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Sustaining Mental Health among Educators by Understanding Factors of Students' Failure

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Abstract
Purpose: Understanding the factors that contribute to students' failure is crucial to sustaining the mental health of educators. When educators can identify these factors, they can create a more supportive learning environment and reduce stress and frustration for them and their students. This study investigates the failure factors among students in Introduction to Statistics subject.
Design/methodology/approach: 200 students were involved in this study and the collected data was analyzed using SPSS. Multiple linear regression is used to analyze the failure factors such as test score, absentee, gender, and repetition.
Findings: Based on the findings, early warning signs can be determined by educators for struggling students, based on their attendance and test score. Gender and repetition are not important in predicting academic performance. Screening test on mathematics literacy and topic by topic understanding should be done prior to official test, so that weak students can be determined and supported.
Research limitations/implications: Better relationships can be developed by having effective communication on students' needs and expectations. By understanding the factors contributing to students' failure and proactively addressing them, educators can create a more inclusive and supportive learning environment.
Practical implications: This, in turn, can contribute to better mental health outcomes for both educators and students.
Originality/value: To be completed

Keywords: Academic performance, performance predictor, educator, failure, mathematics literacy

Introduction

The mental health of educators is important as they shape the minds of the students and contribute significantly to their development and learning. However, the pressures of dealing with various student needs, administrative expectations, and the inherent responsibilities of their role often expose educators to high levels of stress and anxiety, potentially impacting their overall mental well-being. A myriad of factors, including student failures, can increase the educators' burden, necessitating a comprehensive understanding and strategy to overcome the problem.

Student failures can caused by the teaching method, facilities, and attitude of the students themselves. The stress emanating from students' struggles and failures is often transferred to educators, who feel responsible for students' success and are required to adjust their teaching strategies to address the diverse needs and challenges faced by students.
A successful university education system pays attention to variables that affect students' learning and advancement. Academic performance prediction is an important area for educational research since it not only helps educators design timely interventions but also encourages personalized education (Huaxiu et al., 2019).

Students face difficulties when it comes to final exams because passing these exams requires reading a lot of material. Although they have enough time during the course to study the material, students frequently do not make the most of their available time because of other commitments. Continuous assessment is a usual method of evaluation that is most appropriate for obtaining information about learning and teaching processes. Through this type of evaluation, students' intellectual and practical efforts can be increased, in line with academic progress and achievement (Pourahmad et al., 2012).

This paper is done to investigate the factors of students' failure. The exploration of this relationship will provide insights into the strategies and interventions necessary for maintaining a balanced mental state for educators while enhancing the learning experiences and success rates of the students.

Literature Review

Many factors can contribute to students' academic performance in final examination. Several studies on the factor influencing on students' academic performance have been done using different methods. One study by Shahjahan et al. (2021) proposed the factor associates with the poor academic performance of undergraduate students. Data were analyzed using Chi-square test and this study shows that the poor academic performance was found significantly correlated with irregular class attendance, fathers' low education level, partial family cooperation, use of social media and excessive time spent for gossiping.

Wambuguh and Yonn-Brown (2013) examined the correlation performance in routine lecture quizzes and the performance in the final examination by using logistic regression analysis. The results indicated that performance in the quizzes is positively correlated with performance in the final exam. Students who attain a score of 70% or more in the quizzes are nine times as likely to pass the final examination with the same or higher score compare to those who do not.

Latif and Miles (2020) studied the impact of assignments and quizzes on exam grades. Based on a difference-in-difference approach, assignments had a statistically discernible positive impact on exam grades for the overall sample. Assignments had a positive impact on exam grades for males but no statistically discernible impact for females when examined separately by gender. When examined separately by student residency status, assignments and quizzes had a positive impact on exam marks for international students, but there was no statistically significant effect for domestic students.

In addition, student absenteeism can also affect students' academic performance. According to Powers and Carroll (2017), lecture attendance is highly significant with the exam scores. Therefore, students with high attendance had higher exam score. Meanwhile, AKKUŞ and ÇINKIR (2022) used basic qualitative research design in order to determine the impact of student absenteeism towards students' academic performance. There were 22 participants consists of teachers, administrators, experts, and inspectors working in different parts of Turkey to. It was found that, absenteeism is significantly influencing the students' academic and social development.

