**International Journal for Research in Educational Studies**
(ISSN: 2208-2115)
Volume 12, Issue 03, October 2026
DOI:10.65327/es.v12i3.2548

# ACADEMIC PROCRASTINATION, FEAR OF FAILURE, AND THEIR ASSOCIATIONS WITH UNIVERSITY STUDENTS ACADEMIC PERFORMANCE

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**Received:** 22/01/2026 **Revised:** 11/06/2026 **Acceptance:** 03/10/2026 **Published:** 27/10/2026

## ABSTRACT

Predicting and understanding student performance patterns in technology-empowered higher education is significant for predicting student performance and making better educational decisions. The purpose of this study was to analyse the academic performance pattern, explore the relationship of the assessment indicators at a particular course level to cumulative grade point average (GPA) and to compare the performance of the various statistical and machine learning models in predicting academic outcomes. A quantitative, retrospective observational design was used, secondary academic records were obtained from a publicly available repository, Mendeley Data. This study utilized 1,656 undergraduate automotive engineering student records from which the following demographic characteristics, course grades and cumulative GPA were retrieved. Descriptive statistics, Pearson correlation analysis and predictive modeling were used. The performance of four prediction methods was tested namely, Linear Regression, Decision Tree Regression, Random Forest Regression, and Support Vector Regression. Analysis of the results showed that the mean cumulative GPA was 2.40 ± 0.51 with comparatively high GPA in practical training and specialized engineering subjects as compared to the fundamental courses. The technical diagnostics ($r = 0.551$) and Computer-Aided Design ($r = 0.531$) were relatively positively correlated with cumulative GPA. Random Forest Regression ($R^2 = 0.517$) was the second best predictive model, with the best predictive model being Support Vector Regression ($R^2 = 0.578$). Demographic variables were limited in scope and there are no individual assessment components, which limits the interpretation of the results.

**Keywords** – Academic Performance; Assessment Patterns; Machine Learning; Engineering Education; Learning Analytics

**International Journal for Research in Educational Studies**
(ISSN: 2208-2115)
Volume 12, Issue 03, October 2026
DOI: 10.65327/es.v12i3.2548

## 1. Introduction

In the field of higher education, academic performance is a significant measure of the quality of education, educational achievement, and institutional effectiveness. Systematic assessment approaches for the evaluation of student knowledge, competencies and academic progress are increasingly used in universities. Academic achievement is typically determined by academic performance based on coursework, examinations, practical activities and cumulative grade point average (GPA) all of which provide evidence of learning outcomes. Knowing what aspects of academic success are important is crucial to enhance educational planning and student support mechanisms (Alyahyan & Düştegör, 2020). The rise of digital technologies in higher education has also influenced the way teaching, learning and assessment is done, providing opportunities for more systematic academic monitoring (Bond et al., 2020). Learning analytics can be used to view and analyze academic records and education indicators, but it is necessary to interpret the information about student performance in a meaningful way for it to be effective (Guzmán-Valenzuela et al., 2021). These methods can be used to aid school decisions in academics and can be used to detect students who need further educational support (Ifenthaler & Yau, 2020).

The Technology-based courses are especially engineering, computer science and information technology, which include theory and analysis, technical skills, and application. Students studying these subjects often have challenging study demands that can impact their success in other subjects. There has been existing literature which has shown the value of academic records in the study of undergraduate achievement and the identification of indicators of undergraduate achievement (Asif et al., 2017). The importance of engineering education is the previous academic achievement and foundational knowledge, which is especially significant in predicting achievement in educationally challenging subjects (Huang & Fang, 2013). With the aid of artificial intelligence (AI) based methods, more opportunities have also been provided to investigate patterns in performance across engineering education and to determine how students with differing outcomes achieve them (Jiao et al., 2022). Performance prediction and learning analytics integration can also enhance the understanding of learning progress in technology-enhanced learning environments (Ouyang et al., 2023). Researchers have focused on how machine learning can be used to gain insights into students' academic performance in university engineering programs (Turkmenbayev et al., 2025).

The ability to predict a student's academic performance is an essential part of educational research for schools to plan for academic challenges and to support early interventions. The methods for educational data mining enable the analysis of relationships between academic indicators and student achievement (Alwarthan et al., 2022). The effectiveness of various predictive approaches to identifying academic performance patterns and making student outcome predictions has been studied (Chaka, 2021). Association between course grades, previous achievement and other educational characteristics can be found using statistical and machine learning methods (Khan &

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Ghosh, 2021). The use of predictive algorithms with academic records and learning-related information has been identified by systematic reviews (Namoun & Alshanqiti, 2020). The application of educational data mining also offers the chance to compare the different predictive methods and to discover the academic indicators that are relevant to the task. Educational information has been shown to be suitable for student achievement estimation with machine learning methods such as regression-based and tree-based methods (Yağcı, 2022).

