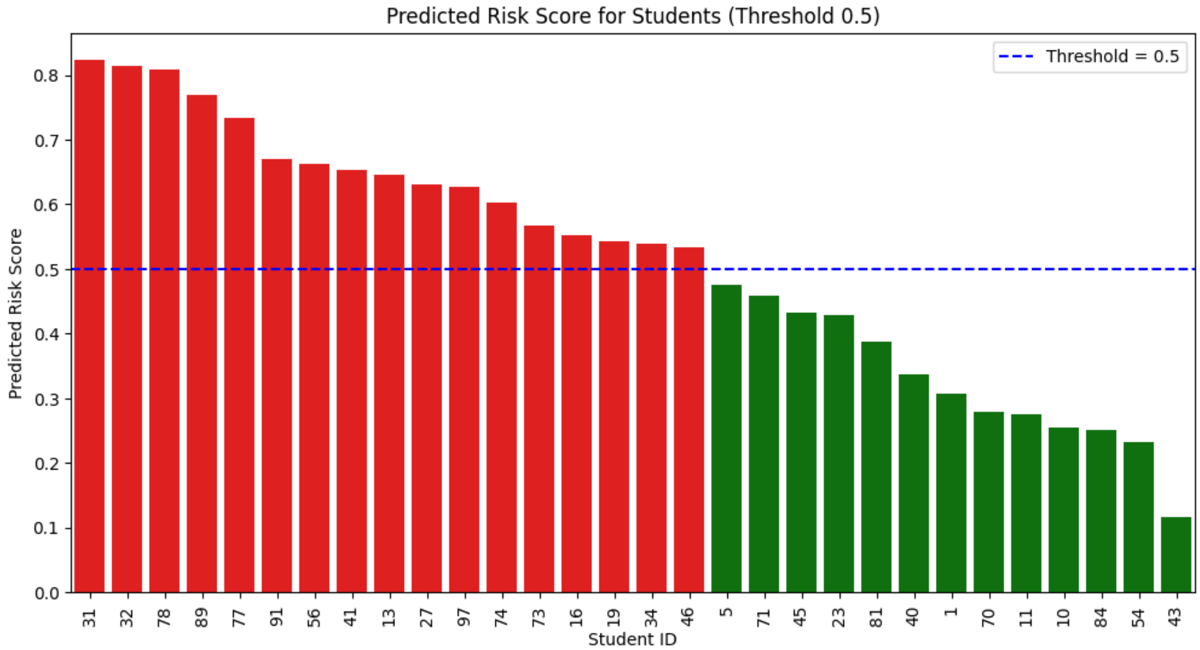
4.5. Integration with Moodle and LRS

In practical implementation, student activity data is collected directly from Moodle through a Learning Record Store (LRS), which acts as an intermediary that standardizes xAPI statements generated by Moodle activities. Each statement records key information about learner actions.

This approach allows the Random Forest model to access detailed behavioral data for predictive analysis without requiring direct integration with external analytics platforms like Google CoHub. Once extracted, the data from the LRS can be exported in a structured format (e.g., CSV or database table) and imported into Python in Google Colab for preprocessing, model training, and visualization.

By using the LRS as a central data collection layer, the workflow ensures compatibility with standard xAPI statements, facilitates scalable data extraction from Moodle, and maintains data integrity for AI-based predictive modeling. This method supports timely identification of at-risk students and allows educators to design personalized interventions based on reliable, real-time activity data.

Figure 1. Predicted Risk Scores for Students Using Random Forest Regression



This bar chart visualizes the predicted probability of academic failure (Risk Score) for each student, calculated using a Random Forest regression model. The model considers multiple indicators of student activity, including assignments completed, hours studied, forum participation, attendance, and engagement with digital resources. Students are sorted from highest to lowest predicted risk to highlight those who may require immediate attention.

The colours indicate the risk levels relative to a threshold of 0.5: red bars represent students with a high risk of academic failure (Risk Score > 0.5), while green bars represent students with a low risk (Risk Score ≤ 0.5). A horizontal blue dashed line marks the threshold at 0.5 for easy reference.

This visualization allows educators to quickly identify at-risk students and plan targeted interventions or personalized support strategies, thereby supporting timely measures to improve student outcomes. The chart was generated in Python using Matplotlib and Seaborn within Google Colab, demonstrating both the predictive capabilities of the Random Forest model and the practical application of AI-based analytics for educational data.

5. Conclusion

The integration of AI-based predictive modeling within the COLOURS Alliance framework represents a significant shift from reactive to proactive educational support. By leveraging the granularity of Moodle (and further more on the xAPI) data and the robust classification power of Random Forest models, this study demonstrates that Moodle activity, specifically assignment completion, study hours, and attendance, serve as a reliable predictor of student success. While the current proof-of-concept utilizes simulated data to validate the Python-based workflow, the infrastructure is now in place to transition to real-world datasets across the Alliance's interoperable platforms. However, as these models move toward implementation, it is essential to balance technical accuracy with ethical responsibility. To avoid the "labeling effect" identified in recent literature, future efforts must ensure that AI insights are used as a discreet background tool for educators rather than a "black box" that stigmatizes learners. Ultimately, this approach provides a scalable roadmap for European university alliances to foster a more personalized, challenge-based learning environment that proactively addresses academic risk not just before failure occurs, but to navigate it towards personalized successful journey.

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