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The effect of learning intensity on students' statistics course scores: A multiple regression approach with Ridge regularization

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Original Article

The effect of learning intensity on students' statistics course scores: A multiple regression approach with Ridge regularization

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Abstract
Low achievement in statistics courses is a persistent concern in higher education, yet the contributions of study time and attendance remain underexplored, particularly in Indonesian undergraduate contexts and without correcting for predictor multicollinearity. This study addresses this gap by applying Ridge regularization to estimate the independent effects of daily study hours and attendance rate on statistics course scores among 20 Indonesian undergraduates. Classical OLS assumptions were tested; Ridge regression with Leave-One-Out Cross-Validation was applied when violations occurred. Study hours and attendance jointly explained 97.54% of score variance ($R^2 = 0.975$; $F = 337.70$; $p < 0.001$); however, severe multicollinearity ($VIF = 11.77$) destabilized OLS estimates. Ridge regression ($\lambda = 1.0$) produced stable coefficients ($b_1 = 2.87$; $b_2 = 0.80$) with negligible accuracy loss ($R^2 = 0.974$). The near-perfect collinearity of the predictors indicates that study hours and attendance are part of the same underlying construct academic engagement rather than acting through independent pathways. These findings challenge the conventional additive model of learning time and imply that interventions targeting self-regulated learning may be more effective than policies addressing attendance or study time in isolation.

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1. Introduction

Academic achievement in quantitative courses such as statistics has long been a critical concern in higher education (Cui et al., 2019; Schneider & Preckel, 2017). Statistics is foundational to research methodology across disciplines, (Schwab-McCoy, 2019) yet it remains among the courses with the highest failure and withdrawal rates at the undergraduate level (Onwuegbuzie & Wilson, 2003). Low student performance in statistics is not merely an academic inconvenience; it constrains the development of research competencies and limits students' ability to contribute meaningfully to evidence-based fields (Feldon et al., 2015). Understanding the factors that drive variation in statistics course scores is therefore both theoretically important and practically urgent (Ramirez et al., 2012). Among the most frequently cited determinants of academic performance are behavioral and engagement-related variables, particularly study time and class attendance (Ma & Xiao, 2026). These two factors are consistently identified as malleable, that is, subject to change through institutional policy and individual decision, making them especially valuable targets for educational intervention (Ecclestone & Lewis, 2014). Despite their intuitive appeal, however, the precise nature and relative strength of their effects on statistics achievement remain underexplored, particularly in the context of Indonesian higher education where instructional resources and learning cultures differ substantially from those in Western research settings.

In a longitudinal study of college students (Plant et al., 2005) demonstrated how weekly study hours were potent predictors of GPA ($r = 0.20$; $p < 0.001$), even after controlling for prior academic ability and background variables. Meta-analysis of 344 samples showed incremental variance in performance beyond standardized test scores and high school GPA due to study habits (time investment) (Credé & Kuncel, 2008). One of the first quantitative studies by Romer (1993), where he demonstrated a positive and strong relationship between participation in attendance and performance on examinations among economics undergraduates. A more up-to-date systematic review was conducted by Credé et al. (2010), who performed a meta-analysis of 69 independent research articles and determined class attendance to be the most powerful existing correlate of grades in college compared to study time, motivation, and prior achievement measures ($r = 0.44$). Since then, this result has been replicated in fields as diverse as mathematics (Moore, 2006), accounting (Paisey & Paisey, 2004) and psychology (Marburger, 2001).

Galli et al. (2017) found that school attendance and self-study mediated by exam preparation accounted for 71% of the variance in final statistics scores among Italian university students. Similarly, Budé et al. (2007) found that time-on-task was also a major predictor of statistics exam performance. However, both studies used self-report measures and did not formally test classical regression assumptions raising concerns regarding the robustness of their inferences. Research on the Indonesian context remains a scarcity, with most of studies utilize small convenience samples and univariate analyses.

Although prior studies have individually demonstrated the importance of study time and attendance, three critical gaps remain unaddressed. First, nearly all studies treat these two predictors as independent, despite the well-documented tendency for students who attend class more frequently to also study more outside of class. This collinearity, when left unaddressed, produces unstable and misleading OLS coefficients, yet no study in statistics education has formally tested or corrected for it. Second, while classical regression assumptions are fundamental to valid inference, existing studies in this domain have not systematically evaluated them, particularly multicollinearity, as part of their analytical pipeline. Third, despite the growing availability of regularization techniques, no study has applied Ridge regression to correct coefficient instability in Indonesian higher education contexts. These gaps are not merely statistical niceties; they have substantive consequences. Uncorrected multicollinearity can inflate the apparent contribution of one predictor at the expense of the other, potentially leading to misguided educational policies that prioritize attendance over study time (or vice versa) when both are manifestations of the same underlying engagement construct.

