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PREDICTING ACADEMIC ACHIEVEMENT IN ARTIFICIAL INTELLIGENCE EDUCATION USING STUDENT ASSESSMENT INDICATORS

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ABSTRACT

In Higher Education, prediction of student performance based on assessment signals has become a critical task in accurately evaluating performance and as a support to data-driven decision making. This study aimed to evaluate the final exam grades prediction performance of machine learning algorithms for the Artificial Intelligence Course students. Data were 560 student records and data were analyzed using quantitative predictive approach. Three predictive indicators – Quiz scores, Midterm examination marks and three assignment scores – were analyzed. Four regression models namely Linear Regression, Random Forest, Support Vector Regression and XGBoost were tested based on mean absolute error (MAE), root mean square error (RMSE) and coefficient of determination (R^2). The model with the highest predictive accuracy was XGBoost with an RMSE of 5.252, an MAE of 3.949 and an R^2 of 0.393. The feature importance analysis showed that the important predictors were the performance of the midterm exam and Assignment 3. The results do indicate the potential for using assessment-based machine learning models for academic monitoring and educational decision making; however, the accuracy was moderate. A model should be further tested by other education contexts to enhance the generalizability of the mo.del.

Keywords – Academic Achievement; Artificial Intelligence Education; Educational Data Mining; Machine Learning; Predictive Analytics

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1. Introduction

In AI offers a transformative technology in higher education, ushering in new opportunities to enrich teaching practice, assess learning and inform evidence-based academic decision making. As AI's role in education expands, colleges and universities are increasingly turning to data analysis to gain insights into student results and correlate performance with various factors. Current assessment methods are limited to using examination marks and grades to assess performance, with little consideration given to how learning difficulties can be identified and addressed prior to final exams. AI-driven predictive analytics, on the other hand, allows for a systematic analysis of the pattern in student assessment data to uncover academic trends and make predictions about future performance. These strategies can help to ensure that interventions are delivered in a timely fashion and that educational assessment systems are effective (Jokhan et al., 2022). In addition, there is the potential to leverage machine learning to convert the vast amount of educational data, collected routinely, into meaningful information for academic monitoring and support for students (Hooda et al., 2022).

Consequently, one of the most important research areas of educational data mining has been the academic achievement prediction problem, particularly with the amount of assessment data that is generated in higher education institutions. This is a multi-dimensional phenomenon where students' assessment results, learning strategies, involvement and previous academic knowledge all have an impact on their academic achievement. A machine learning algorithm has more capabilities in modelling complex and potentially nonlinear relationships, whereas conventional statistical approaches can find relationships between these variables. It has been demonstrated that predictive algorithms can be employed to predict students' academic performance, and to identify students who require additional academic support in the previous studies (Yağcı, 2022). Similarly, predictive modeling frameworks employed in higher education have proven to be promising of a process-oriented approach to AI analysis used to support institutional decision making and enhance student achievement monitoring (Pacheco-Mendoza et al., 2023). These techniques are, however, useful only if the predictors are relevant, the data is of a suitable quality, the model is suitable, and the evaluation of the model is predictable.

Student assessment indicators are especially important sources as they directly reflect the demonstrated academic performance over the course. Quizzes, assignments, midterm examinations and other continuous assessments are designed to engage various aspect of a student's understanding and knowledge application. Assessment indicators are indicators that are specific to the course and can be used in a predictive model without having to gather a lot of personal information, unlike broad indicators of demographic characteristics. Analytical frameworks of student assessment based on research have been identified as having the potential to enhance the evaluation of education and performance estimation in the field of education (Lam et al., 2024). Furthermore, research on student learning outcomes has highlighted the need to

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assess and enhance AI performance to achieve accurate predictions in educational environments (Farhood et al., 2024). These are positive signs that assessment indicators can be used as an effective basis for building interpretable and institutionally useful academic achievement prediction systems.