There are some difficulties that still need to be addressed in embedding course-level assessment patterns in the academic performance prediction, especially in technology-based higher education. Previous research has focused on the skills and techniques that can be used to predict early, but the results are limited due to the various assessment indicators, academic settings, and prediction approaches used in the field. (López-Zambrano et al., 2021) Also, the wide variety of education variables and forecasting techniques suggest the need to look into the performance relationship of each academic field (Roslan & Chen, 2022). This is the reason to focus on establishing an understanding of the relationship between performance across the key subjects and cumulative academic achievement. The objectives of this study are, therefore, to explore the academic performance of university students who attend technology-based courses, to find out relationships between academic indicators, student characteristics and overall academic achievement and to analyse the predictive capacity of selected statistical and machine learning models in predicting the academic results.

## 2. Materials and Methods

### 2.1. Study Design

The quantitative, retrospective observational study design with the secondary academic data was used for this study to critically analyse the pattern of academic performance prediction and assessment of the courses that are run in technology-based courses by the University students. This study centered on students' performance in academic achievement, the differences in the grades of the courses, the relationship between the academic indicators, and the predictive accuracy of some statistical and machine learning models. The study used anonymised longitudinal academic records of undergraduate automotive engineering students. The overall objective was to assess academic performance and determine relevant indicators of student achievement using descriptive statistics, correlation analysis, regression and predictive modeling.

### 2.2. Data Source and Study Population

The data used in this study is a publicly available dataset for Higher Education Analytics (HEA) provided by the A Harmonized Longitudinal Academic Records Dataset (HUE), which is published on Mendeley Data (Hue et al., 2026). The data source consists of academic administrative data for 1,656 undergraduate students in an application-oriented university in

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Vietnam, where students are studying automotive engineering. Records were from five cohorts of admissions in a year, and several versions of the curriculum. The repository has two harmonized files with 56 variables, including 50 course-grade measures, demographic, cumulative grade point average (GPA), information on scholarships, and academic-status variables. The labeled version was chosen for interpreting academic performance, the harmonized coded version and the accompanying variable dictionaries for course classifications and the academic semester information.

### 2.3. Study Variables and Academic Performance Indicators

Overall academic achievement (cumulative GPA) was the primary outcome variable. Academic and demographic characteristics were selected as predictor variables available. Academic factors encompassed grades from basic engineering courses, general engineering courses, specialized automotive engineering courses, practical training, and project based courses. The technology-related subjects were: Mechatronics, computer-aided design, automotive systems, automotive electronic control systems and technical diagnostics. Student characteristics were measured as sex and birthplace, and contextual information, as scholarship and disciplinary. Students' marks were given on a four-point scale. The assessment pattern was operationalized as the differences in the course-level grades, performance in subject groups and academic achievement as measured across the semester instead of the actual score on quizzes and exams.

### 2.4. Data Preparation and Processing

The academic records were analyzed to identify any missing data, inconsistencies, duplicate entries and invalid numerical data. The labeled file was utilized to differentiate between unavailable course observations and grades recorded as zero in the coded file, since there was zero in the coded file, which may have been a code for an observation unavailable or a code for a grade that is not comparable to the one desired. Academic failure was not automatically considered to be due to missing course grades. The course dictionary and information for the semester mapping were used to identify the course variables. Valid observations for each of the variables available were used for descriptive analyses, and a consistent set of eligible academic indicators was used for predictive modeling. Imputations/exclusions were to be decided based on the missingness pattern and documented prior to model development. Standardisation was done for the selected models when necessary, using numerical predictors.

### 2.5. Assessment of Academic Performance Patterns

Academic performance patterns were investigated by comparing the individual course grade, subject groups, and indicators of academic performance on a semester level, descriptively. To summarize data for performance on relevant technical and nontechnical courses, mean scores and standard deviations were computed. The results of the course level performance were analyzed

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for the basic engineering courses, specialized courses related to the automotive sector, training and project based courses. Demographic and academic characteristics were used to determine differences in academic performance. Selected course grades and Cumulative GPA were also compared to find academic indicators related to overall achievement. The comparisons were made with the purpose of describing patterns of performance observed rather than with the assumption that course grades were part of continuous assessment and/or examination.

### 2.6. Academic Performance Prediction Models

The academic performance prediction was developed based on the cumulative GPA as the main continuous outcome variables. Selected course grades and potentially available student characteristics were selected as candidate predictors. Academic performance prediction was assessed by using course indicators from the previous harmonized semesters with the assumption that the levels of these course indicators would be more available than the later semester grades and the outcome-derived variables, while the latter were excluded from the sets of predictors. The four prediction methods were chosen: Linear Regression, Decision Tree Regression, Random Forest Regression and Support Vector Regression. Observations that could be made were split between the training and testing groups in an 80:20 split. Model development and parameter selection was carried out in the training subset, and was performed in five-fold cross-validation. The testing subset was used only for the final assessment of the predictive performance.