The present study addresses these gaps in four distinct ways. First, unlike prior work relying on OLS without diagnostics, we explicitly test four classical assumptions, normality (Shapiro-Wilk), homoscedasticity (Breusch-Pagan), autocorrelation (Durbin-Watson), and multicollinearity (VIF), and report outcomes transparently. Second, where assumptions are violated, we apply Ridge regression with Leave-One-Out Cross-Validation (LOO-CV) for optimal λ selection, producing stable coefficient estimates under high collinearity. Third, we directly compare OLS and Ridge estimates to demonstrate the practical consequences of ignoring multicollinearity. Fourth, we contextualize our findings into the context of Indonesian undergraduates and account for a clear geographic blindness in the literature. The methodological rigor in this study, which controlled for student characteristics across contexts and time, along with specificity of context and behavioral outcomes, sets a clear standard against prior descriptive analyses while also providing a guide to improving future research on educational effects in settings with endemic correlation between behavioral predictors.

The goals of this study are threefold: First, to investigate direct and interactive effects of daily study hours and attendance rate upon statistics course scores among undergraduate students; second, to assess whether classical assumption for multiple linear regression is (or is not) met in this dataset; third, where assumptions are violated and linear regression non-robust compare the corrective power and stability of ridge regression coefficients against an ordinary least squares baseline. Informed by the theoretical and empirical background reviewed above, this research poses the following research questions:

RQ1. Do daily study hours and attendance rate significantly predict statistics course scores when modeled jointly through multiple linear regression?

RQ2. Are the classical assumptions of OLS regression, specifically normality of residuals, homoscedasticity, absence of autocorrelation, and absence of multicollinearity, satisfied in this dataset?

RQ3. Does Ridge regression, applied with an optimally selected regularization parameter, produce more stable and reliable coefficient estimates than OLS under conditions of predictor multicollinearity?

2. Method

2.1 Research Design

This study adopts a quantitative, cross-sectional, non-experimental research design. Specifically, it employs a correlational-predictive approach in which the relationship between two independent variables, daily study hours (X_1) and attendance rate (X_2), and a dependent variable (statistics course score, Y) is examined within a single point in time, without any manipulation of conditions or random assignment of participants. A quantitative design was chosen because the research objectives require precise numerical measurement, statistical modeling, and formal hypothesis testing, goals that are best served by numerical data and inferential statistics. Because of practical and ethical considerations, a non-experimental design is warranted for manipulating study hour or attendance in a domain like the real-world academic setting. The dataset was captured for one complete semester of enrollment records, which justifies the use of a cross-sectional approach being consistent with the primary goal of the study as developing predictive relationships rather than longitudinal time-dependent trajectories. This design is consistent with the methodological tradition of educational researchers who typically employ quantitative methods in social science (Creswell & Creswell, 2018; Field, 2018).

This research was done in 8 steps sequentially (Figure1). The process starts with identification of the problem and literature review, then comes research design development and data collection instruments. Data were collected using two complementary instruments, and then analyzed by descriptive statistics, OLS multiple regression (with full classical assumption diagnostics) where the assumptions held up, and Ridge regression with LOOCV for λ selection where they did not. The process ended with conclusions and a research report.