Predictive analytics has particularly relevance to education in the field of AI because students need to learn the conceptual understanding, analytical reasoning, mathematical skills, and problem-solving skills that are required for this field. Success in AI courses might thus be based on performance in a combination of assessment elements, not just on one exam. In technically oriented educational environments, such as engineering education, machine learning-based prediction methods have shown great promise for predicting student achievement (Jiao et al., 2022). Moreover, research into the digital learning interactions in which students engage has demonstrated how information about educational activities can be used to gain insight into student performance and assessment processes (Borna et al., 2024). In traditional classrooms, however, it is not always possible to have digital engagement metrics and therefore a pattern of regularly collected assessment scores is an accessible alternative for creating predictive models.

Many studies in the past have investigated the prediction of academic outcomes using AI-based techniques such as regression, support vector machines (SVM), ensemble learning and other supervised algorithms. Comparative experiments have shown that the performance of prediction can significantly differ from one dataset to another, depending on the features extracted and the parameters used for the algorithms (Ahmed, 2024). The application of machine learning in education is also found to have ongoing problems in terms of generalizability, interpretability, and consistency of the models across learning contexts (Wang & Ab Rahman, 2024). While advanced algorithms may enhance the predictive power, the educational use of models rests on the ability to interpret, make sense of model outputs and translate into appropriate educational decisions. Therefore, the assessment of the predictive accuracy of the indicators of the assessment process is very important to create academically useful predictions.

Recent studies have also highlighted the significance of taking education into account when interpreting measures of performance predicted by AI. Assessment-based models are considered predictive, rather than explanatory, factors of achievement, and learning strategies and individual academic background can affect achievement (Bressane et al., 2024). Furthermore, AI-powered performance tracking systems have been shown to track learning performance and contribute to educational decision-making during the learning process (Haron et al., 2025). Other research in the field of predictive analytics in higher education education again highlights the importance of systematically studying the usability of AI methods for assessing academic performance (Dasuki, 2025). However, more studies are needed to determine the degree of prediction of continuous assessment indicators of the subsequent examination performance in the academic domain.

Even with these advances, there is an important methodological issue related to the difference

between what is truly predictive of academic achievement and what is merely reconstructing the existing grades from the scores on their constituent assessments. The results from models that use final examination marks or cumulative grades as predictors of outcomes that are closely related to those may be misleadingly optimistic due to information leakage. To address this concern, targets need to be assessed with indicators that can be measured in advance of target achievement and using assessments of previously unseen cases of the target. Based on this, the present study aims to examine the prediction power of quiz, midterm, and assignment scores on achievement of final examination in the artificial intelligence course. The study uses an openly available student performance database to compare supervised regression algorithms, assess predictive accuracy and robustness, and explore the relative effects of each measure of student performance. The results are expected to progress the research of assessment-based educational predictive analytics and provide insights in evidence-based monitoring of academic success in AI education. The objectives of this study are as known as:

1. To examine relationships between continuous assessment indicators and final examination achievement among students enrolled in artificial intelligence education.

2. To develop and compare machine learning regression models for predicting academic achievement using student assessment indicators.

3. To identify the most influential assessment indicators and evaluate their relative contributions to academic achievement prediction.

2. Materials and Methods

2.1. Research Design and Dataset Characteristics

The research design used in this study was a quantitative research design with a predictive approach.This study used a quantitative research design with a predictive approach to investigate the relationship between the indicators and the achievement of students in learning artificial intelligence (AI). The data were collected from 560 students on 12 variables including Assessment scores, Examination performance and Academic classification. Selected were five assessment indicators as explanatory variables, and the final examination marks was the primary outcome. Descriptive statistics, correlation analysis and supervised machine learning were combined to create a framework. This allowed for systematic exploration of the achievement prediction and of the performance of different regression algorithms.

2.2. Data Preprocessing & Predictor Selection

The data preprocessing steps included checking for missing values, numerical consistency, duplicates, and appropriate data for predictive modeling. There were no missing or duplicate records in the data set so all 560 observations were retained. The variables that were chosen as

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predictors were: quiz scores, marks on the midterm exam, and scores for three of the assignments. Final examination marks were used as dependent variable. Student identifiers, total scores, and grades and academic categories were not included to prevent irrelevant identification effects and information leakage. The training of algorithms that are sensitive to predictor scaling were standardized.