### 2.7. Statistical Analysis and Model Evaluation

Data on categorical variables were summarized as frequencies and percentages, while data on continuous variables were summarized as means ± standard deviations or medians and interquartile ranges, depending on the distribution. The relationship between course performance indicators and cumulative GPA were investigated using Pearson or Spearman correlation coefficients. Suitable comparisons of two groups were set as independent samples t-tests or Mann-Whitney U test. To explore correlations between academic indicators and overall performance, simple linear regression was performed. The ability of predictive models were assessed with the mean absolute error (MAE), root mean square error (RMSE), and coefficient of determination ($R^2$). The performance of predictions was better as the values of MAE and RMSE were lower and $R^2$ values were higher. Appropriate inferential tests were used for statistical significance at $p < 0.05$.

### 2.8. Ethical Considerations

This research applied anonymised secondary academic data from Mendeley Data that was published under the Creative Commons Attribution 4.0 license. There was no direct contact with students or any extra personal information was collected. The released analytical files contained no information on individual student identities. The study adhered to the principles of

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confidentiality, responsible secondary data analysis and proper citation of the primary source.

## 3. Results

### 3.1. Demographic and Academic Characteristics of Students

A total of 1656 records of undergraduate students in the automotive engineering program from an institution were included in the study. One thousand, six hundred and fifty two students (99.76%) were reported as having a sex of 0, and four students (0.24%) were reported as having a sex of 1. These classifications were not incorporated into meaningful written labels and the original classifications were used. The data consisted of 65,845 course-grade observations of 79.5% of the 82,800 student-course combinations available. A total cumulative GPA value was found in all 1,656 records. The mean cumulative GPA was 2.40 ± 0.51, with a median of 2.49 and an observed range of 0.00-3.48. The demographic characteristics, availability of cumulative GPA records, and distribution of course-grade observations are summarized in Table 1.

**Table 1. Demographic and Academic Characteristics of University Students**

| Characteristic | Frequency | Percentage |
|---|---|---|
| Total student records | 1,656 | 100.00 |
| Sex code 0 | 1,652 | 99.76 |
| Sex code 1 | 4 | 0.24 |
| Records with GPA available | 1,656 | 100.00 |
| Available course-grade observations | 65,845 | 79.52 |

Note: The final row represents the percentage of available student-course observations out of 82,800 possible entries, rather than a percentage of students.

### 3.2. Distribution of Academic Performance Indicators

Academic outcomes for students were different among the selected technology-related and engineering courses. On the whole, the mean performance in the practical and advanced engineering components were found to be better when compared with that of Theoretical Mechanics and Advanced Mathematics 1. The percentage of zero grades was also found to be different. The results suggest differences in the learning outcomes of students in the three areas of foundational learning, specialized learning, and applied learning. The descriptive statistics of the selected academic performance indicators, including valid observations, mean grades, standard

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deviations, and zero-grade percentages, are presented in Table 2. The distribution of cumulative GPA among all 1,656 students is illustrated in Figure 1, with a mean GPA of 2.40 and a median of 2.49.

**Table 2. Descriptive Statistics of Selected Academic Performance Indicators**

| Academic Performance Indicator | Valid Observations (n) | Mean Grade | Standard Deviation (SD) | Zero Grades (%) |
|---|---|---|---|---|
| Theoretical Mechanics | 1,638 | 1.68 | 0.83 | 6.2 |
| Advanced Mathematics 1 (Calculus I) | 1,637 | 2.08 | 0.92 | 2.8 |
| Automotive Electrical and Electronics | 1,617 | 1.98 | 0.87 | 4.3 |
| Mechatronics | 1,601 | 2.52 | 0.86 | 1.7 |
| Computer-Aided Design (CAD) | 1,547 | 1.49 | 0.95 | 16.0 |
| Automotive Systems | 1,534 | 2.96 | 0.88 | 4.0 |
| Automotive Practice and Experiment | 1,592 | 3.24 | 0.53 | 0.7 |
| Technical Diagnostics | 1,532 | 2.89 | 0.86 | 1.8 |
| Internship / Practicum | 1,546 | 3.73 | 0.51 | 0.8 |
| Capstone Project / Graduation Thesis | 280 | 3.97 | 0.16 | 0.0 |

Note: Academic grades were measured on a four-point scale (0–4). Valid observations represent the available grades for each course. Zero-grade percentages were calculated using valid

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observations within the corresponding course. Differences in observation counts reflect variation in course availability and student participation. Values are rounded to two decimal places for means and standard deviations and one decimal place for percentages.

