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MULTIVARIATE STATISTICAL MODELING OF ACADEMIC, BEHAVIORAL, AND LEARNING FACTORS ASSOCIATED WITH UNIVERSITY STUDENT PERFORMANCE

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Abstract:

Academic performance among university students is influenced by multiple academic, behavioral, demographic, and learning-related factors. Understanding these relationships through multivariate statistical analysis can support more effective identification of factors associated with student achievement. A quantitative, retrospective, secondary-data analytical design was used. Information from 1,194 university students was analyzed. Current cumulative grade point average (CGPA) was considered the primary outcome. Descriptive statistics, independent-samples t-tests, chi-square tests, Pearson or Spearman correlation, and multiple linear regression were applied. Statistical significance was set at $p < 0.05$. *Previous academic performance showed the strongest positive relationship with current CGPA. Attendance was also positively associated with academic achievement. Significant group differences were observed according to scholarship status, learning mode, probation history, and living arrangement. In the multivariable model, previous SGPA, attendance, completed credits, and scholarship status were positive predictors of CGPA, while lower English-language proficiency, health issues, teacher consultation, and increasing age were associated with poorer performance. The regression model explained a substantial proportion of variation in current academic achievement. University student performance is influenced by a combination of academic, behavioral, and background characteristics. Multivariate statistical modeling provides a useful approach for identifying independent predictors and can support targeted academic monitoring and student-support strategies.*

Keywords: *Academic performance; Multivariate analysis; University students; Statistical modeling; Learning behavior*

1. Introduction

Academic performance is an important indicator of student progress and institutional effectiveness in higher education. A variety of academic, behavioral, demographic, and learning variables can affect the success of the university. As more and more educational information becomes available, relationships between these factors and student outcomes are being identified using statistical and computational methods. Multidimensional time-series analysis has demonstrated that online learning behavior can offer valuable insights for the prediction of academic performance (Shou et al., 2024). Likewise, Wang et al. (2025) found that behavioral involvement in online learning is linked to variations in university students' academic outcomes.

Understanding of student performance has further improved using multisource and multifeature data. Behavioral information from different sources has been used to develop predictive models of academic achievement (Zhao et al., 2020). In addition, daily behavioural patterns have been related to academic outcomes, indicating that student success is not just reflected by academic measures (Kassarnig et al., 2018). Similarly, campus behavior data have been used to find patterns of behaviors that are linked to academic performance among college students (Yao et al., 2019). These practices have been recently developed to incorporate multiple aspects of student information. In the realm of behavioral, financial and wearable data, researchers have applied these to predict and profile academic performance (Urs & PK, 2025). Factors that influence the academic outcomes of university students have also been identified using machine-learning methods (Marín et al., 2025). The use of multiple predictors in deep learning has also shown its effectiveness in predicting student success, adding more diverse elements to the mix (Al Husaini et al., 2025). These studies make a point of the need to analyze academic performance using a multidimensional statistical approach.

However, there are a number of methodological gaps in the use of predictive models. Many studies mainly focus on prediction accuracy and provide limited interpretation of the independent contribution of individual factors. The results of multivariate analysis indicate that a number of student characteristics have the potential to influence academic outcomes simultaneously, which makes it necessary to develop integrated approaches to statistical analysis (Pustovalova & Avdeenko, 2022). Principal component regression (PCR) has also been shown to be a beneficial approach for reducing correlated variables to meaningful components for the study of academic and behavioral outcomes (Begdache et al., 2019). Although learning-behavior data have been successfully utilized for prediction and influence-factor analysis, these methods mainly target digital learning environments (Ni et al., 2023). Some studies have looked at academic and spatial behaviours but have not necessarily included demographic, academic and learning characteristics in an interpretable model (Musaddiq et al., 2022). There is also research on the use of machine learning to predict educational outcomes, but complex models may offer little explanation of the relationship between the variables and the outcome (Musso et al., 2020). Thus, there is a need for a multivariate statistical framework that allows for the inclusion of several student characteristics without losing the effect of a clear interpretation.