2.3. Exploratory Data Analysis and Statistical Assessment

This was preceded by exploratory analyses, which describe student assessment performance, and explore relationships between academic indicators. Descriptive statistics (the mean, standard deviation, median, minimum and maximum) were used to summarize score distribution. Pearson correlation coefficients were obtained to compute linear relationships between the 5 predictors and final exam scores. In addition, pairwise correlation of assessment variables were studied to look for possible multicollinearity. The statistical significance was calculated by two-sided tests at the 5% level. The results of these analyses were the basis for predictive modelling.

2.4. Machine Learning Model Development and Optimization

Multiple Linear Regression, Random Forest, Support Vector Regression, and Extreme Gradient Boosting (XGBoost) were the supervised regression algorithms used. The dataset was partitioned into 80% train set and 20% test set and the random seed was fixed to 42. For Random Forest, it took 150 trees and XGBoost it took 150 estimators, depth = 3, learning_rate = 0.05. The Support Vector Regression was done using a RBF kernel. Five-fold cross validation technique was used to validate the performance of the models with the mentioned set-ups without any additional hyperparameter optimization.

2.5. Model Evaluation and Explainability Framework

The mean absolute error (MAE), root mean squared error (RMSE) and coefficient of determination (R^2) were used to assess the predictive performance. Smaller prediction errors were shown by lower MAE and RMSE values while higher R^2 values were shown by explaining the variation in the outcome. The performance stability was tested by five-fold cross-validation (CV), which was performed entirely within the training partition. The independent test set was used for final model comparisons. Repeated shuffling of the predictors was used to compute the importance of features for the best model, drawing a connection between the error in the prediction and the importance of each assessment indicator.

3. Results

3.1. Descriptive Characteristics and Distribution of Student Assessment Scores

A descriptive analysis of 560 students' records indicated that there was variation in the assessment

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components and in students' performance on the final examination. The mean final examination score was 31.17 ± 8.17, with the range of observed values being between 4.00 and 39.50. The mean score of the midterm exam was 8.55 ± 3.74 and the mean score for the quiz was 6.48 ± 2.13. The standard deviations for the scores of assignments were comparatively smaller ranging from 0.88 to 0.91. The final examination score was skewed by lower examination scores as the median final examination score was 34.00, higher than the mean final examination score (Figure 1) (Table 1).

Table 1. Descriptive Statistics of Student Assessment Indicators and Final Examination Performance

Assessment indicator	Mean	SD	Median	Min	Max
Quiz	6.48	2.13	6.56	0.00	9.98
Midterm	8.55	3.74	8.07	0.12	15.00
Assignment 1	3.49	0.91	3.56	0.09	4.98
Assignment 2	3.67	0.91	3.98	0.21	4.98
Assignment 3	3.51	0.88	3.63	0.12	4.98
Final examination	31.17	8.17	34.00	4.00	39.50