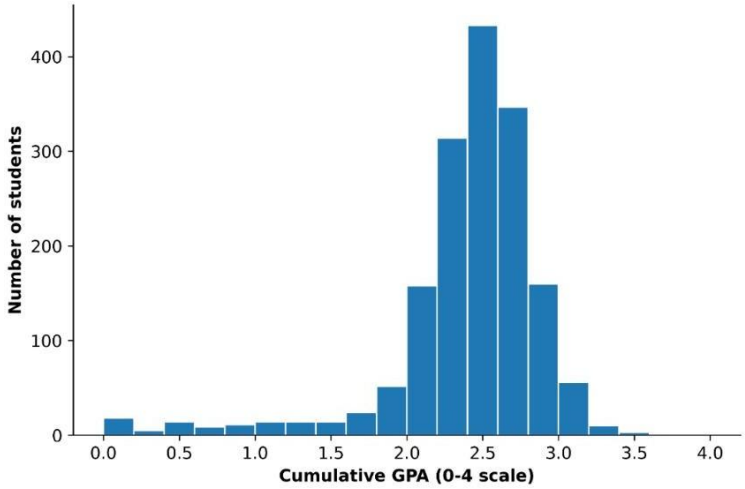


**Figure 1. Distribution of Overall Academic Performance Among University Students**

### 3.3. Patterns of Student Assessment Performance

For the 6 academic subject groups, there were various assessment patterns. The mean grade for Practice, Internship, and Project courses was the highest (3.20 ± 1.05) followed by Specialized Major courses (2.82 ± 0.90), and Skills and Management courses (2.68 ± 0.96). The mean grade in Foreign Languages (2.03 ± 0.77) was comparatively low, as was the case with General Education (2.06 ± 0.86) and Fundamental Engineering (2.07 ± 1.06). The semester-based descriptive analysis also revealed changes in the average of course grades recorded. The mean got higher from 1.91 in semester 1 to 3.77 in semester 8.

**Table 3. Course-Level Assessment Performance Across Subject Groups**

| Subject group | Courses | Available grades | Mean ± SD |
|---|---|---|---|
| Practice/Internship/Project | 7 | 8,633 | 3.20 ± 1.05 |
| Specialized Major | 13 | 15,896 | 2.82 ± 0.90 |
| Skills & Management | 3 | 3,443 | 2.68 ± 0.96 |
| Fundamental Engineering | 12 | 17,774 | 2.07 ± 1.06 |
| General Education | 9 | 12,826 | 2.06 ± 0.86 |

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| | | | |
|---|---|---|---|
| Foreign Languages | 6 | 7,273 | 2.03 ± 0.77 |

Note: Means and SDs are based on available student-course grades. Individual students can contribute grades to multiple groups.

The course-level assessment performance across the six academic subject groups, including the number of courses, available grades, and mean scores, is summarized in Table 3. The differences in mean academic performance across the six subject groups are illustrated in Figure 2.

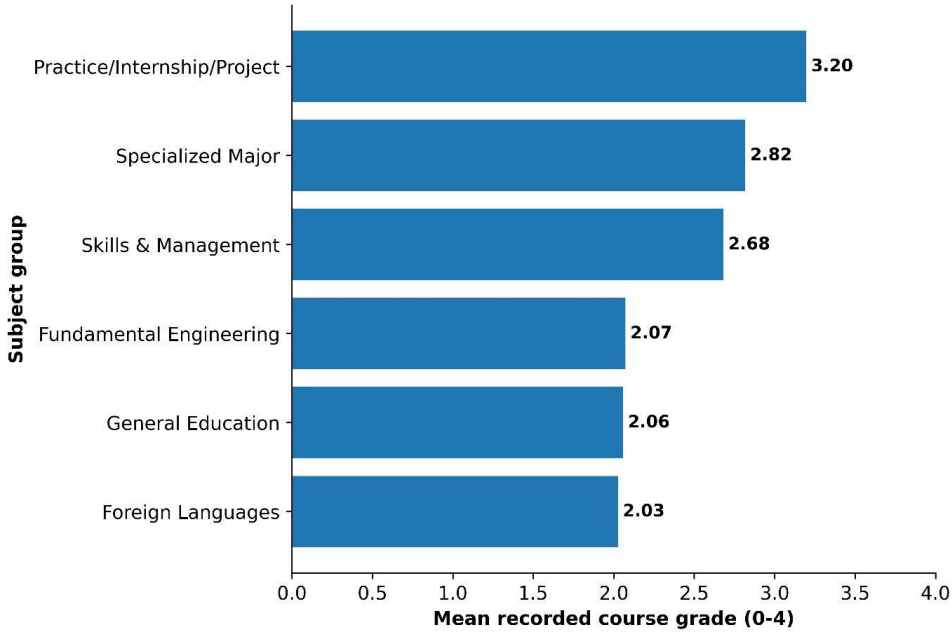


**Figure 2. Mean Academic Performance Across Subject Groups**

Figure 3 presents the mean academic grades across eight harmonized semesters. Descriptive differences were observed between earlier and later semesters, with particularly high mean grades in semester 8. The figures are based on varying course coverage across semesters. The semester-wise variations in academic performance, including the number of courses, available grade observations, and mean scores, are presented in Table 4.