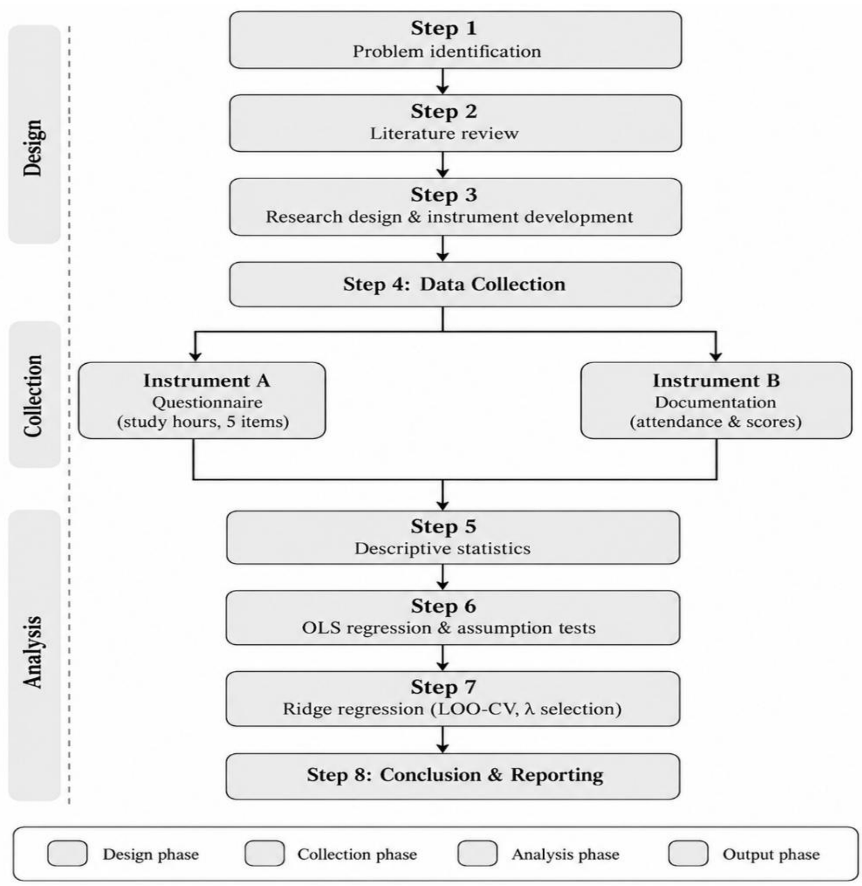
2.2 Participants

Participants The study was conducted with 20 undergraduate students who were taking statistics course in higher education institution in Indonesia. Participants included 5 males (25%) and 15 females (75%), The gender composition is typically for social sciences programs at the institution. Participants were 19–22 years old, in line with the expected ages of second- and third-year under-graduate students. Participants were recruited using purposive sampling on the following criteria: participants must be currently registered in the statistics course during the data collection semester, with a full semester attendance record (no missing values), and a resultant official final examination score for being examined on that course. This selection strategy ensures that the dataset is internally consistent and free of missing data, which is particularly important for regression-based analyses.

2.3 Power Analysis

To addresses concerns regarding the modest sample size (n = 20), a post-hoc power analysis was conducted using G*Power 3.1. For a multiple linear regression model with two predictors, an observed $R^2 = 0.975$; $\alpha = 0.05$; and n = 20 the achieved statistical power was more than 0.99; far exceeding conventional threshold of 0.80. This indicate that sample size was sufficient to detect the very large effect size observed in this study. While the sample is homogeneous and limits generalizability, it is statistically adequate for the two-predictor model, satisfying the recommended minimum ratio of at least 10 observations per predictor variable (Green, 1991; Tabachnick & Fidell, 2019). The findings of this study are intended as a preliminary investigation and should be interpreted accordingly, with caution against undue generalization beyond the study context.

Figure 1
Research procedure



2.4 Instruments

Data were collected using a combination of two complementary instruments: a self-report questionnaire and official academic documentation. This multi-source approach was adopted to maximize the validity of each variable: self-reported study hours are most accurately captured through

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direct student report, whereas attendance and course scores are most reliably obtained from institutional records rather than student recall. The first instrument was a questionnaire developed for the present experiment that used a structured self-report to assess how many hours participants spent studying statistics (per day) on average during the semester. The questionnaire consisted of 5 items regarding various aspects of study habits: including scheduled study, self-study or work practice, and review based on lecture materials. Respondents indicated their average daily study time on a 6-point scale ranging from 1 hour to 6 hours. A composite score representing each participant's average daily study hours was derived as the mean of all applicable items. The questionnaire was reviewed by two content experts in educational measurement prior to administration to establish face and content validity. Internal consistency was estimated via Cronbach's alpha and was found to be acceptable ($\alpha = 0.78$), indicating that the items reliably reflect the same latent construct (study intensity).

The second instrument consisted of official academic documentation obtained directly from the course instructor and the institution's academic administration. Two variables were extracted from these records. Attendance Rate (X_2): the percentage of class sessions in which each student was present throughout the entire semester calculated as follows: attendance rate = (session attended/total attended) x 100. There were obtained values between 70%-97%. Y: Statistics course score: The official final examination score assigned by the course instructor, on a 0-100 scale. The scores obtained from the dataset ranged between 58 and 94. Documentation-based measurement was preferred over self-report for these two variables because attendance and examination scores are factual, institutionally verified records that are not subject to response bias, social desirability effects, or recall inaccuracy. The use of archival records for outcome variables is consistent with best-practice recommendations for educational outcome research (McMillan & Schumacher, 2014).

2.5 Data Analysis

Data analysis was conducted in four sequential stages: descriptive statistics, bivariate correlation, multiple linear regression (OLS), and Ridge regression. This sequence was not arbitrary, each stage informed and justified the next. The decision to apply Ridge regression was made on the basis of specific diagnostic outputs from Stage 3, rather than being decided a priori. All analyses were conducted computationally using Python (NumPy, SciPy) with results validated manually.