A multivariate approach is used since academic performance is typically determined by multiple related characteristics instead of a single characteristic. The research based on data collected from the virtual learning environment (VLE) has demonstrated that a combination of various types of educational information can enhance the prediction of academic performance (Waheed et al., 2020). Furthermore, Hybrid regression and classification techniques have shown the feasibility of finding influential factors during the building of predictive models (Alshanqiti & Namoun, 2020).

Past research indicates that there is a relationship between student achievement and academic, behavioral, and contextual variables (Suleiman et al., 2024). The cross-sectional research conducted at the university level has also demonstrated that a number of factors may interact to yield positive academic outcomes (Tadese et. al., 2022). For this reason, secondary student data on academic and behavioral variables and demographic and learning variables were used in the present study to find the most important variables that influence the performance of university students by multivariate statistical modelling.

Research Objectives

1.To describe the academic, behavioral, demographic, and learning characteristics of university students.

2.To examine the associations between selected academic, behavioral, and learning factors and student academic performance.

3.To develop a multivariate statistical model for identifying the strongest predictors of university student performance.

2. Methodology

2.1 Study Design

This study was designed quantitatively, retrospectively, and as a secondary-data analysis. A cross-sectional method was adopted to analyse the relationships among academic, behaviour, demographic and learning characteristics and the performance of university students based on the information obtained from the questionnaires.

2.2 Data Source

The study used publicly available student academic performance information obtained from Mendeley Data (Rahman et al., 2024). The original data were gathered using a structured questionnaire and comprised demographic variables, study behaviors, learning patterns, academic background and academic performance indicators. Finally, 1,194 student records and 31 student variables were available for analysis.

2.3 Study Variables

The current Cumulative Grade Point Average (CGPA) was taken as the major output variable to measure the students' academic performance. Previous academic performance, attendance, study hours, learning mode, social-media use, English-language ability, teacher consultation, skill-development activities, co-curricular activities, health status, family income and selected demographic and academic characteristics were all predictor variables.

2.4 Data Cleaning and Preparation

Records were examined for missing data, duplicated data, inconsistencies in data coding and any mixed formats of data prior to analysis. If needed, categorical data were recoded in order to facilitate interpretation, and continuous data were checked for implausible values and distributional patterns. Clearly incorrect responses were carefully checked, and all variables were formatted correctly prior to statistical analysis.

2.5 Statistical Analysis

Study data were summarized using descriptive statistics: frequencies and percentages for categorical data and mean ± standard deviation or median with interquartile range for continuous data. Independent-samples t-tests were used to compare the mean CGPA of categorical variables with two groups, and chi-square tests were used to explore associations between categorical variables. Pearson correlation or Spearman correlation was performed to measure the association between continuous or ordinal variables based on their distribution. Multiple linear regression was conducted to find the independent predictors of CGPA after adjustment for relevant factors. A p-value < 0.05 was considered to be statistically significant.

3. Results

3.1 Demographic and Background Characteristics

The total number of students included in the analysis was 1194, with a mean age of 21.34 ± 1.61 years. The percentage of males was slightly higher than females. The majority of the participants were single, with smaller percentages in a relationship, married or engaged. Over half of the students were not recipients of a meritorious scholarship and were not availed of University transportation. There was a balance in living arrangements, with living with family being more prevalent. The study population was mostly free from major reported physical health limitations, with most participants reporting no health issues and no physical disability (Table 1).

Table 1. Demographic and Background Characteristics of the Students

Variable	Category	f	%
Gender	Male	672	56.3
	Female	522	43.7
Relationship status	Single	896	75.0
	Relationship	187	15.7
	Married	96	8.0
	Engaged	15	1.3
Meritorious scholarship	No	671	56.2
	Yes	523	43.8
University transportation	No	697	58.4
	Yes	497	41.6
Living arrangement	Family	642	53.8
	Bachelor	552	46.2
Health issue	No	987	82.7
	Yes	207	17.3
Physical disability	No	1,167	97.7
	Yes	27	2.3

Figure 1 provides a visual summary of the overall distribution of selected background characteristics, which can be compared to the relative representation of student groups in key demographic and personal factors.