**Table 4. Semester-Wise Academic Performance Patterns**

| Semester | Courses | Available grades | Mean ± SD |
|---|---|---|---|
| 1 | 7 | 10,663 | 1.91 ± 0.86 |
| 2 | 8 | 11,434 | 1.87 ± 0.97 |

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| | | | |
|---|---|---|---|
| 3 | 5 | 6,993 | 2.57 ± 0.88 |
| 4 | 6 | 8,211 | 2.54 ± 0.86 |
| 5 | 8 | 9,792 | 2.22 ± 1.17 |
| 6 | 9 | 11,342 | 2.97 ± 0.86 |
| 7 | 5 | 5,584 | 3.01 ± 0.87 |
| 8 | 2 | 1,826 | 3.77 ± 0.48 |

Note: Semester means are descriptive averages of available grades, not paired longitudinal changes in the same students. Semester 8 includes only two course variables.

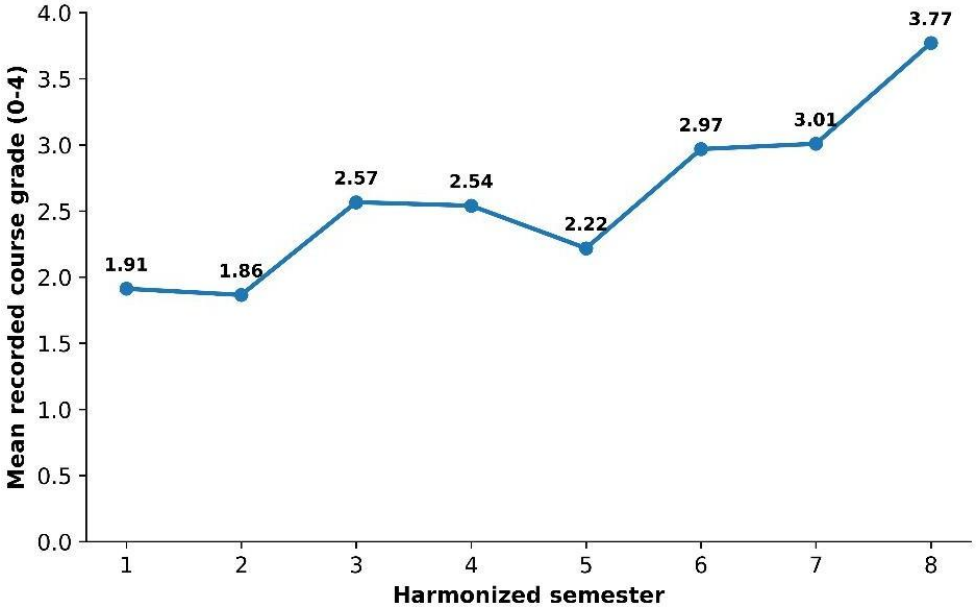


**Figure 3. Semester-Wise Academic Performance Patterns**

### 3.4. Relationships Between Assessment Indicators and Academic Achievement

The Pearson correlation analysis revealed that, statistically, several course grades and cumulative GPA were correlated positively. Technical Diagnostics had the highest correlation ($r = 0.551$, $p < 0.001$), followed by CAD ($r = 0.531$), Automotive Practice and Experiment ($r = 0.519$), Automotive Systems ($r = 0.518$), and Automotive Electrical and Electronics ($r = 0.516$). Theoretical Mechanics ($r = 0.371$) and Advanced Mathematics 1 ($r = 0.362$) were moderate positive correlation with fundamental subjects. The relationships between the selected course

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indicators and cumulative academic achievement were positive for all ten course indicators, but should not be assumed to be causal. The Pearson correlation coefficients, valid paired observations, and statistical significance of the relationships between selected course grades and cumulative GPA are presented in Table 5. The strength and direction of the associations between selected academic indicators and cumulative GPA are illustrated in Figure 4.