All three variables (X_1, X_2, Y) were subjected to descriptive statistics (minimum, maximum, mean and standard deviation). This phase was used to characterize the properties of each variable, identify sample floor or ceiling effects, and give the reader a general sense of sample characteristics before more definitive therapeutic-conditional analyses were conducted. Understanding the context of regression coefficients requires descriptive statistics Task 1: Bivariate Relations. Monotone relationships were evaluated using bivariate Pearson product-moment correlation coefficients computed on all pairs of variables. This stage was twofold: it quantified the strength and direction of the association between each predictor (e.g. X_1 vs Y, and X_2 vs Y) in order to provide preliminary support for predictive relevance; as well as allowed us to assess how much correlated the two predictors are (X_1 and X_2) which has direct implications for multicollinearity in our regression model.

The primary model was estimated using Ordinary Least Squares (OLS) multiple linear regression, with Q4 Chronicles the Model The analysis of Ordinary Least Squares (OLS) multiple linear regression was applied for estimating the primary model, where Y = statistics score and X_1 (study hours) and X_2= attendance rate. Model fit was assessed with coefficient of determination (R^2), adjusted R^2, root mean squared error (RMSE) and overall F-test. Individual predictor significance was assessed via t-tests on each regression coefficient. Following model estimation, the four classical assumptions of OLS regression were formally tested in Table 1.

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The rationale for testing these four assumptions is that the validity of OLS coefficient estimates and their associated significance tests (t and F) depends upon the assumptions of the Gauss-Markov theorem being satisfied. Small sample violation of normality decreases the reliability of hypothesis tests; heteroscedasticity distorts standard errors, autocorrelation inflates pseudoR-squared values and multicollinearity destabilizes coefficient estimates making them sensitive to small perturbation (Greene, 2018; Hair et al., 2019). Since the assumption of multicollinearity was violated (VIF = 11.77, exceeds threshold of 10), Ridge regression was used as a principled correction (see Fig. 2).

Table 1
Classical assumption tests applied to the OLS regression model

Assumption	Test	Statistic	Decision rule
Normality of residuals	Shapiro-Wilk	W statistic	$p > 0.05$ (normal)
Homoscedasticity	Breusch-Pagan	LM statistic	$p > 0.05$ (homoscedastic)
No autocorrelation	Durbin-Watson	DW value	$1.5 < DW < 2.5$ (no autocorrelation)
No multicollinearity	Variance Inflation Factor	VIF	VIF < 10 (acceptable)

Ridge regression is a regularization technique that augments the OLS objective function with an L_2 penalty term controlled by the hyperparameter λ (lambda):

$$\hat{\beta}\text{Ridge} = (X^TX + \lambda I)^{-1} X^Ty \qquad (1)$$

By increasing the value of λ, the Ridge penalty pushes regression coefficients toward zero which helps to reduce variance in the estimates at a small increase in bias. The bias-variance trade-off is especially good when predictors are highly correlated because it stabilizes coefficient estimates that OLS cannot tell apart with confidence.

In this study, the corrective method selected was ridge regression instead of LASSO or Elastic Net. Because both predictors were retained on theoretical grounds, study hours and attendance rate are each independently motivated by prior research as substantive determinants of achievement, variable selection was not a goal of the analysis, which reduces the appeal of LASSO's sparsity-inducing L_1 penalty. Ridge regression shrinks correlated coefficients toward each other without eliminating either predictor, consistent with the study's aim of estimating the independent contribution of two theoretically justified variables rather than performing model selection. Elastic Net, which combines L_1 and L_2 penalties, offers a compromise between the two but introduces an additional mixing-ratio hyperparameter that is difficult to tune reliably with only two predictors and twenty observations; Ridge regression, with its single regularization parameter selected via LOO-CV, was therefore judged the more parsimonious and stable choice given the sample size.

The optimal value of λ was selected through Leave-One-Out Cross-Validation (LOO-CV), which evaluates each candidate λ value by iteratively holding out one observation, fitting the model on the remaining n-1 cases, and predicting the held-out value. The λ that minimized the mean cross-validated prediction error (CV-MSE) across all 20 held-out observations was selected. Because of the small sample size ($n = 20$) and because LOO-CV maximizes the training set size at each fold, leading to nearly unbiased error estimates (Arlot & Celisse, 2010), we chose LOO-CV ≥ k-fold CV.