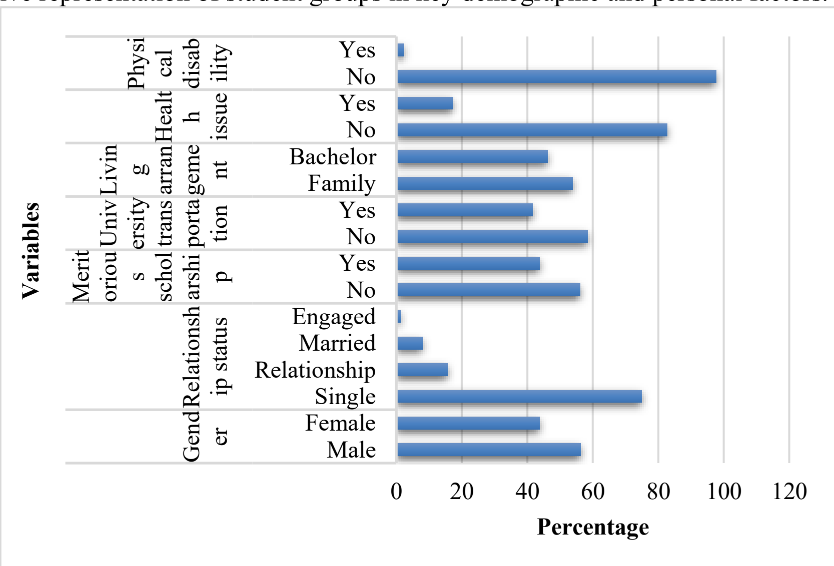

Figure 1. Distribution of Student Background Characteristics

The figure shows distinct differences between the makeup of various groups of students. Particularly marked differences are found in relation to relationship status, health condition and physical disability, while gender and living arrangement tend to be more evenly distributed. The visual pattern overall shows that there were some background categories that were significantly overrepresented when compared with their respective groups.

3.2 Differences in Academic Performance Across Student Groups

Independent-samples t-tests demonstrated that academic achievement was significantly different among selected student characteristics. On average, scholars' academic outcomes were higher than those of students who were not scholars. Students preferring offline learning also performed better than those preferring online learning. The results from the previous probation status indicated that students with bachelor accommodation performed less well than those who were living with the family, while the results for the previous probation status indicated a clear association with lower academic performance. There was no difference by gender, transportation use, computer ownership, teacher consultation, co-curricular involvement, health status, or physical disability, however. In Table 2, the full group comparisons and significance tests are given.

Table 2. Independent-Samples t-Test Comparisons of Current CGPA

Variable	**Group 1**	**Mean ± SD**	**Group 2**	**Mean ± SD**	**t**	**p-value**
Gender	Male	3.26 ± 0.49	Female	3.29 ± 0.47	-0.84	0.400
Scholarship	Yes	3.40 ± 0.46	No	3.18 ± 0.48	8.07	<0.001
Learning mode	Offline	3.30 ± 0.47	Online	3.20 ± 0.50	3.18	0.002
Probation	No	3.37 ± 0.40	Yes	3.00 ± 0.58	9.94	<0.001
Teacher consultation	Yes	3.26 ± 0.48	No	3.29 ± 0.48	-1.29	0.197
Co-curricular activity	Yes	3.28 ± 0.50	No	3.27 ± 0.47	0.15	0.880
Living arrangement	Bachelor	3.23 ± 0.52	Family	3.31 ± 0.44	-2.86	0.004
Health issue	No	3.28 ± 0.48	Yes	3.25 ± 0.51	0.84	0.401
Physical disability	No	3.28 ± 0.48	Yes	3.10 ± 0.58	1.50	0.146

In learning mode, there was a significant difference in academic performance, with the mean CGPA of students who learned offline being higher when compared with that of the students who learned online. The pattern is displayed graphically in Figure 2.

