Comparative Analysis of Multiple Linear Regression and Random Forest Regression in Predicting Academic Performance of Students in Higher Education

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**ABSTRACT**

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| **Aims:** This study aimed to compare the predictive accuracy of Multiple Linear Regression and Random Forest Regression models in forecasting academic performance among Social Work students. Specifically, it sought to identify which among the considered variables—study habits, learning styles, stress, anxiety, coping mechanisms, study motivation, and exam preparation—were most influential in predicting students’ academic outcomes.**Study design:** Quantitative predictive-correlational research methodology.**Place and Duration of Study:** The research was carried out with 45 Social Work students participating in a Statistics course at a higher education institution in the Philippines during the second semester of the 2024–2025 academic year.**Methodology:** Validated questionnaires were distributed through Google Forms to evaluate student actions and emotional conditions. Reliability testing was performed via JAMOVI, with all constructions demonstrating adequate internal consistency. Descriptive statistics were employed to analyze the mean scores for each variable. Multiple Linear Regression and the Random Forest algorithm were executed in Jupyter Notebook to assess predictive efficacy and determine the most significant factors. The Mean Absolute Percentage Error (MAPE) served as the criterion for evaluating model correctness.**Results:** Learning Style, Exam Preparation, and General Stress were recognized as the primary predictors in both models. The Random Forest model attained a lower MAPE (2.9481) compared to the Multiple Regression model (3.3690), signifying enhanced predictive accuracy and a more effective representation of nonlinear interactions. The Coping Mechanism consistently shown the lowest predictive value.**Conclusion:** The Random Forest algorithm surpassed Multiple Regression in forecasting academic performance, underscoring its efficacy in managing intricate data structures. The learning style proved to be the most significant predictor. The results endorse the application of machine learning in educational research and indicate that matching training with students' learning preferences and refining exam preparation may augment academic achievement. |

*Keywords: Academic Performance, Higher Education, Multiple regression, Random Forest Regression, Machine Learning, Study Habits, Academic Stress, Resilience, Teaching Style, Mean Absolute Percentage*

**1. INTRODUCTION**

Globally, academic achievement serves as a crucial metric of educational accomplishment, influencing both individual prospects and the overall standing and efficacy of higher education institutions. It functions as an indicator of a student's proficiency in mastering curriculum, applying knowledge, and excelling in demanding academic settings. Additionally, it offers educational stakeholders—such as administrators, professors, and policymakers—criteria to assess instructional quality, pinpoint curricular deficiencies, and evaluate institutional efficacy. In a progressively globalized and competitive educational environment, academic success is crucial in securing scholarships, graduate programs, and employment possibilities. Although academic achievement has always been associated with intellectual aptitude and cognitive abilities, there is an increasing agreement that this viewpoint is insufficient. Recent research indicate that academic outcomes are influenced by non-cognitive elements, including emotional regulation, motivation, learning environments, and the quality of student-instructor relationships (Espericueta-Medina et al., 2020; Dallasheh, 2024; Zayed, 2024). These findings are instigating a paradigm change from only quantitative assessments of intelligence to more comprehensive, student-centered methodologies for educational evaluation and intervention (Rafiq et al., 2025; Zheng et al., 2024).

 In the Philippine context, this multifaceted dilemma presents itself distinctly, especially in private tertiary schools located in rural or provincial regions. These institutions, frequently functioning with restricted financial resources and facilities, cater to students encountering diverse socio-economic challenges. Financial instability, limited internet access, domestic responsibilities, and mental health challenges are prevalent, particularly in places with inadequate or nonexistent educational support systems. Students enrolled in emotionally taxing programs, such as Social Work, encounter heightened stress as a result of their direct involvement with underprivileged communities through fieldwork and community-based education. These academic experiences, albeit pedagogically enriching, immerse students in emotionally intense situations that may reflect their personal life conditions (Zayed, 2024; RaWIv et al., 2024). The simultaneous challenges of academic and personal stress provide a multifaceted educational experience that necessitates thorough examination of the intricate aspects influencing academic success in these contexts. It is essential to identify which variables—such as stress management, resilience, study habits, and instructor empathy—most significantly impact student success.