**Table 5. Correlation Between Selected Course Grades and Cumulative GPA**

| Academic Indicator | Valid n | Pearson r | p-value |
|---|---|---|---|
| Theoretical Mechanics | 1,638 | 0.371 | <0.001 |
| Advanced Mathematics 1 | 1,637 | 0.362 | <0.001 |
| Automotive Electrical and Electronics | 1,617 | 0.516 | <0.001 |
| Mechatronics | 1,601 | 0.309 | <0.001 |
| Computer-Aided Design (CAD) | 1,547 | 0.531 | <0.001 |
| Automotive Systems | 1,534 | 0.518 | <0.001 |
| Automotive Practice and Experiment | 1,592 | 0.519 | <0.001 |
| Technical Diagnostics | 1,532 | 0.551 | <0.001 |
| Internship / Practicum | 1,546 | 0.294 | <0.001 |
| Capstone Project / Graduation Thesis | 280 | 0.274 | <0.001 |

Note: Valid n represents the number of available paired observations for each course grade and cumulative grade point average (GPA). Pearson correlation coefficients (r) indicate the strength and direction of linear associations. All reported correlations were positive and statistically significant ($p < 0.001$). These associations should not be interpreted as causal relationships because individual course grades also contribute to cumulative academic performance.

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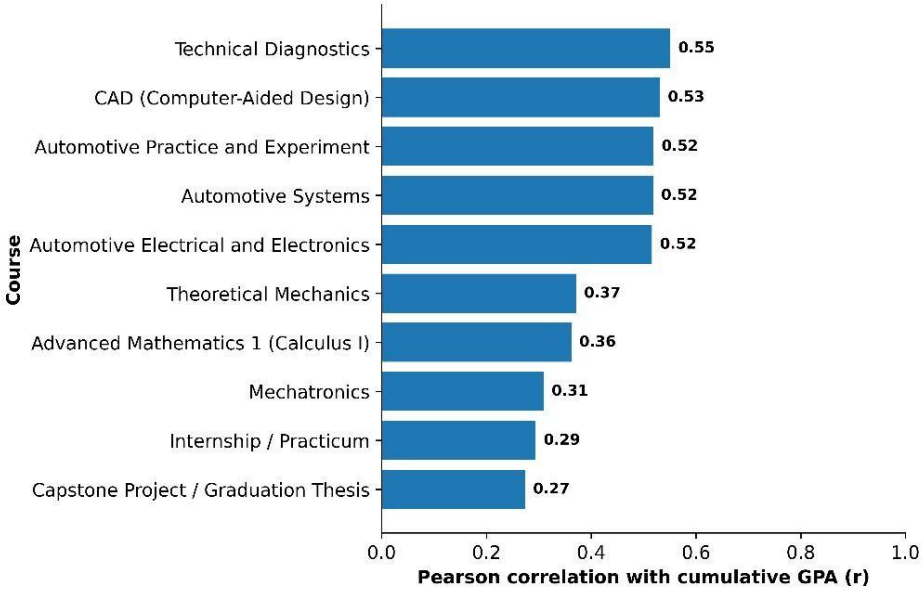


**Figure 4. Correlation Between Academic Indicators and Cumulative GPA**

### 3.5. Predictive Factors Associated with Academic Performance

The academic performance prediction was done with grades from the seven first-semester courses, and the available sex-code variable. This predictor selection aimed to examine the predictive power of early academic data on cumulative GPA without considering later-semester course grades. Predictor values were missing following the median imputation method and the indication of missingness was added to the models. Each student was eligible since cumulative GPA was available for all 1,656 records. Previous course achievement resulted in measurable predictive information for cumulative achievement. However, its sex-code distribution was extremely skewed and did not have much value in meaningful demography. Model comparisons were used to evaluate predictive relationships.

### 3.6. Comparative Performance of Academic Prediction Models

An 80:20 split of the data, with 1,324 training records and 332 testing records, was used to evaluate four approaches to prediction. A mean absolute error (MAE) of 0.2345, root mean squared error (RMSE) of 0.3436, and coefficient of determination ($R^2$) of 0.5779 were obtained for Support Vector Regression. The second-best model was the Random Forest Regression, whereas Decision Tree Regression and Linear Regression were the next two. The findings show that these indicators had better predictive performance using the nonlinear prediction models, as compared to the conventional linear regression for the selected testing sample.The comparative performance of Linear Regression, Decision Tree Regression, Random Forest Regression, and Support Vector Regression, evaluated using MAE, RMSE, and $R^2$, is presented in Table 6.

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**Table 6. Comparative Performance of Academic Prediction Models**

| Prediction model | MAE | RMSE | $R^2$ |
|---|---|---|---|
| Linear Regression | 0.2865 | 0.4147 | 0.3851 |
| Decision Tree Regression | 0.2855 | 0.4104 | 0.3978 |
| Random Forest Regression | 0.2545 | 0.3676 | 0.5166 |
| Support Vector Regression | 0.2345 | 0.3436 | 0.5779 |

Note: Evaluation is based on the held-out test sample. Lower MAE and RMSE and higher $R^2$ indicate better predictive performance. These results are based on one train-test split and do not establish external generalizability.