One of the methods that was wildly used by researchers to predict students' performance is multiple linear regression (Yang et al., 2018). El Aissaoui et al. (2020) used multiple linear regression to determine the factors that affect students' performance in academic institutions. The students' attributes that can affect their final grade results are the mother education level, the student's age, the student' romantic situation, the time spent with friends and the extra educational support. In the same way, Mahmud et al. (2022) investigated the factors that affect students' academic performance during COVID-19 pandemic using multiple linear regression . The outcome demonstrated that the hometown locations and preparation time before class significantly influenced the model.

A summary of past studies done to determine the factors that contribute to academic performance is shown in Table 1.

Table 1 : Summary of past study on the factors contribute to academic performance

No	Researcher	Method	Significant factors that contribute to Academic performance
1	Wambuguh and Yonn-Brown (2013)	Logistic regression analysis	Performance in the quizzes
2	Powers and Carroll (2017)	ANOVA test	Lecture attendance
3	Latif and Miles (2020)	Difference-in-difference approach	Assignments Quizzes
4	Shahjahan et al. (2021)	Chi-square test	Irregular class attendance Fathers' low education level Partial family cooperation Use of social media Excessive time spent for gossiping
5	AKKUŞ and ÇINKIR (2022)	Basic qualitative research design	Absenteeism

This present study was conducted to analyze factors that affect the performance of Statistics subject in the final examination using multiple regression analysis. The factors included in the study are test score, number of absent, frequency of course enrollment, and gender of the students.

Method

This study employed multiple linear regression (MLR), which targeted all diploma students who enrolled in Introduction to Statistics (QMT181/STA104) subject. Out of all students who enrolled in this course, there are only 191 students who participated in this study. The research focused exclusively on three specific course topics: Correlation & Regression, Index Number, and Time Series Analysis. The study did not consider the other three topics within the course, which were Introduction to Statistics, Describing Data, and Introduction to Probability.

Data was collected during Mac-August 2023 semester, spanning 14-weeks period. The test was administered in week 12, while the final exam took place in week 15. For the final exam, the study exclusively utilized scores from questions 5, 6, and 7. These questions were selected because they pertained to the three targeted topics mentioned earlier. This study encompassed several variables which is examination score as dependent variable. The test score, number of absences, frequency of course enrollment and gender as independent variables.

This method of data analysis was used to determine which factors significantly contribute to the student examination score. Before using MLR, the data must meet all five assumptions which are linearity, normality of the data, multicollinearity, homoscedasticity, and independence of errors. Data were analyzed using software SPSS version 23.

Findings

The study was designed to analyze the impact of test scores, absences, course enrollment frequency and gender on student's examination scores in a specific topic of Introduction to Statistics course (QMT181/STA104) as shown in Table 2.

Table 2: Set of variables.

Variable	Types of variables	Variable Code
Final examination score	Quantitative Continuous	Exam_score
Test Score	Quantitative Continuous	Test_score
Number of absences	Quantitative Discrete	Absent
Frequency of course enrollment	Quantitative Discrete	Taken_No
Gender	Qualitative	Gen

$$y = \beta\_0 + \beta\_1 X\_1 + \beta\_2 X\_2 + \beta\_3 X\_3 + \beta\_4 X\_4 + \varepsilon$$

where

$$y \text{ is exam score}$$
$$\beta\_1 \ldots \beta\_4 \text{ are the regression coefficient}$$
$$X\_1 \text{ is test score}$$
$$X\_2 \text{ is number of absent}$$
$$X\_3 \text{ is number of times subject taken}$$
$$X\_4 \text{ is gender of the students}$$
$$e\_i \quad \text{is model}^{\wedge\prime} \text{ serrpor term or residuals}$$

a) Checking of MLR Assumptions

In regression analysis, multiple assumptions are made about the model, particularly in the case of the multiple linear regression (MLR) model, which is considered one of the most sensitive statistical techniques due to its reliance on several data assumptions. According to Daoud

(2018), when one or more of these assumptions are violated, the model's reliability is compromised, rendering it unsuitable for estimating population parameters.