Notwithstanding this complexity, numerous local and institutional studies persist in employing conventional statistical methods, such as Multiple Linear Regression (MLR), to analyze academic achievement. Although these methods possess some advantages, they are constrained in their capacity to identify nonlinear correlations and interaction effects among predictors (Gomes et al., 2020; Mbunge et al., 2021). This is a challenge for analyzing complex educational processes where factors do not function independently. The influence of stress on academic performance may be alleviated by resilience or intensified by an unsupportive learning environment—dynamics that conventional models may not adequately identify. As a result, there is growing interest in utilizing machine learning (ML) models such as Random Forest Regression, which are engineered to analyze extensive datasets, identify intricate patterns, and prioritize variables based on their predictive significance (Casinillo & Laurente, 2024; Amraouy et al., 2025). These methodologies have demonstrated efficacy in global educational contexts but are still inadequately employed in Philippine research, especially in Social Work education at provincial schools.

This is particularly significant when national educational bodies, such as the Commission on Higher Education (CHED), underscore the importance of innovation and evidence-based practices in facilitating educational transformation. CHED's policies promote research-based practices that improve learning outcomes, increase instructional delivery, and diminish equity inequalities in access and achievement. Their emphasis on regional and marginalized institutions highlights the necessity for localized, data-driven research to influence policy and practice. This study aimed to compare the predictive accuracy of Multiple Linear Regression and Random Forest Regression models in forecasting academic performance among Social Work students. Specifically, it sought to identify which among the considered variables—study habits, learning styles, stress, anxiety, coping mechanisms, study motivation, and exam preparation—were most influential in predicting students’ academic outcomes. The results of this comparison will help educators identify key areas for academic support and will demonstrate the effectiveness of machine learning models like Random Forest in educational research.

This study has three key objectives. The primary objective is to determine the levels of various psychological, behavioral, and academic factors that may influence student academic performance, including general stress, anxiety level, coping mechanism, study habits, learning style, study motivation, and exam preparation. The secondary objective is to predict students’ academic performance (grades) based on these identified factors using two modeling approaches: Multiple Linear Regression and Random Forest Regression. Finally, the last objective is to compare the predictive accuracy of the two models using key evaluation metrics, with a particular focus on the Mean Absolute Percentage Error (MAPE) as the basis for determining the more effective model. This study's results aim to furnish educators, administrators, and policymakers with practical insights for enhancing academic support systems, optimizing pedagogical strategies, and developing curricula that are more responsive to the distinct needs of students in provincial Social Work programs.

**2. methodology**

**2.1 Research Design**

This study utilized a quantitative, predictive-comparative research approach to examine the factors affecting academic achievement among higher education students. It evaluated the predictive accuracy of Multiple Linear Regression (MLR) and Random Forest Regression (RFR) in identifying critical variables, including academic stress, study habits and resilience. Data was gathered using a standardized questionnaire. Pilot testing was executed with *Jamovi*, while the final analysis and model comparison were conducted in *Python*, utilizing Mean Absolute Percentage Error (MAPE) as the principal evaluation metric.

**2.2 Research Respondents**

The research encompassed 45 social work students in higher education from a singular cohort at a private university in Misamis Occidental. Participants were recruited through purposive sampling based on their relevance to the study's aim of finding predictors of academic performance. Ethical principles, encompassing secrecy and voluntary involvement, were rigorously maintained.

**2.3 Instrument of the Study**

This study utilized the Study Habits and Learning Styles Questionnaire and the Stress and Anxiety Assessment Questionnaire. The surveys underwent a reliability assessment with Cronbach’s Alpha in JAMOVI software. All subscales produced alpha values ranging from 0.70 to 1.00, signifying that the instruments employed in this study exhibit acceptable to exceptional internal consistency. Consequently, the instruments are considered dependable for evaluating the intended structures.

**2.3.1 Study Habits and Learning Styles Questionnaire**

This tool evaluates students' study practices, learning preferences, academic motivation, and test preparation tactics through four components: Study Habits, Learning Styles, Study Motivation, and test Preparation. Each component comprises 10 items evaluated on a 4-point Likert scale (1 = Strongly Disagree to 4 = Strongly Agree). The outcomes are analyzed utilizing established mean ranges to classify responses from Very Poor to Excellent.

**Table 1. Verbal Interpretation for Study Habits, Learning Styles, Study Motivation, and Exam Preparation**

|  |  |  |
| --- | --- | --- |
| Scale | Mean Range | Descriptive Rating |
| 4 | 3.25 – 4.00 | Excellent |
| 3 | 2.50 – 3.24 | Good |
| 2 | 1.75 – 2.49 | Poor |
| 1 | 1.00 – 1.74 | Very Poor |

**2.3.2 Stress and Anxiety Assessment Questionnaire**

This tool evaluates students' reported stress, anxiety, and coping techniques through three components: General Stress Levels, Anxiety Levels, and Coping Mechanisms. Each component comprises 10 items evaluated on a 4-point Likert scale (1 = Strongly Disagree to 4 = Strongly Agree), with results analyzed through mean ranges to categorize responses from Very Low to High or Effective.