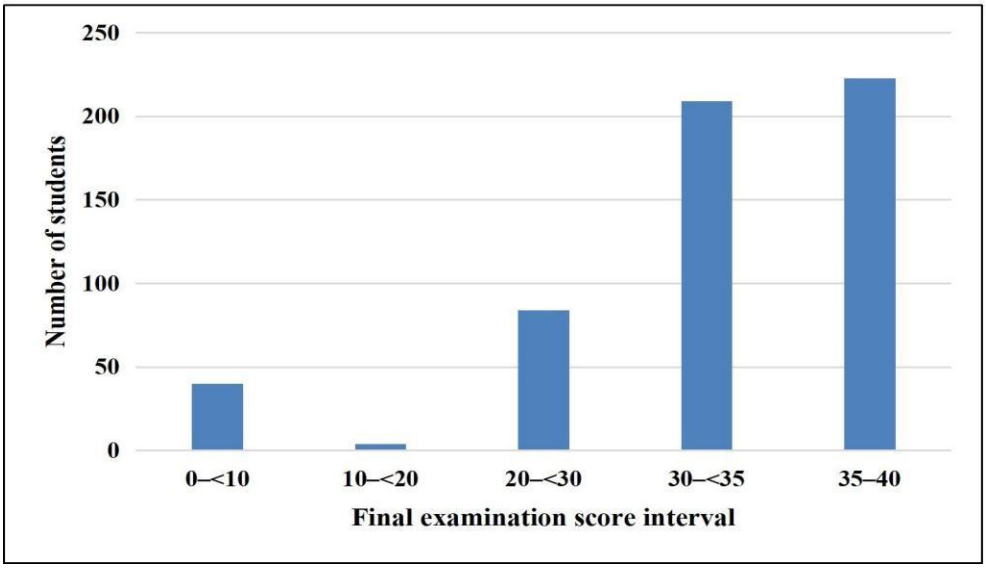

Figure 1. Distribution of Final Examination Scores Among AI Course Students

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3.2. Correlation Patterns Between Assessment Indicators and Academic Achievement

Pearson correlation analysis revealed positive and/or negative relationships between assessment indicators and final examination scores. The highest positive correlation was found between the midterm scores and the examination results ($r = 0.290$, $p < 0.001$). Assignment 3 showed a weaker positive association ($r = 0.100$, $p = 0.018$), followed by Assignment 1 ($r = 0.090$, $p = 0.034$). There was a weak, nonsignificant correlation between Quiz scores ($r = 0.073$, $p = 0.085$). Limited linear association with performance in examinations was evident as a weak negative correlation in Assignment 2 ($r = -0.065$, $p = 0.127$) (Table 2) (Figure 2).

Table 2. Pearson Correlation Between Student Assessment Indicators and Final Examination Marks

Assessment indicator	Pearson r	p-value	r^2
Quiz	0.073	0.085	0.005
Midterm	0.290	<0.001	0.084
Assignment 1	0.090	0.034	0.008
Assignment 2	−0.065	0.127	0.004
Assignment 3	0.100	0.018	0.010

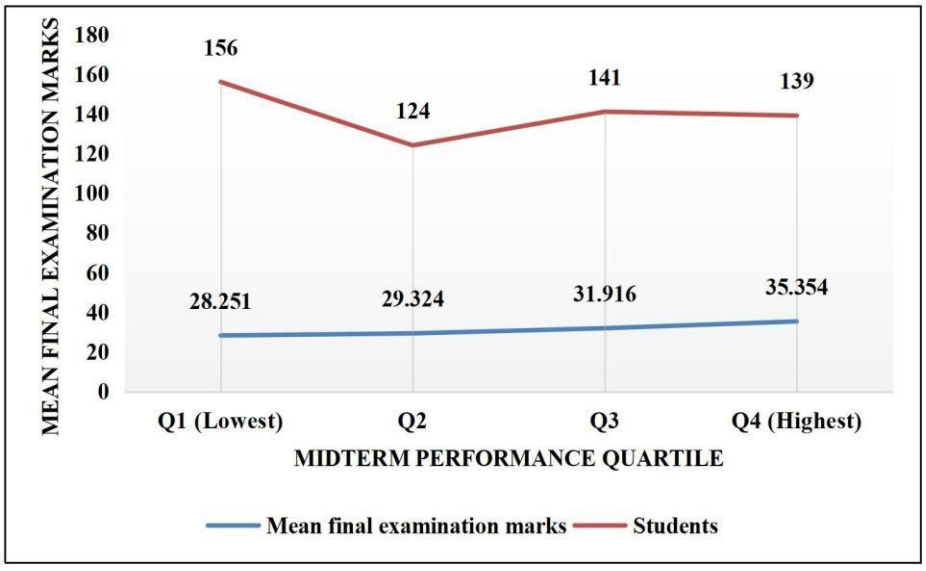

Figure 2. Mean Final Examination Achievement Across Midterm Performance Quartiles

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3.3. Comparative Predictive Performance of Machine Learning Models

Comparative evaluation showed that there was a difference between the accuracy with which the four regression algorithms could predict the data. The results on the independent test set yielded best results for XGBoost (MAE: 3.95, RMSE: 5.25, R^2: 0.393). Random Forest was a close second with an RMSE of 5.69 and an R^2 of 0.288. Linear Regression and Support Vector Regression both gave negative test R^2 value which means they perform worse than constant-mean prediction benchmark. In general, ensemble tree-based methods performed better than linear and kernel-based methods for the modeling configurations and test conditions used (Table 3) (Figure 3).