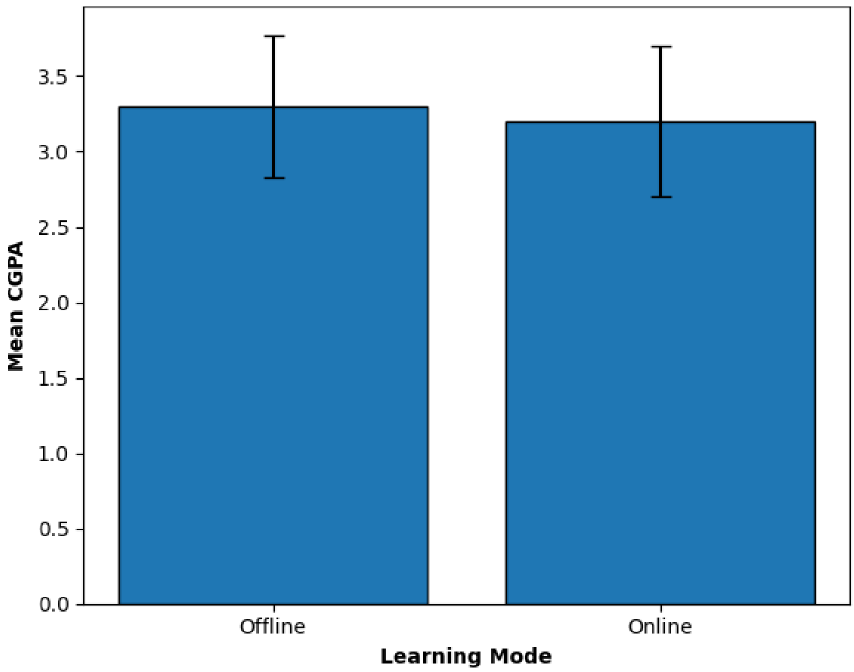

Figure 2. Academic Performance by Learning Mode

There is a slight difference in the mean CGPA of the two learning modes as shown in the figure. The academic performance of both online and offline groups was broadly comparable, but the offline group had a higher mean CGPA. Error bars are a measure of the variation within each group and demonstrate a lot of overlap, which means that although the difference is statistically significant, it is not very great in size.

3.3 Associations Among Academic and Behavioral Factors

Chi-square analysis revealed that there were significant relationships between various categorical academic and behavioural traits. Learning mode had a significant relationship with probation status, and involvement in co-curricular activities was also significantly related to probation. Probation showed the strongest relationship of the categorical comparisons examined with the status of being on scholarship. There was a significant relationship between the level of

English language proficiency and learning mode preference, thus indicating different learning preferences based on English language proficiency level. By contrast, there was no significant relationship between teacher consultation and health status and probation. Except for the relatively strong relationship between scholarship status and probation, the effect-size estimates showed that most significant relationships were relatively weak (Table 3).

Table 3. Chi-Square Associations Between Categorical Factors

Variables	χ^2	df	p-value	Cramér's V
Learning mode × Probation	4.11	1	0.043	0.059
Teacher consultation × Probation	0.16	1	0.689	0.012
Co-curricular activity × Probation	4.38	1	0.036	0.061
Scholarship × Probation	55.01	1	<0.001	0.215
English proficiency × Learning mode	6.95	2	0.031	0.076
Health issue × Probation	0.02	1	0.883	0.004

3.4 Correlation of Academic and Behavioral Factors With Academic Performance

The relationship between the respective dependent and independent variables (current CGPA and selected academic, behavior and socio-economic factors) was investigated using correlation analysis. Previous academic performance had the highest positive correlation with the current CGPA, and attendance also had a positive correlation. Age and social-media use were negatively associated with academic performance, while study hours, study sessions, skill-development time, completed credits and family income were weakly or not associated with academic performance. A general correlation structure is given in Figure 3.