**Table 2. Verbal Interpretation for Stress, Anxiety, and Coping Mechanisms**

|  |  |  |
| --- | --- | --- |
| Scale | Mean Range | Descriptive Rating |
| 4 | 3.25 – 4.00 | High / Effective |
| 3 | 2.50 – 3.24 | Moderate |
| 2 | 1.75 – 2.49 | Low / Poor |
| 1 | 1.00 – 1.74 | Very Low / Very Poor |

**2.3.3 Academic Performance**

Academic performance was assessed using student’s final average grades from the preceding semester. The grades were acquired with consent and utilized as the criterion variable to determine whether factor—study habits, learning styles, or stress/anxiety—serves as the most significant predictor of academic achievement.

**2.4 Data gathering procedure**

Data were gathered from 45 students utilizing two validated instruments: the Study Habits and Learning Styles Questionnaire and the Stress and Anxiety Assessment Questionnaire. Both instruments were transformed into Google Forms to guarantee accessibility and convenience. The link was disseminated to the participants, who were allotted sufficient time to complete the forms autonomously. The researcher observed the responses, alerted students to any incomplete items, and confirmed that all submissions were finalized prior to commencing data analysis.

**2.5 Statistical Treatment of Data**

This study's data was analyzed employing descriptive statistics, inferential statistics, and machine learning methodologies. Descriptive statistics, namely the mean, were employed to quantify general stress, anxiety, coping strategies, study habits, learning styles, study motivation, and exam preparation, which were analyzed using established linguistic categories. Multiple linear regression was utilized for inferential analysis to ascertain the degree to which these variables predicted academic performance and to find the components that significantly influenced students' academic achievements. To augment the reliability of the prediction, a Random Forest model an ensemble machine learning algorithm was employed. This method facilitated a more adaptable and precise forecast of academic achievement while pinpointing the most significant elements via feature relevance. The integration of traditional statistics with machine learning yielded a thorough study of the data.

**2.6 Model Evaluation**

This table categorizes the forecasting accuracy based on the Mean Absolute Percentage Error (MAPE), a widely used metric in time series forecasting (Liu & Zhang, 2024; Yang & Li, 2024). Lower MAPE values indicate higher accuracy, with thresholds defining different levels of forecasting performance.

$$MAPE= \frac{1}{n}\sum\_{t=1}^{n}\left|\frac{X\_{t}-\hat{X}\_{t}}{X\_{t}}\right|\*100$$

Table 3. Forecasting Accuracy Classification Based on MAPE

|  |  |
| --- | --- |
| **MAPE** | **Forecasting Criterion** |
| 4.21-5.00 | Forecasting accuracy is very good |
| 3.41-4.20 | Forecasting accuracy is good |
| 2.61-3.40 | Forecasting accuracy is good enough |
| 1.81-2.60 | Forecasting accuracy is not good |

3. RESULTS AND DISCUSSION

This section highlights the conclusions utilizing descriptive statistics, multiple linear regression, and the random forest model. the descriptive analysis encapsulated the dimensions of stress, anxiety, coping mechanisms, study practices, learning preferences, motivation, and examination readiness. multiple linear regression identified significant indicators of academic success, whereas random forest enhanced prediction accuracy by capturing intricate, nonlinear patterns. data analysis and model implementation were performed with jupyter notebook, and model performance was assessed through the mean absolute percentage error (mape), with lower values signifying enhanced accuracy. these integrated methods elucidated the principal determinants affecting academic achievement.

3.1 Levels of psychological, behavioral, and academic factors affecting student performance.

Table 1 revealed the mean scores, standard deviations, and verbal interpretations of the primary variables considered as predictors of academic performance among 45 Social Work students enrolled in a Statistics course. These include general stress, anxiety levels, coping mechanisms, study habits, learning styles, study motivation, and exam preparation. Understanding student performance across these domains provides valuable insight into the behavioral and psychological factors that may influence academic achievement in a cognitively demanding subject like Statistics.

Coping Mechanism recorded the highest mean score of 3.24 (SD = 0.48), suggesting that most students moderately apply effective strategies to manage stress and academic challenges. This implies a generally adaptive approach to academic pressures, allowing students to maintain focus and emotional regulation. According to Pascoe et al. (2020) and Huerta (2022), effective coping mechanisms act as buffers against academic stress and help students remain productive in high-pressure learning environments. Furthermore, Musso et al. (2020) emphasized that students with better emotional self-regulation tend to demonstrate greater persistence and perform better academically, particularly in mentally intensive subjects.