Linearity Relationship Between Dependent and Independent Variables.

Based on Table 3, it shows that test score has a strong positive correlation with exam score (r=0.759). Gender has a weak correlation with exam score (r=0.089) while frequency of course enrolment (r=-0.436) and number of absences (r=-0.269) have a weak negative correlation with exam score.

Table 3: Correlations (N=191)

		Exam_Score	Test_Score	Absent	Taken_No	Gen
Pearson Correlation	Exam_Score	1.000	.759*	-.436*	-.269*	.089
	Test_Score	.759*	1.000	-.352*	-.372*	.197*
	Absent	-.436*	-.352*	1.000	.238*	-.001
	Taken_No	-.269*	-.372*	.238*	1.000	-.019
	Gen	.089	.197*	-.001	-.019	1.000

**Significant at 1% level*

Multicollinearity

Multicollinearity arises when there is a high degree of correlation among dependent and independent variables within regression model. Table 4 shows that the VIF (Variance Inflation Factor) scores are below 10, and the tolerance scores are above 0.1. Consequently, this indicates the absence of multicollinearity among the independent variables. It's worth noting that several studies, including those by Mahmud et al. (2022) and Noora, S. (2020), have suggested that VIF scores between 5 to 10 are indicative of the absence of multicollinearity.

Table 4: Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	31.501	5.202		6.056	.000		
	Test Score	.639	.047	.716	13.596	.000	.752	1.330
	Absent	-2.593	.659	-.194	-3.935	.000	.859	1.164
	Taken No	1.609	1.871	.043	.860	.391	.846	1.181
	Gen	-1.944	1.776	-.051	-1.094	.275	.953	1.049

a. Dependent Variable: Exam Score

Homoscedasticity

Homoscedasticity, also referred to homogeneity of variances. It shows the consistency in the dispersion of differences between predicted and observed values for any given random variable within an experiment. Based on Figure 1, it reveals that no obvious signs of funneling, indicating that the assumption of homoscedasticity has been satisfied.

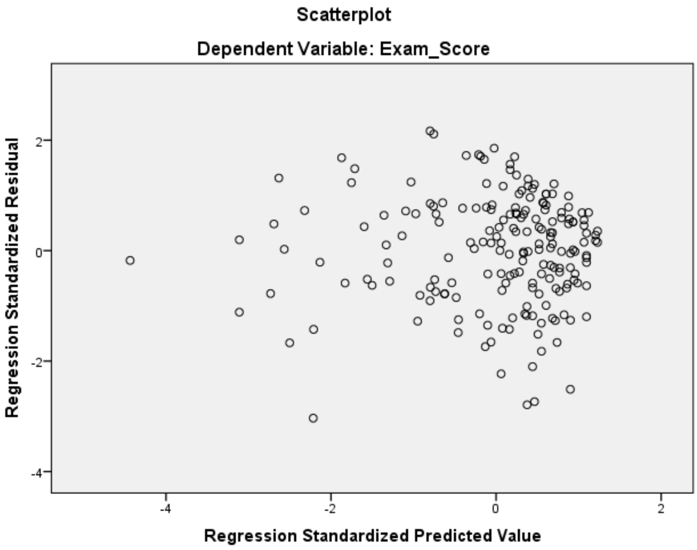

Figure 1: The plot of standardized residuals versus standardized predicted values.

The Values of Residuals are Normally Distributed

The P-P plot in Figure 2 shows that, all the points follow the diagonal line. Therefore, the assumption of normality of the residuals can be concluded.