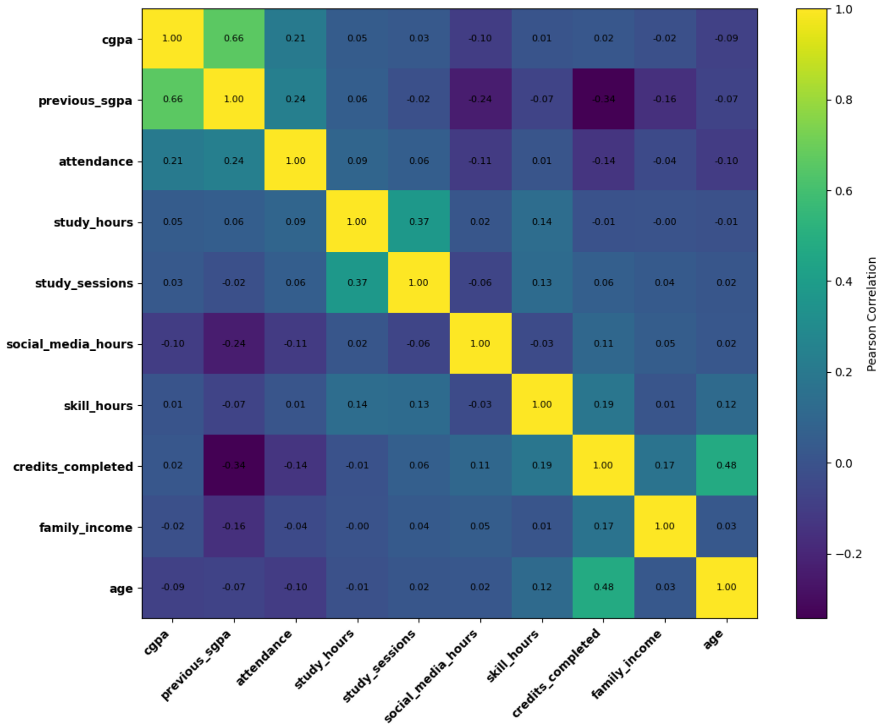

Figure 3. Correlation Matrix of Academic and Behavioral Factors

The heatmap also shows the correlation between the predictor variables. There was a relatively stronger relationship between age and completed credits, which represented academic progression, with most other predictor-to-predictor relationships being relatively weak. This pattern suggests that there is not a strong correlation between the explanatory variables, which is good to show there is some independence to use them together in the multivariable analysis later in the paper.

3.5 Multivariate Predictors of Academic Performance

The multiple linear regression model was found to be statistically significant and accounted for a significant amount of variance in current academic performance. Among the independent variables, previous SGPA turned out to be the most significant positive predictor, with attendance, scholarship status, and completed academic credits also being positive. There was an independent relationship between lower English language skill and poorer performance, as well as between teacher consultation, health problems, and older age. There was an inverted bivariate correlation for social-media use, and the adjusted association was positive, which may be due to possible confounding or suppression. The other factors such as gender, type of study, hours spent on study, participation in co-curricular activities, hours spent in the development of skills, and family income did not have significant independent effects (Table 4).