The comparison of root mean squared errors across the four academic performance prediction models is illustrated in Figure 5.

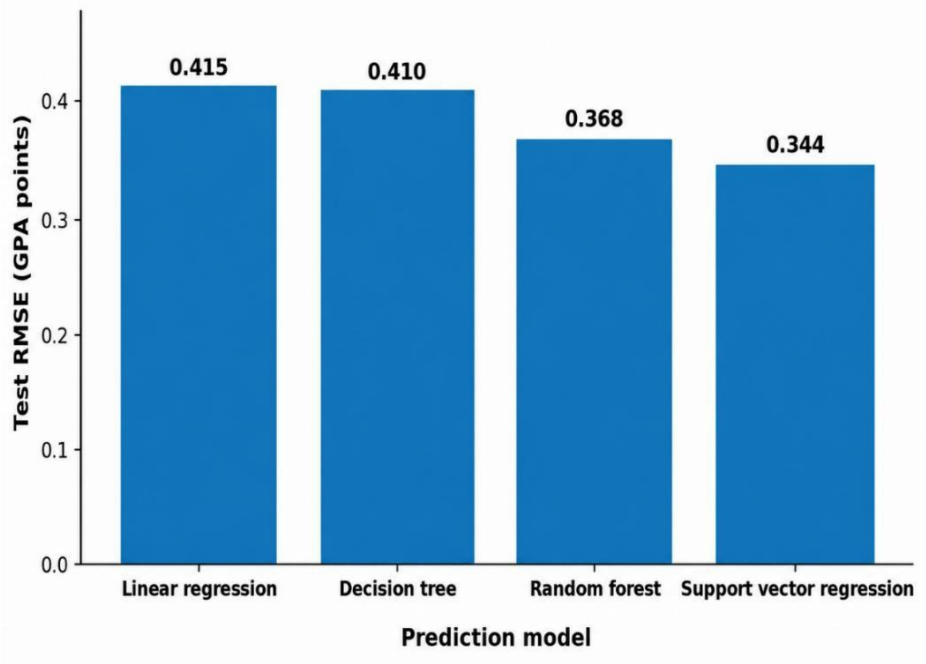


**Figure 5. Comparative Performance of Academic Prediction Models**

### 3.7. Relative Importance of Academic Performance Predictors

Results of the correlations indicated that the Technical Courses, especially Technical Diagnostics, CAD, Automotive Practice and Experiment and Automotive Systems, were relatively well correlated with cumulative GPA. These correlations, however, do not measure the importance of

the features in the prediction models themselves. The prediction models are limited to academic predictors from the first semester of school, thus technical courses from later in the semester were not included in the prediction sets. Thus, the relative importance of the different models in the present analyses cannot be determined. Further analyses of the model based on the interpretation of its components (e.g. permutation-important analyses) would be needed to determine the relative contributions of the individual first-semester predictors.

## 4. Discussion

This study focused on academic performance, course-level assessment patterns and predictive modeling of 1,656 university students in technology-based engineering courses. The results showed a mean cumulative GPA of 2.40 ± 0.51, which meant that there was variation in the academic performance of the students. There were differences between the subjects, with the highest mean grades in the practical training and special engineering courses compared to the fundamental engineering and general education courses. The technical diagnostics had a strong positive correlation with cumulative GPA ($r = 0.551$) followed by Computer-Aided Design ($r = 0.531$). The Support Vector Regression ($R^2 = 0.578$) showed the best performance and followed by the Random Forest Regression ($R^2 = 0.517$) from among the predictive methods. The results of this study underscore the need to use nonlinear predictions and course-specific academic indicators to explain student achievement.

Results of academic performance were found to vary greatly between the subjects that were investigated. The grade means were highest in the case of the Practice, Internship, and Project courses, with a value of 3.20 ± 1.05, while the Fundamental Engineering (2.07 ± 1.06) and Foreign Languages (2.03 ± 0.77) courses showed comparatively low performances. The differences could be due to variations in content, pedagogical approaches, assessment, and hands-on learning needs. Assessment feedback for student learning has been highlighted in previous studies as being of critical importance for students and for determining academic challenges (Banihashem et al., 2022). Assessment with the support of artificial intelligence has also been explored as a means to grasp student outcomes and enhance assessment practices (Bashraheel & Ghinea, 2026). The variations in the performance of students in different assessments may be analyzed using statistical modeling and simulation methods (Caro et al., 2014). In addition, structured learning practices and students' epistemic beliefs have been related to academic achievement, which means that learning behaviours might be related to the observed differences in academic achievement (Kivimäki, 2023). Final course grades are reported in the present records, however, no specific grade is reported for the continuous assessment of the various components of the course, so that direct comparisons between assignments and examinations are not possible.