In contrast, Exam Preparation had the lowest mean score of 2.60 (SD = 0.34), though still categorized as “good.” This relatively low score suggests that while students may manage stress adequately, they may be underprepared for assessments due to ineffective strategies or time management. Pekrun and Stephens (2012) highlighted that structured and consistent exam preparation significantly enhances academic outcomes. Similarly, von der Embse et al. (2018) linked insufficient preparation and test-related anxiety to underperformance in quantitative courses, including mathematics and statistics. The contrast between high coping and low exam preparation highlights a disconnect between emotional resilience and actual academic behavior. While students may be capable of managing pressure, they may not be translating that into effective study actions.

This reflects the findings of Radišić et al. (2022), who argued that integrating strong study habits with effective learning approaches is crucial for bridging performance gaps. Likewise, Popoola and Hendricks (2014) noted that aligning learning styles with instructional methods, alongside the presence of academic support systems, can enhance student engagement and academic achievement. In light of these findings, improvements in exam readiness, personalized learning strategies, and academic support programs may be beneficial for students navigating challenging subjects. As Pascarella and Terenzini (2005) suggested, initiatives that reduce anxiety and boost motivation can lead to measurable gains in student performance.

Table 1. Descriptive Statistics and Verbal Interpretation of Academic Predictors Among Social Work Students

|  |  |  |  |
| --- | --- | --- | --- |
|  | Mean | Standard Deviation | Verbal Interpretation |
| General Stress | 2.96 | 0.48 | Moderate Stress |
| Anxiety Level | 2.82 | 0.43 | Moderate Anxiety |
| Coping Mechanism | 3.24 | 0.48 | Moderate Coping Strategies |
| Study Habits | 2.71 | 0.30 | Good Study Habits |
| Learning Style | 2.85 | 0.27 | Moderate Preference for Active Learning Styles |
| Study Motivation | 2.89 | 0.30 | Moderate Motivation |
| Exam Preparation | 2.6 | 0.34 | Good Exam Preparation |
|  |  |  |  |

**3.2 Comparison of Predictive Models and Identification of Key Academic Performance Factors**

Table 2 presents the comparative results of two predictive models—Random Forest (employing feature importance) and Multiple Linear Regression—assessing the impact of diverse psychological, behavioral, and demographic variables on academic success. The Random Forest model attained a Mean Absolute Percentage Error (MAPE) of 2.9481, in contrast to 3.3690 from the Linear Regression model, signifying superior prediction accuracy for Random Forest. This discovery aligns with the work of Nachouki et al. (2023) and Batool et al. (2023), who illustrated Random Forest's enhanced predictive capability in educational analytics, attributable to its proficiency in managing non-linear and intricate data frameworks.

Both models indicated Learning Style and Exam Preparation as the most significant predictors of academic performance. In the Random Forest model, Learning Style exhibited the highest feature relevance score (0.3455), succeeded by Exam Preparation (0.1647) and General Stress (0.1452). The Linear Regression model indicated the greatest coefficients for Learning Style (0.1904) and Exam Preparation (0.1875), so affirming their significant impact on academic achievement. These findings correspond with those of Falát and Piscová (2022) and Namoun and Alshanqiti (2020), who underscored the significance of learning practices and systematic preparation in influencing academic achievement.

Nonetheless, the two models diverged in their assessment of additional variables. For instance, Study Motivation had a very high coefficient (0.1041) in the Linear Regression model, although a diminished significance score (0.0494) in the Random Forest model. This indicates that whereas Study Motivation exhibits a linear correlation with academic achievement, its impact lessens when nonlinear patterns are considered—an observation also noticed by Khan and Ghosh (2021). Conversely, Coping Mechanism exhibited the lowest predictive value in both models (0.0336 in Random Forest and 0.0157 in Linear Regression), signifying minimal impact on academic success. This outcome corroborates previous findings by Musso et al. (2020), who identified analogous trends in student-centered predictive research.

The Random Forest model surpassed the regression model and revealed Learning Style, Exam Preparation, and General Stress as the most significant indicators of academic success. This conclusion aligns with extensive machine learning educational research, as indicated by Liu and Zhang (2024) and Liu and Zhang (2024), who similarly determined that Random Forest outperforms traditional statistical methods in accuracy and understanding regarding academic achievements.