Table 3. Comparative Predictive Performance of Machine Learning Models on the Test

Machine learning model	MAE	RMSE	R^2
Linear Regression	5.209	6.958	−0.065
Random Forest Regression	4.037	5.690	0.288
Support Vector Regression	4.711	6.887	−0.043
XGBoost Regression	3.949	5.252	0.393

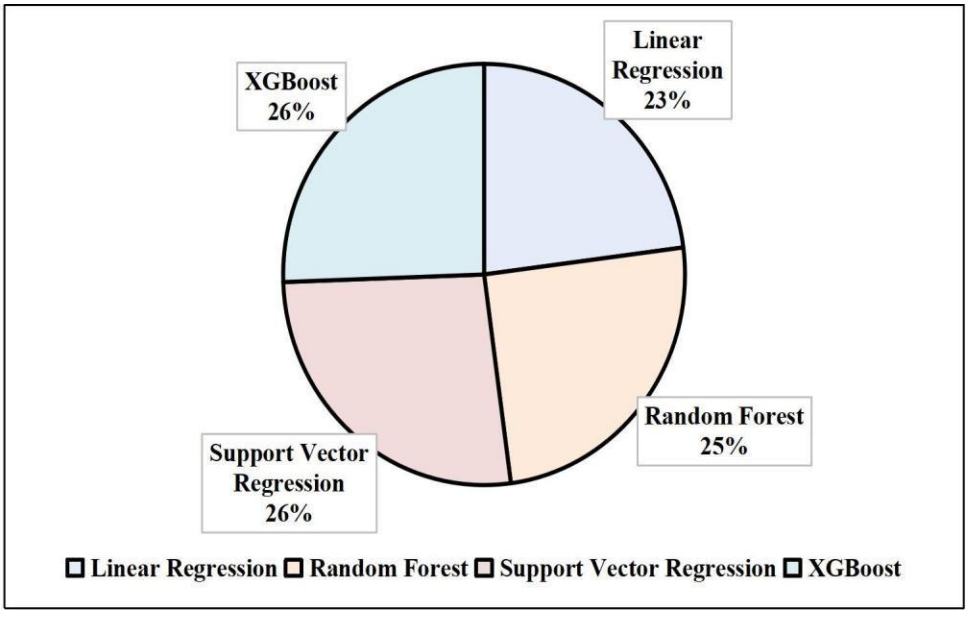

Figure 3. Percentage of Test Predictions Within Five Marks of Actual Examination Scores

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3.4. Prediction Accuracy, Error Distribution, and Model Robustness

Five-fold cross-validation revealed that there were variations in the predictive stability of the regression algorithms. XGBoost achieved the lowest average validation RMSE (5.68 ± 0.86) and highest mean R^2 (0.533 ± 0.128). The validation performance of the Random Forest model was also similar, with RMSE = 5.86 ± 1.11 and R^2 = 0.495 ± 0.174. Linear Regression had the highest mean prediction error with an RMSE of 8.00. Moderately good performance was achieved with Support Vector Regression (SVR) that achieved an RMSE of 7.55. The results show relatively high level of validation in ensemble models for all training folds (Table 4) (Figure 4).