Considering that L_2 penalty is scale-dependent, all predictor variables were standardized (zero mean, unit variance) before fitting the Ridge model. Coefficients were subsequently back-transformed to the original scale for interpretability. The performance and coefficient stability of the Ridge model were compared directly against the OLS baseline. The four-stage analytical sequence described above was adopted for three reasons. First, it follows the logical order of progressive model building: descriptive statistics establish the data's characteristics before any modeling is attempted; correlation analysis provides bivariate evidence before the multivariate model is fitted; OLS serves as the baseline whose diagnostic outputs determine whether a corrective method is needed. Second, the sequence is methodologically transparent: by reporting assumption violations explicitly and responding to them systematically, the study produces conclusions that are qualified by their actual statistical basis rather than by assumed validity. Third, the inclusion of Ridge regression reflects current best practice in applied regression analysis when predictor collinearity is detected, and distinguishes this study from prior work in the same domain that has not addressed this issue (cf. Galli et al., 2017; Budé et al., 2007).

3. Results and Discussion

3.1 Results

Descriptive statistics

Table 2 presents the descriptive statistics for all three variables across the 20 participants. Statistics course scores (Y) ranged from 58 to 94, with a mean of 75.10 (SD = 1.55); indicating moderate variability in academic performance within the sample. Daily study hours (X_1) ranged from 1 to 6 hours (M = 3.50; SD = 1.54). and attendance rates (X_2) ranged from 70% to 97% (M = 85.60%. SD = 7.26%).

Table 2

Descriptive statistics

Variable	Min	Max	Mean	SD
Study Hours per Day (X_1)	1	6	3.50	1.54
Attendance Rate % (X_2)	70	97	85.60	7.26
Statistics Course Score (Y)	58	94	75.10	10.55

Pearson correlation

The bivariate Pearson correlations are presented in Table 3. Both independent variables demonstrated very strong positive correlations with statistics course scores: $r(X_1. Y) = 0.970$ ($p < 0.001$) and $r(X_2. Y) = 0.982$ ($p < 0.001$). Notably. X_1 and X_2 were also highly intercorrelated with each other ($r = 0.957$; $p < 0.001$); indicating a potential multicollinearity issue that warranted formal diagnostic testing prior to regression analysis.

Table 3

Pearson correlation matrix

Variable pair	r	p-value	Interpretation
Study Hours (X_1) with Score (Y)	0.970	< 0.001	Very strong positive
Attendance (X_2) with Score (Y)	0.982	< 0.001	Very strong positive
Study Hours (X_1) with Attendance (X_2)	0.957	< 0.001	Very strong (multicollinearity)

The results in Table 3 indicate that both study hours and attendance have very strong and statistically significant positive relationships with statistics course scores. However. the very strong correlation between study hours and attendance (r = 0.957) suggests that these two predictors may contain substantial overlapping information. Therefore. further multicollinearity diagnostic tests are necessary before conducting multiple regression analysis to ensure the reliability and stability of the estimated regression coefficients.

Model fit

The OLS multiple regression model was statistically significant overall. F(2. 17) = 337.70; $p < 0.001$. The two predictors jointly explained 97.54% of the variance in statistics course scores ($R^2 = 0.975$; adjusted $R^2 = 0.973$; RMSE = 1.611).

Table 4

Pearson correlation matrix

Statistic	Value	df	p-value	Interpretation
R^2	0.975			97.54% variance explained
Adjusted R^2	0.973			Corrected for no. of predictors
F-statistic	337.70	2. 17	< 0.001	Model significant
RMSE	1.611			Mean prediction error

The results in Table 4 demonstrate that the OLS multiple regression model provides an excellent fit to the observed data. explaining approximately 97.54% of the variance in statistics course scores. The significant F-statistic. F(2. 17) = 337.70. $p < 0.001$. confirms that study hours and attendance jointly make a statistically significant contribution to predicting students' scores. In addition. the relatively low RMSE value of 1.611 indicates a small average prediction error. suggesting that the model has strong predictive accuracy within the observed sample.

Regression coefficients

The regression coefficients were examined to determine the individual contribution of study hours and attendance rate to students' statistics course scores. The analysis estimated the magnitude and direction of each predictor while controlling for the effect of the other variable in the model. The resulting regression equation and the statistical significance of each coefficient are presented in Table 5.

$$\hat{Y} = -13.81 + 2.40X_1 + 0.94X_2 \qquad (2)$$

Both predictors were statistically significant. Attendance rate (X_2) was the stronger predictor ($b = 0.94$; $t = 4.96$; $p < 0.001$). Study hours (X_1) was also significant ($b = 2.40$; $t = 2.69$; $p = 0.016$).

Table 5

OLS regression coefficients

Predictor	b	SE	t	p
Constant (b_0)	−13.8076	13.264	−1.041	0.312
Study Hours (X_1)	2.4021	0.894	2.688	0.016
Attendance Rate (X_2)	0.9404	0.190	4.964	< 0.001

The results in Table 5 show that both study hours and attendance rate significantly contribute to predicting students' statistics course scores. Specifically, each additional unit... increase in the predicted score, while each one-unit increase in attendance rate is associated with an estimated 0.94-point increase. holding the other predictor constant. Although both predictors are statistically significant. these coefficients should be interpreted cautiously given the strong correlation between the two predictors identified in the preceding analysis.