Table 4. Multiple Linear Regression Predicting Current CGPA

Predictor	B	SE	95% CI	p-value
Previous SGPA	0.506	0.015	0.476 to 0.536	<0.001
Attendance	0.002	0.001	0.0004 to 0.0029	0.010
Study hours	-0.004	0.006	-0.016 to 0.007	0.452
Social media hours	0.011	0.004	0.003 to 0.019	0.010
Credits completed	0.003	0.0003	0.003 to 0.004	<0.001
Age	-0.052	0.007	-0.066 to -0.039	<0.001
Scholarship: Yes	0.054	0.022	0.011 to 0.098	0.015
English proficiency: Basic	-0.140	0.032	-0.202 to -0.078	<0.001
English proficiency: Intermediate	-0.079	0.026	-0.131 to -0.027	0.003
Teacher consultation: Yes	-0.075	0.019	-0.113 to -0.037	<0.001
Health issue: Yes	-0.050	0.025	-0.099 to -0.001	0.046
Co-curricular activity: Yes	0.024	0.019	-0.015 to 0.061	0.225

Model summary: N = 1,153; $R^2 = 0.564$; adjusted $R^2 = 0.558$; F = 91.88; $p < 0.001$. Multicollinearity was not evident, as all assessed VIF values were within acceptable limits.

4. Discussion

Multivariate statistical analysis was performed to study academic, behavioral, demographic and learning-related factors associated with university student performance in the present study. Results show that the factors of prior achievement, attendance, academic progression, language proficiency, scholarship status, health status and selected behavioral characteristics were all factors in academic performance. Among the positive predictors, previous SGPA turned out to be the most significant, pointing to the fact that previous academic attainment continues to be a significant factor in predicting future academic attainment. A positive association was also found between attendance and current achievement, suggesting that regular attendance in the classroom might be related to ongoing achievement. In comparisons between the academic performance of the recipients of the scholarship and students living with family, the former had better results. However, earlier probation was linked to poorer performance, indicating that academic problems are ongoing for students who have already struggled with academic issues during their previous probation. A significant percentage of the variance in CGPA was accounted for by the regression model, indicating the effectiveness of the multivariate method in comprehending students' achievement.

Social media use was an interesting finding. The bivariate correlation with CGPA was negative, while the adjusted regression coefficient was positive once the other variables were taken into consideration. This shift is suggestive of possible suppression or confounding effects, and it suggests that social-media use cannot be understood without consideration of academic and demographic attributes. Likewise, learning mode was an important difference in the group comparison without adjustment, but was not an independent factor in the multivariable model. This suggests that the apparent distinction between online and offline learning could be partly due to other student attributes and not just the learning mode.

This finding aligns with the work of El Jihaoui et al. (2025), who employed both factor analysis and multiple linear regression in their study of factors affecting students' academic performance. The results of the present study, which showed that academic engagement-related characteristics prove to be significant in academic achievement, are also in line with those found by Acosta-Gonzaga (2023), who also found that academic engagement plays an important role in university achievement. Similarly, the role of learning behaviour and academic indicators aligns with the findings from learning analytics research that learning activities can be used to help predict student outcomes (Mwalumbwe & Mtebe, 2017). The results also corroborate the general findings that a combination of academic and behavioral variables is more suitable to understanding student performance than individual variables. In a review of predictive models for student outcomes, Rastrollo-Guerrero et al. (2020) found that a variety of student-related factors are included in predictive models. This is also in line with the results of studies that have been conducted on the connection between personal learning features, self-management, and self-efficacy in students' academic achievement (Al-Abyadh & Abdel Azeem, 2022). Further, the impact of digital behavior in university environment has been proved in different countries of the world as technology-related attitudes and use differed based on various personal and educational factors (Abdaljaleel et al., 2024). All of these studies, together, confirm the current practice of using an integrated statistical framework to examine student performance.

The results have implications for academic monitoring and student-support strategies. Prior academic achievement and attendance can be good predictors to help identify students in need of early academic support. Structured academic support and regular monitoring of progress can be especially helpful for students who have had previous problems with probation. The correlation between English language attainment and achievement indicates that there may also be benefit in specific language-support programmes. Scholarship status and living conditions also suggest that academic success could be affected by overall educational and social conditions. Importantly, the results show that it is better to use a mix of appropriate behaviour and demographic factors to assess student performance than to use a single one.