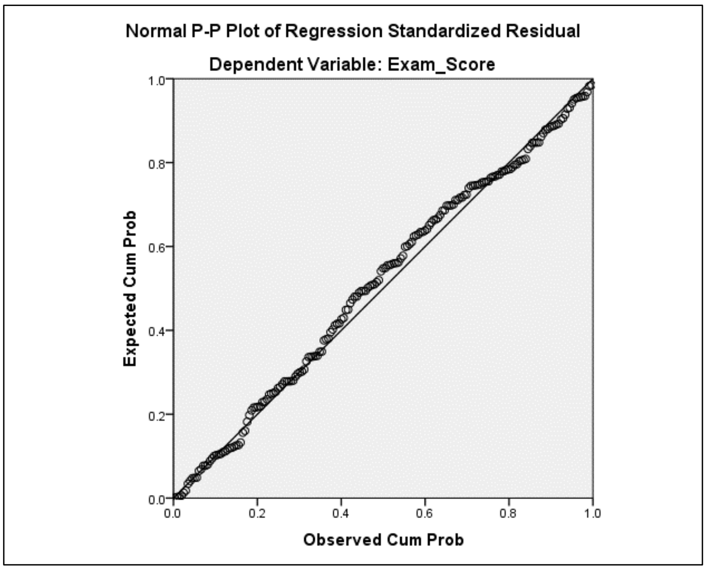

Figure 2: P-P Plot

The Independence of the Residual Value

According to Table 5, the Durbin-Watson test value is 1.622 which is close to 2. This proximity to 2 suggests that there is no significant issue of autocorrelation detected.

Table 5: Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.782[a]	.612	.603	11.80506	1.622

a. Predictors: (Constant), Gen, Absent, Taken_No, Test_Score
b. Dependent Variable: Exam_Score

b) Evaluate the Model

Fitness of the Model

The aim of this test is to evaluate the fitness of the model and help assess how well a model fits the data it was trained on. This is important for determining the model's capability to accurately capture the fundamental patterns and relationships present in the data. In other words, it will identify whether all or subsequent of the independent variables should remain in the model. The criterion test used is *F-test statistics*. The null and alternative hypothesis are as below.

$$H_0: The\ regression\ model\ is\ not\ significant$$
$$H_a: The\ regression\ model\ is\ significant$$

The statistical output in table ANOVA (Table 5) below indicates the value of F-test and its significance value (p-value). To test the hypothesis, the p-value of the F-test must be compared to a 5% significance level. If the p-value is less than the significance value, it informs that the data provide enough evidence to conclude that the independent variables in the model fit.

Based on Table 6, the value of significance is 0.00 and it is less than 5%. That means, the null hypothesis is rejected. Therefore, the data provide sufficient evidence to state that the regression model is significant.

Table 6: ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	40851.543	4	10212.886	73.284	.000[b]
	Residual	25920.865	186	139.359		
	Total	66772.409	190			

a. Dependent Variable: Exam_Score
b. Predictors: (Constant), Gen, Absent, Taken_No, Test_Score

Goodness of fit in Linear Regression

In regression models, the coefficient of determination or R-square (r^2) is the standard measure for goodness of fit. In Table 4, the value of R^2 is 61.2%. That means, the total variation in Exam_Score can be explained by Test_Score, Absent, Taken_No and Gen.

Statistically Significance of the Independent Variables.

The independent is significant when the p-value (sig-value) is less than 5% significance level. According to Table 3, it shows that two variables contributed significantly to the model namely Test_Score (B=0.639, $p < 0.05$) and Absent (B=-2.593, $p < 0.05$). However, another two variables which are Taken_No (B=1.609, $p>0.05$) and Gen (B=-1.944, $p>0.05$) did not.

c) Estimate Model Coefficient.

According to Table 4, the estimated model coefficient is:

Exam_Score = 31.501 + 0.639 Test_Score – 2.593 Absent + 1.609 Taken_No – 1.944 Gen

The analysis determines that the factors that contributed to student's final examination score are test score and number of absent.

Discussion and Conclusion

Consistent with literature review in this study, this study supports the failure factors of the test score and number of absentees. Gender and number of enrolling in the course are not important in predicting the failure rate among students.

With the knowledge, educators whom teaching the statistics subject should do an early intervention towards weak students by screening their mathematics proficiency and capability of topics understanding week by week as there are only 14 weeks of lecture in a semester. Welcoming text can be delivered to students to encourage their presence, do monitoring on weekly basis and report of absentee should be submitted to student management office for further action.

These actions shall be the guide to educators of statistics subject for preparing intensive exercises chapter by chapter, collectively, so that the burden of handling repeated students will be eased and reducing the stress among the educators.

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