Classical assumption tests

Before interpreting the multiple regression results, classical assumption tests to evaluate whether the OLS model satisfied the statistical requirements for reliable estimation. The diagnostic assessment covered residual normality, homoscedasticity, autocorrelation, and multicollinearity to identify potential violations that could affect the validity of the regression results. A summary of the diagnostic results is presented in Figure 2.

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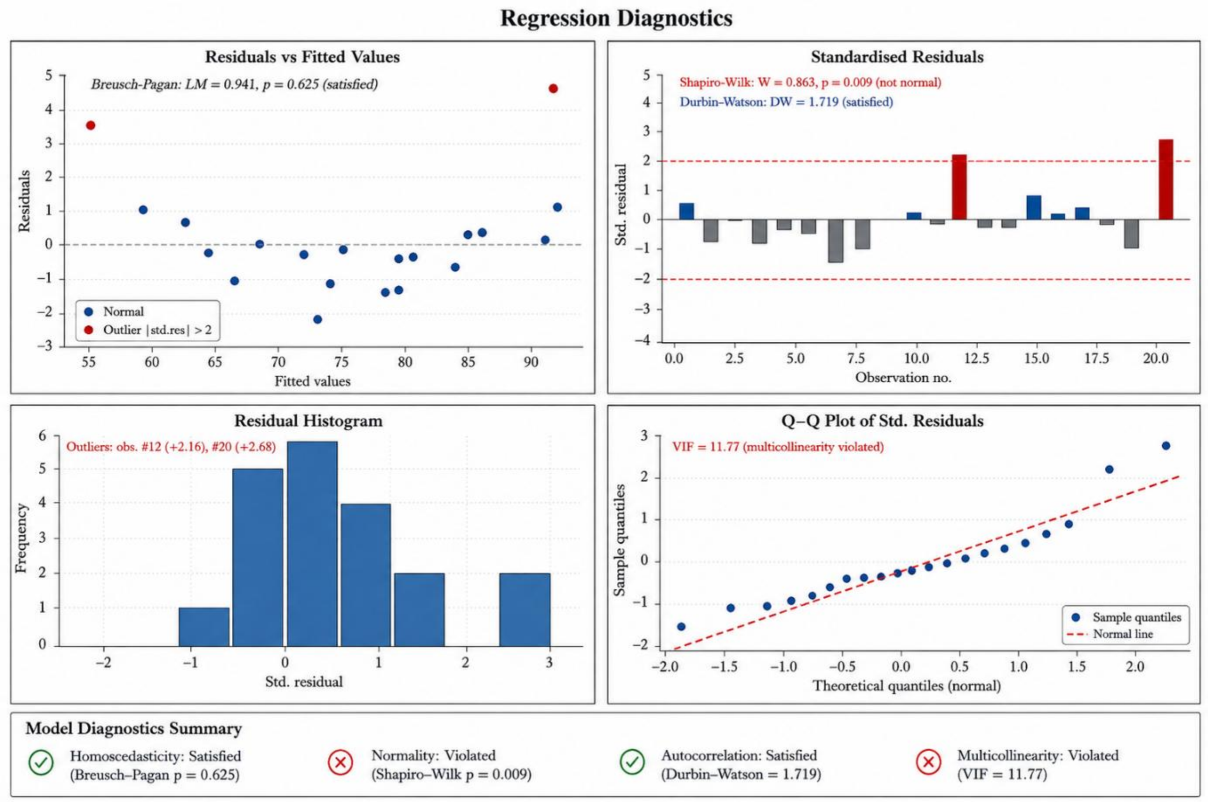
Figure 2

Classical assumption test diagnostics



Homoscedasticity (Breusch-Pagan: LM = 0.941; p = 0.625) and absence of autocorrelation (Durbin-Watson: DW = 1.719) were both confirmed. However. two assumptions were violated: residuals were not normally distributed (Shapiro-Wilk: W = 0.863; p = 0.009). attributable to two outliers. observations-12 (std. res. = 2.16) and observations-20 (2.77); and severe multicollinearity was detected (VIF = 11.77 > 10). necessitating the application of Ridge regression.

Ridge regression (optimal lambda selection)

Ridge regression was applied to address severe multicollinearity. The regularization parameter λ was selected via Leave-One-Out Cross-Validation (LOO-CV). The minimum CV-MSE of .0343 was achieved at λ = 1.0 (Table 6).