There are several caveats to consider. The cross-sectional secondary-data design is not conducive to causal inferences about the patterns found. Self-report and recall biases may have influenced the collection of some of the information via questionnaires. Additional non-cognitive, institutional, instructional or socioeconomic factors that affect academic achievement may not have been included in the variables available. The analysis also relied on data from a particular student group, which might not be generalizable to universities operating in different education systems or having different student characteristics. Further, certain academic records could not be utilized for outcome analysis due to missing data on CGPA or SGPA.

Future research is needed to replicate these results with other student populations and with long-term data to investigate the development of academic and behavioral outcomes over time. Longitudinal assessments could help to elucidate if the predictors found in cross-sectional analyses persist across the years of university studies. Further factors like motivation, self-efficacy, psychological well-being, quality of the teaching and institutional support may be added to explanatory models. Future studies could also be conducted to compare interpretable regression methods to machine learning models and determine if better predictive accuracy can be obtained while maintaining clear interpretation of the characteristics that affect students' academic performance.

5. Conclusion

The present study showed that a mixture of academic, behavioral, demographic, and learning-related factors are linked to university student performance. Previous SGPA proved to be the most significant determinant of current CGPA, showing that there was a high correlation between the two and previous academic performance is still an important indicator of subsequent academic performance. Scholarship status and completed academic credits were also found to positively contribute to the multivariable model, and attendance was found to have a positive relationship with academic achievement. However, weaker English language skills, health problems, teacher referral and older age were linked to poorer academic achievement after accounting for other factors. The group comparisons also indicated differences in CGPA based on scholarship status, mode of learning, previous probation status and place of residence. Results also indicated that certain factors were altered in significance upon simultaneous adjustment. For instance, social-media use had a negative bivariate association with CGPA but a small positive adjusted association, underlining the importance of the multivariate analysis to uncover more complex associations among student characteristics. Combined statistical assessment was found to be useful and overall the regression model accounted for a large portion of variation in academic performance. The findings indicate that universities could consider implementing a more comprehensive approach to monitoring a range of relevant background factors to help support students' academic progress, including previous achievement, attendance, and academic progress. This could be one way to assess students who might need early advice and support.

References:

[1]. Abdaljaleel, M., Barakat, M., Alsanafi, M., Salim, N. A., Abazid, H., Malaeb, D., ... & Sallam, M. (2024). A multinational study on the factors influencing university students’ attitudes and usage of ChatGPT. Scientific reports, 14(1), 1983.

[2]. Acosta-Gonzaga, E. (2023). The effects of self-esteem and academic engagement on university students’ performance. Behavioral Sciences, 13(4), 348.

[3]. Al Husaini, Y. N., Al Kishri, W., Al Husaini, M. A., Al Bahri, M., & Abrar, M. (2025). Predicting student academic success using deep learning: A multi-factor approach to performance prediction. Journal of Logistics, Informatics and Service Science, 12(1), 263-283.

[4]. Al-Abyadh, M. H. A., & Abdel Azeem, H. A. H. (2022). Academic achievement: Influences of university students’ self-management and perceived self-efficacy. Journal of Intelligence, 10(3), 55.

[5]. Alshanqiti, A., & Namoun, A. (2020). Predicting student performance and its influential factors using hybrid regression and multi-label classification. Ieee Access, 8, 203827-203844.

[6]. Begdache, L., Kianmehr, H., Sabounchi, N., Marszalek, A., & Dolma, N. (2019). Principal component regression of academic performance, substance use and sleep quality in relation to risk of anxiety and depression in young adults. Trends in neuroscience and education, 15, 29-37.

[7]. El Jihaoui, M., Abra, O. E. K., & Mansouri, K. (2025). Factors affecting student academic performance: A combined factor analysis of mixed data and multiple linear regression analysis. IEEE access, 13, 15946-15964.

[8]. Kassarnig, V., Mones, E., Bjerre-Nielsen, A., Sapiezynski, P., Dreyer Lassen, D., & Lehmann, S. (2018). Academic performance and behavioral patterns. EPJ Data Science, 7(1), 10.