The correlation analysis showed positive correlations between a few special engineering courses and cumulative GPA. There were moderate positive relationships of technical diagnostics,

computer-aided design, automotive systems, and automotive practice and experiment with academic achievement. The results indicate that achievement in technical specialties is similar to achievement in school overall. Student performance in previous educational levels and educational characteristics were found to be significant factors that affect student achievement in the previous studies (Alturki et al., 2022). Academic markers have also been found to be early indicators of students' risk for poor outcomes in STEM education (Bernacki et al., 2020). In the same way, the capability of predicting academic result before the end of the course has been studied for learning-related information (Riestra-González et al., 2021). In addition, from the perspective of academic progress analysis, it can be seen that the importance of considering more than one educational indicator to gain insight into the performance of students (Yang & Li, 2018). However, some correlations seen may be related to the relative importance of the individual course grades in the calculation of cumulative GPA, and are not causal.

The predictive analysis revealed that there were differences in the performances of statistical and machine learning models. The prediction errors of the models in the list SVM (RMSE = 0.344), RFR (RMSE = 0.368) and LR (RMSE = 0.449) were lowest, medium and highest, respectively. These findings indicate that there may be nonlinearities among the early academic indicators that are relevant to cumulative achievement. The potential of machine learning in predicting student performance and engagement in the learning process has been proven in previous systematic studies (Chen et al., 2025). Comparisons of predictive algorithms and performance metrics are also important in making a selection of the algorithm in an educational context (Shoukath & Chakkaravarthy, 2025). In engineering education, the significance of the assessment-related information for the creation of academic prediction models has also been pointed out (Wu et al., 2026). The effectiveness of predictions, however, depends on the variables available and the educational context and the type of modeling strategy used (Yuan et al., 2026).

The results have practical applications for monitoring and supporting students in technology based higher education. Performance measures from the first half of the semester can be used to identify students who need extra academic support, including in fundamental engineering courses. A number of learning analytics frameworks have been proposed that combine predictive modeling with pedagogical interventions to aid in educational decision-making (Alalawi et al., 2025). However, the results of predictions should not be limited to numerical classification but should be translated into meaningful learning support (Ifenthaler et al., 2021). Learning analytics dashboards can also help educators to understand academic progress and recognize learning needs (Paulsen & Lindsay, 2024). Implementations of learning analytics interventions also highlight the need to assess the effectiveness of educational outcomes of predictive information (Larrabee Sønderlund et al., 2019).

There are a number of restrictions to be noted. The study was a secondary academic study in one engineering discipline and therefore limited to generalizability to other universities and technology based programs. The assessment analysis was hampered by the lack of course

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Volume 12, Issue 03, October 2026
DOI:10.65327/es.v12i3.2548

observations, available demographic data and assignment and examination scores separated. The validation of the predictive findings is also done in one training-testing split, and without an external validation. The relevance of learning related behavioral indicators has been previously demonstrated in predicting student performance, indicating that there is potential to include other educational information (Romero et al., 2013). Future studies are expected to involve the participation of several academic institutions, several assessment components, learning engagement indicators and external model validation, which will help to build the reliability and applicability of academic performance prediction.

## 5. Conclusion

The present research investigates academic performance prediction and pattern of assessment for courses of engineering courses for University students taking courses on technology. The results showed that there were significant differences in the learning outcomes of students in basic engineering, technical and applied learning. There were differences in student performance overall, with the mean cumulative grade point average (GPA) being 2.40 ± 0.51. Academic performance in practical training and specialized engineering courses was generally found to be more successful, while average grades in core engineering and general education courses were found to be less successful. The results suggest the need for subject-specific academic evaluation to understand university students' achievement.

The results of the correlation analysis showed that there were significant positive correlations between some of the technical course grades and their cumulative GPAs. Overall academic performance was associated with Technical Diagnostics and Computer-Aided Design, comparatively showing higher relationships, which suggests the relevance of these indicators in academic performance. The predictive models that are shown, Support Vector Regression and Random Forest Regression, both had high $R^2$ values (0.578 and 0.517 respectively) reflecting the potential for these models to be useful for predicting academic outcomes and the value of nonlinear approaches. The results indicate that academic records and predictive modeling can play a role in student performance monitoring, identification of learning difficulties, and evidence-based educational planning. But the lack of individual assessment components, demographic data and the fact that the study was based on one engineering discipline make it difficult to make broader interpretations. More research with multiple universities, indicators of assessment, and model validation with external data is suggested. There is potential to help enhance academic monitoring, student intervention, and decision making in technology-based higher education by incorporating course-level academic assessment with predictive methods.

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