Table 4. Five-Fold Cross-Validation Performance and Model Robustness

Model	MAE (mean ± SD)	RMSE (mean ± SD)	R^2 (mean ± SD)
Linear Regression	5.758 ± 0.529	8.000 ± 0.821	0.088 ± 0.082
Random Forest	4.137 ± 0.700	5.865 ± 1.109	0.495 ± 0.174
Support Vector Regression	4.990 ± 0.666	7.548 ± 0.755	0.181 ± 0.149
XGBoost	4.138 ± 0.588	5.677 ± 0.864	0.533 ± 0.128

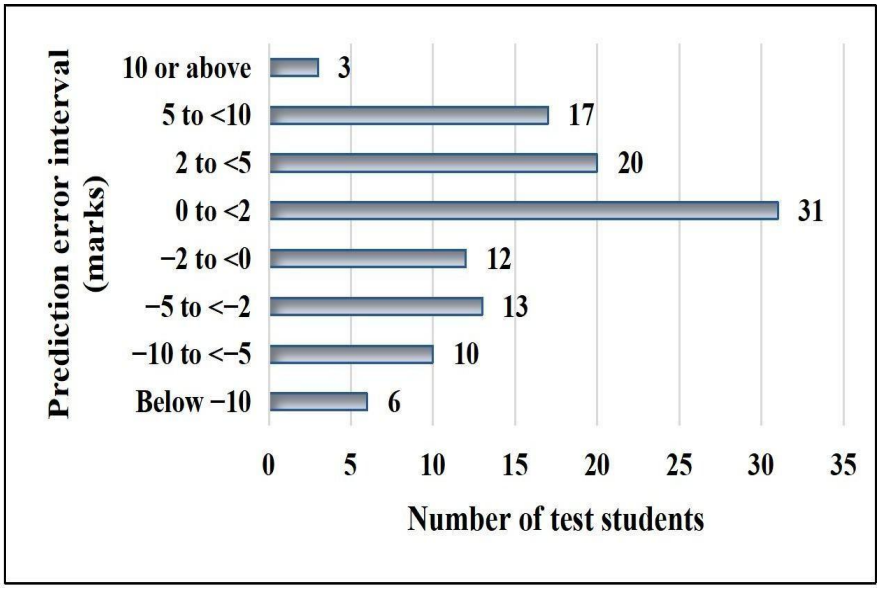

Figure 4. Distribution of Prediction Errors in the Random Forest Regression Model

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3.5. Feature Importance and Interpretation of Academic Achievement Predictors

Among all the variables used for training the model, midterm examination performance was the most important based on the permutation importance analysis of the XGBoost model, resulting in an average RMSE value increase of 0.847 when it was shuffled. The second highest contribution (0.644) was from Assignment 3, followed by Assignment 1, (0.174) and Quiz scores (0.167). The lowest mean importance was found for Assignment 2 (0.065) where large variations occurred between permutations. The results of this analysis indicate that the information found in midterm results and Assignment 3 was relatively more informative about the subsequent performance. The usage of importance estimates, however, does not capture causal effects on academic outcomes, but rather model dependence (Table 5) (Figure 5).

Table 5. Permutation Feature Importance of Assessment Indicators Using XGBoost

Assessment indicator	Mean RMSE increase	SD	Importance rank
Midterm	0.847	0.236	1
Assignment 3	0.644	0.157	2
Assignment 1	0.174	0.082	3
Quiz	0.167	0.076	4
Assignment 2	0.065	0.151	5