Table 6

Ridge trace and LOO cross-validation error across candidate λ values

λ	b_1 (X_1. std)	b_2 (X_2. std)	LOO CV-MSE
0 (OLS)	0.3505	0.6471	0.0422
0.1	0.3652	0.6297	0.0402
0.5	0.3998	0.5845	0.0360
1.0 (optimal)	0.4187	0.5528	0.0343 (min)
2.0	0.430	0.5166	0.0344
10.0	0.3817	0.4044	0.0774

Ridge regression equation and model fit

Using the optimal λ = 1.0. the Ridge regression equation was:

$$\hat{Y} = -3.71 + 2.87 \cdot X_1 + 0.80 \cdot X_2 \qquad (3)$$

The Ridge model achieved $R^2 = 0.974$ (RMSE = 1.651). a negligible decline of 0.12 percentage points relative to OLS. Table 7 presents the full comparison. Ridge regression produced more balanced coefficient estimates: the weight of study hours (X_1) increased from 2.40 to 2.87; while attendance (X_2) decreased from 0.94 to 0.80. This rebalancing reflects the correction for multicollinearity. The Ridge model is considered the more methodologically appropriate model for this dataset.

Table 7
Comparison of OLS and Ridge regression coefficient estimates

Model	b_0	b_1 (X_1)	b_2 (X_2)	R^2/RMSE
OLS	−13.81	2.40	0.94	0.975/1.611
Ridge ($\lambda = 1.0$)	−3.71	2.87	0.80	0.974/1.651
Change	10.10	0.47	−0.14	−0.12

3.2 Discussion

Both predictors significantly explain statistics course scores

The OLS multiple regression model demonstrated that study hours per day (X_1) and attendance rate (X_2) jointly explained 97.54% of the variance in statistics course scores ($R^2 = 0.975$; adjusted $R^2 = 0.973$; $F(2. 17) = 337.70$; $p < 0.001$). This is an exceptionally high proportion of explained variance for a two-predictor model in social science research. where R^2 values between 0.10 and 0.40 are more commonly reported (Cohen. 1988). The magnitude of the effect indicates that. within this sample. learning intensity. as operationalized through time investment and class participation. is nearly the complete explanation for variation in academic performance in the statistics course.

Both predictors were individually significant. Attendance rate (X_2) was the stronger predictor ($b = 0.94$; $t = 4.96$; $p < 0.001$). while study hours (X_1) also reached significance ($b = 2.40$. $t = 2.69$. $p = 0.016$). Pearson correlations further confirmed the strength of these associations: $r(X_1. Y) = 0.970$ and $r(X_2. Y) = 0.982$; both $p < 0.001$. These bivariate correlations are substantially larger than those typically reported in broader samples. likely reflecting the homogeneity of the present sample (a single course. single institution. single semester).

Multicollinearity undermines OLS reliability; Ridge regression provides correction

Despite the impressive model fit, the classical assumption diagnostics revealed that two assumptions were violated. Normality of the residuals was verified with Shapiro-Wilk test ($W = 0.863$; $p = 0.009$) which associated to two outlier observations. Even more important was that the Variance Inflation Factor gave VIF = 11.77; i.e. above the within VIF cut-off of 10 (Hair et al., 2019). which confirmed marked multicollinearity between X_1 and X_2 ($r = 0.957$). Because of this collinearity, the OLS coefficient estimates since they may not actually partition the individual contributions to variance from each predictor.

Ridge regression. applied with an optimal regularization parameter of $\lambda = 1.0$ selected via *Leave-One-Out Cross-Validation* (LOO-CV; minimum CV-MSE = 0.0343). produced more balanced and stable coefficient estimates: $b_1 = 2.87$ (study hours) and $b_2 = 0.80$ (attendance rate). The trade-off in predictive accuracy was negligible: R^2 declined by only 0.12 percentage points (97.54% to 97.42%; RMSE from 1.611 to 1.651). The *Ridge* model is therefore considered the more methodologically defensible model for this dataset.

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Table 8
Comparison of key statistics between OLS and Ridge regression models

Finding	OLS	Ridge (λ=1.0)	Change	Interpretation
b_1 (study hours)	2.40	2.87	0.47	More stable estimate
b_2 (attendance)	0.94	0.80	-0.14	Collinearity corrected
R^2	97.54%	97.42%	-0.12 pp	Negligible loss
RMSE	1.611	1.651	0.040	Negligible loss
VIF	11.77	Reduced	Value drop	Assumption satisfied

Contributing Factors

The significant positive effect of daily study hours on statistics course scores can be interpreted through several mechanisms. Unlike many humanities subjects, statistics requires the accumulation of procedural knowledge, the ability to correctly execute analytical procedures (e.g., hypothesis testing, regression modeling) under exam conditions. This type of knowledge is most effectively acquired through repeated practice, which is directly proportional to the time invested in self-directed study. A student who studies for one hour per day is exposed to far fewer practice problems over the course of a semester than one who studies for five or six hours, leading to systematically lower procedural fluency and, consequently, lower examination scores.