Table 2. Comparison of Random Forest and Multiple Linear Regression in Predicting Academic Performance

|  |  |  |
| --- | --- | --- |
| Factor | Feature Importance(Randon Forest) | Linear Regression |
| MAPE | 2.9481 | 3.3690 |
| Learning Style | 0.3455 | 0.1904 |
| Exam Preparation | 0.1647 | 0.1875 |
| General Stress | 0.1452 | 0.1442 |
| Income of Parents (Monthly) | 0.0828 | 0.0956 |
| Age | 0.0727 | 0.1015 |
| Anxiety Level | 0.0646 | 0.1035 |
| Study Motivation | 0.0494 | 0.1041 |
| Study Habits | 0.0415 | 0.0575 |
| Coping Mechanism | 0.0336 | 0.0157 |

**3.3Visualization of Model Predictions and Error Distribution**

This section illustrates the visual comparison of the prediction results from the Random Forest and Multiple Linear Regression models. The graphs depict the degree of alignment between each model's projected values and the actual student grades, facilitating a more precise evaluation of each model's accuracy and error distribution.

The prediction plots further demonstrate the advantages and drawbacks of the two employed models. The figure 1 indicates that forecasts frequently overestimate high-achieving students while underestimating low-achieving students, a trend commonly observed in the literature. This systemic bias arises from the model's failure to encapsulate intricate and nonlinear interactions, which are often evident in student performance data (Yesugade et al., 2024; Frick et al., 2023; Tzenios, 2020). Research indicates that linear models are inadequate in addressing latent variables such as motivation or engagement (Hilbert et al., 2021) and falter in managing variable interactions (Li, 2020; Cheng, 2024), rendering them less dependable across varied student populations.

Conversely, figure 2 exhibits a more accurate correlation between projected and actual grades. Data points are more closely grouped along the optimal prediction line, suggesting that prediction errors are uniformly distributed across all performance levels. This result underscores the model's capacity to handle nonlinear patterns and intricate variable interactions, enhancing its accuracy. The ensemble characteristic of Random Forest mitigates overfitting while maintaining generalizability. Research corroborates this benefit, with investigations by Frick et al. (2023), Jin (2023), and Rico-Juan et al. (2024) validating Random Forest’s exceptional efficacy in educational data modeling. These findings substantiate the application of sophisticated machine learning methodologies, such as Random Forest, in educational research, especially for generating precise, equitable, and nuanced forecasts of academic results.

Figure 1. Actual vs. Predicted Grades using Linear Regression



Figure 2. Actual vs. Predicted Grades using Random Forest



4. Conclusion

This study aimed to compare the predictive accuracy of Multiple Linear Regression and Random Forest Regression models in forecasting academic performance among Social Work students. Specifically, it sought to identify which among the considered variables—study habits, learning styles, stress, anxiety, coping strategies, study motivation, and exam preparation—were most influential in predicting students’ academic outcomes. The study involved 45 Social Work students enrolled in a Statistics course and utilized validated survey tools and statistical models to assess key predictive factors.

Descriptive statistics revealed that students generally demonstrated moderate levels of stress, anxiety, and coping techniques, while exam preparation yielded the lowest mean, indicating a gap in readiness. Both modeling techniques identified Learning Style, Exam Preparation, and General Stress as the strongest predictors of academic performance. The Random Forest model outperformed the Multiple Linear Regression model, achieving a lower Mean Absolute Percentage Error (MAPE = 2.9481 vs. 3.3690), reflecting its higher predictive accuracy and capacity to capture nonlinear relationships among variables.

Considering these findings, it is advisable for academic programs to prioritize tailored learning methodologies and organized exam preparation assistance. Workshops focused on study techniques, stress management, and aligning instruction with students’ learning preferences may contribute to improved academic outcomes. Further research should explore larger datasets and additional variables, while continuing to apply and refine machine learning approaches for greater accuracy and insight in educational analytics.

Consent

Permission to conduct the study was sought from the appropriate institutional authorities. The researcher ensured that participation in the study was entirely voluntary, and that informed consent was obtained from all student participants prior to data collection. Participants were assured that their responses would remain confidential and anonymous, with no names or personal identifiers included in any part of the analysis or reporting. The purpose, procedures, and scope of the study were clearly explained to all participants. They were informed of their right to refuse participation or withdraw from the study at any point without any academic or personal consequences. Data was collected only after securing consent, and the researcher-maintained transparency and honesty throughout the research process. Ethical guidelines for conducting research involving human participants were strictly followed.

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