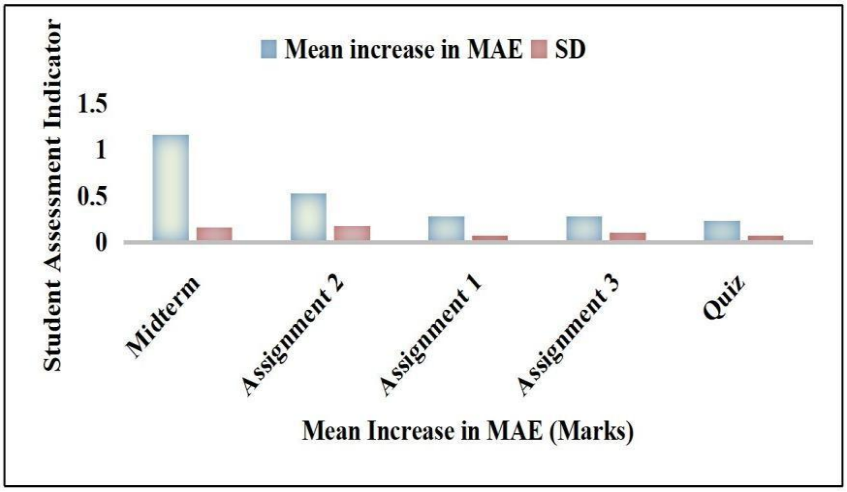

Figure 5. Permutation-Based Feature Importance of Student Assessment Indicators

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4. Discussion

The predictive ability of continuous assessment indicators for the achievement of final exams in education of artificial intelligence. Results showed that academic outcomes could be moderately well predicted from typically collected assessment scores. Overall, XGBoost had the highest test R^2 of 0.393, RMSE of 5.252, and MAE of 3.949 of the four algorithms tested. The above results show that the chosen assessment indicators accounted for about 39.3 % of the variance in the final examination scores in the test set that is not included in the training set. There was still a lot of variation in the results that didn't fit the model, however, which shows how complex academic achievement can be.

The observed predictive capability is generally consistent with educational data mining studies that have shown the feasibility of using machine learning to predict academic performance (Sarker et al., 2024). This has been the focus of past studies, as well, which have focused on the use of supervised algorithms for patterns of achievement recognition from educational data (Yakubu & Abubakar, 2022). There are, however, limitations in the ability to compare the predictive accuracy of datasets because of variations in outcome definitions, and in the methodology used to validate them. Most importantly, the current results suggest that assessment-based prediction can yield valuable information without a large number of demographic or behavioral records. Although the explanatory power was moderate, this also indicates that assessment scores are not the best representation of the cognitive, instructional and contextual factors that shape student achievement.

The correlation and feature importance analysis revealed significant variations in the predictive power of the assessment indicators. In the case of the midterm exam, the best correlation with the final exam score was found with the midterm exam ($r = 0.290$) and the highest permutation importance score (0.847). The contribution of the scores of assignment 3 to the predictive performance were also significant, while the scores of the other assignments (except quiz) were comparatively less informative. The results indicate that there could be different kinds of information that are measured during different phases of instruction. However, the relatively low bivariate relationships suggest that each of the assessment indicators has limited explanatory value as a stand-alone indicator.

Academic assessment records have been shown to be pertinent to predicting future learning outcomes in previous studies, particularly when they become available while the learning process is ongoing (Alhazmi & Sheneamer, 2023). In the same way, research using nonpersonal data in education has shown the viability of predicting academic outcomes without including sensitive information about students (Chavez et al., 2023). The present results expand this evaluation viewpoint and examine the relative predictive role of academic components in AI education.

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Permutation importance, however, is not necessarily to be interpreted as the causal effect of an assessment activity, but as the behaviour of the fitted model. Therefore, a greater importance of midterm performance should not be taken as meaning that higher midterm scores would automatically lead to higher scores on the final exams.

Comparative evaluations showed that ensemble tree-based models performed better than the traditional linear and kernel regression models with the chosen configurations. The test RMSE of XGBoost was the lowest and the R^2 was the highest, indicating that nonlinear relationships and interactions between assessment indicators may be meaningful for the prediction of final examinations. The generated R^2 values for Linear Regression and Support Vector Regression were negative, meaning they had poorer generalization compared to a constant-mean model. XGBoost was also the model with the highest mean validation R^2 (0.533) on the cross-validation results, with some folds performing better than others.

The findings align with comparative studies indicating that algorithmic features and educational dataset architectures play a crucial role in the effectiveness of machine learning (Maulana et al., 2023). Previous research has also investigated the use of artificial neural networks as an alternative approach to modelling potentially complex relationships between student achievement indicators (Baashar et al., 2022). Moreover, the use of intelligent prediction systems for educational assessment has continued to be an interest in implementing algorithms for various education purposes (Alsumaidaie et al., 2024). However, the results of the superiority of XGBoost in this study must be taken into account with the evaluated parameters and not as a general result for all educational datasets. Importantly, the algorithms lack comprehensive hyperparameter tuning, external validation, and formal paired performance testing, constraining definitive statements about algorithmic superiority.