[9]. Marín, Y. R., Huatangari, L. Q., Tuesta, J. N. A., Caro, O. C., Guevara, J. L. M., Bardales, E. S., & Santos, R. C. (2025). Analysis of factors affecting the academic performance of university students using machine learning. Scientific Reports, 15(1), 44027.

[10]. Musaddiq, M. H., Sarfraz, M. S., Shafi, N., Maqsood, R., Azam, A., & Ahmad, M. (2022). Predicting the impact of academic key factors and spatial behaviors on students’ performance. Applied Sciences, 12(19), 10112.

[11]. Musso, M. F., Hernández, C. F. R., & Cascallar, E. C. (2020). Predicting key educational outcomes in academic trajectories: a machine-learning approach. Higher education, 80(5), 875-894.

[12]. Mwalumbwe, I., & Mtebe, J. S. (2017). Using learning analytics to predict students’ performance in Moodle learning management system: A case of Mbeya University of Science and Technology. The Electronic Journal of Information Systems in Developing Countries, 79(1), 1-13.

[13]. Ni, Q., Zhu, Y., Zhang, L., Lu, X., & Zhang, L. (2023). Leverage learning behaviour data for students' learning performance prediction and influence factor analysis. IEEE Transactions on Artificial Intelligence, 5(5), 2422-2433.

[14]. Pustovalova, N., & Avdeenko, T. (2022, May). Multivariate analysis of the influence of students' characteristics on academic performance. In 2022 VIII International Conference on Information Technology and Nanotechnology (ITNT) (pp. 1-6). IEEE.

[15]. Rahman, A. T., Lamia, S., Shishir, A. H., & Barsa, M. M. (2024). Students academic performance evaluation dataset (Version 1) [Data set]. Mendeley Data. https://doi.org/10.17632/dc3797vf3t.1
[16]. Rastrollo-Guerrero, J. L., Gómez-Pulido, J. A., & Durán-Domínguez, A. (2020). Analyzing and predicting students' performance by means of machine learning: A review. Applied sciences, 10(3), 1042.
[17]. Shou, Z., Xie, M., Mo, J., & Zhang, H. (2024). Predicting student performance in online learning: a multidimensional time-series data analysis approach. Applied sciences, 14(6), 2522.
[18]. Suleiman, I. B., Okunade, O. A., Dada, E. G., & Ezeanya, U. C. (2024). Key factors influencing students' academic performance. Journal of Electrical Systems and Information Technology, 11(1), 41.
[19]. Tadese, M., Yeshaneh, A., & Mulu, G. B. (2022). Determinants of good academic performance among university students in Ethiopia: a cross-sectional study. BMC medical education, 22(1), 395.
[20]. Urs, A. A. D., & PK, A. S. (2025). A multi-factor machine learning framework for predicting and profiling student academic performance using behavioral, financial, and wearable data. MethodsX, 103673.
[21]. Waheed, H., Hassan, S. U., Aljohani, N. R., Hardman, J., Alelyani, S., & Nawaz, R. (2020). Predicting academic performance of students from VLE big data using deep learning models. Computers in Human behavior, 104, 106189.
[22]. Wang, Y., Zuo, M., He, X., & Wang, Z. (2025). Exploring students online learning behavioral engagement in university: Factors, academic performance and their relationship. Behavioral Sciences, 15(1), 78.
[23]. Yao, H., Lian, D., Cao, Y., Wu, Y., & Zhou, T. (2019). Predicting academic performance for college students: A campus behavior perspective. ACM Transactions on Intelligent Systems and Technology (TIST), 10(3), 1-21.
[24]. Zhao, L., Chen, K., Song, J., Zhu, X., Sun, J., Caulfield, B., & Mac Namee, B. (2020). Academic performance prediction based on multisource, multifeature behavioral data. Ieee Access, 9, 5453-5465.