The results are also relevant for educational predictive analytics as they show that examination outcomes can be predicted based on a small number of indicators from the course assessments. The present investigation was in contrast to studies predicting graduation outcomes, which concentrated on continuous academic achievement in an individual artificial intelligence course. Academic records are often used in machine learning algorithms to predict university graduation, with systematic evidence showing that this is the case (Pelima et al., 2024); however, due to variations in the definitions of success and the methods used to validate the prediction across the studies, comparisons between them are difficult. The current study thus gives a less broad view of assessment-based prediction.

Interpretability is also a key factor. The results of the two previous tests were "relatively important" predictors of midterm performance and Assignment 3, reinforcing earlier studies that highlight the role of interpretable academic achievement models in studying educational decision-making (Wang & Luo, 2024). The analysis in the present study is however different from the one conducted in the studies of AI-supported instructional interventions, as it measures the predictive

value of records of assessments instead of the effects on learning that AI technology can create in learning. While the accuracy of AI predictive models provides important insights into the potential for AI systems to drive improvements in academic outcomes, the evidence regarding instructional effectiveness from the meta-analysis comes with different conceptual contexts.The evidence on instructional effectiveness from the meta-analysis is conceptually different from that regarding the accuracy of AI predictive models (Dong et al., 2025).

The results indicate that repeatedly collected assessment indicators have the potential to aid academic monitoring in the teaching and learning of AI. Midterm scores and the work of assignments may provide clues to the achievement in later exams of students who need further monitoring by the teacher. Predictive estimates should however, be used alongside rather than in preference to professional academic judgement. The research of educational analytics is focused on the ability to provide the output of models in the form of meaningful decisions in the specific context, but is also aware of the limitations of data quality, algorithmic interpretation, and implementation (de Souza Zanirato Maia et al., 2023). Likewise, the significance of educational context in designing academic assessment methods using AI in blended learning environments is emphasized in prediction research (Hamadneh et al., 2022).

There are some limitations that restrict the interpretation and generalizability of the present findings. The sample consisted of 560 student instances from one context of using AI in a course, which limits generalizability to other schools, subjects, and education populations. Furthermore, other factors that could account for variations in achievement were not included in the analysis: demographic characteristics, attendance, learning engagement, and instructional factors. The relatively low R^2 of the test suggests that there was significant unexplained variation in performance. Additionally, the study used one training-testing partition, internal cross-validation and algorithmic configurations, pre-defined without external validation. Larger multi-centre data sets, possibility of temporal assessment, more educational predictors and uncertainty-aware modeling frameworks should thus be further investigated. This may allow for better prediction, as well as better understanding of how to implement assessment-driven academic monitoring systems in practice.

5. Conclusion

Supervised machine learning Predictive Approaches for academic achievement in AI education with student assessment indicators. Analysis of 560 student records showed that the regular assessment scores collected can be helpful to estimate student performance at the end of the examination. Overall, the XGBoost algorithm was the most effective model in terms of predictive performance, with an R^2 score of 0.393 and an RMSE of 5.252 and an MAE of 3.949 compared to Random Forest, Linear Regression, and Support Vector Regression. Midterm examination performance and Assignment 3 were specifically identified as important predictors through correlation and permutation analysis, suggesting that continuous evaluation may be important for

academic achievement prediction. The findings in this work illustrate the educational relevance of educational data mining for academic monitoring based on evidence and for the identification of pupils who might require further teaching support. However, the moderate predictive validity suggests that the differences in student achievement are not totally accounted for by the assessment indicators. There were a number of limitations in the study: it was based on a single course, predictor availability was limited, and no external validation was conducted. More multi-center data and longitudinal assessment records should be included and other learning-related indicators should be added to future studies to increase predictive reliability and generalizability. In conclusion, the study offers a comprehensible framework for measuring and forecasting student learning outcomes, which can be used to guide academic decisions and contribute to the ethical and responsible use of AI in higher education.

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