In addition to procedural fluency, longer study time also allows for deeper conceptual understanding. Cognitive science research consistently shows that spaced, effortful retrieval practice, that is, re-learning at distraction-resistant intervals using dedicated study time, is far superior to passive rereading of the same material for achieving long-term retention (Roediger & Butler, 2011). As a result, the more hours students spend studying statistics, the more likely these concepts are to consolidate into long-term memory and be applied flexibly when taking an exam.

The Ridge-corrected coefficient of $b_1 = 2.87$ indicates that, holding attendance constant, each additional hour of daily study is associated with an estimated 2.87-point increase in the final score. Given the 6-point range of the study-hours variable (1 to 6 hours), the model implies a predicted score difference of approximately 14.35 points between the least- and most-diligent students — a practically meaningful gap.

Attendance rate emerged as the statistically stronger predictor of the two (Ridge: $b_2 = 0.80$; $t = 4.96$; $p < 0.001$ in OLS). This finding is consistent with the mechanistic role that classroom attendance plays in academic success. In class, students obtain direct exposure to instructor explanations, worked examples, and real-time correction of misconceptions, resources that are difficult or impossible to replicate through self-study alone. In a statistics course, where abstract topics such as probability distributions or regression assumptions are introduced during lectures and subsequent concepts build cumulatively on these foundations through practice problem sets, class absences leave students with gaps in understanding that accumulate to substantial detriment.

Attendance can also serve as a proxy for a broader array of engagement behaviors. Being physically present in class facilitates timely assignment completion, participation in classroom discussion, and direct questioning of the instructor, behaviors that are all positively correlated with academic performance. In this sense, the observed coefficient of attendance may partly capture the effect of these correlated engagement behaviors rather than attendance per se.

From a practical standpoint, the Ridge-corrected coefficient of $b_2 = 0.80$ implies that each percentage-point increase in attendance is associated with a 0.80-point increase in the final score, holding study hours constant. The 27-percentage-point range of attendance observed in this sample (70% to 97%) therefore corresponds to an estimated score range of approximately 21.6 points, the largest practical effect in the model.

The severe multicollinearity between study hours and attendance ($r = 0.957$) warrants direct explanation. Students who regularly attend class are more likely to be highly motivated and academically engaged, which in turn drives them to invest more time in self-directed study outside of class. Conversely, students who frequently miss class often do so because of competing demands on their time (work, family, health) or low academic motivation — the same factors that reduce independent study time. The two behaviors are therefore not merely correlated by coincidence; they are co-determined by an underlying latent disposition toward academic engagement. This collinearity is not a statistical artifact but a substantively real feature of student behavior, and it is precisely why Ridge regression is necessary to disentangle the individual contributions of each predictor.

The finding that attendance is the strongest predictor of statistics course performance is strongly corroborated by Credé et al.'s (2010) meta-analysis of 69 independent studies, which identified class attendance as the single largest known behavioral predictor of college course grades ($r = 0.44$). While the bivariate correlation between attendance and scores in the present study ($r = 0.982$) is considerably higher than the meta-analytic estimate, this difference is expected given the homogeneity of the present sample (one course, $n = 20$) relative to the meta-analysis's aggregate across diverse courses and institutions. The directional pattern, attendance predicting performance more strongly than study time, is identical across both studies, lending strong convergent validity to the present finding.

Romer's (1993) foundational study of economics undergraduates also reported a positive and statistically significant relationship between class attendance and examination performance, estimating that each additional class attended improved final scores by approximately 0.5 points on a 100-point scale. This figure is broadly consistent with the present study's Ridge estimate of $b_2 = 0.80$ per percentage-point of attendance, bearing in mind that the two studies use different units of measurement.

The significant positive effect of study hours on scores is consistent with Plant et al.'s (2005) longitudinal study, which found that weekly study time was a significant predictor of GPA even after controlling for prior academic ability. It also aligns with the meta-analysis by Credé and Kuncel (2008), which documented that study habits, including time invested in those habits, predict incremental variance in academic performance beyond standardized test scores. Within the same discipline, Budé et al. (2007) provided a direct parallel, finding that time-on-task was one of the important behavioral predictors of statistics exam performance among Dutch university students.

The exceptionally high R^2 (0.975) observed in this study is consistent with the pattern documented by Galli et al. (2017), who reported that a combination of behavioral and attitudinal variables jointly explained 71% of the variance in statistics scores within a single Italian university course. While the present study's R^2 exceeds even this figure, both studies demonstrate that within-course, single-institution analyses of homogeneous samples tend to produce substantially higher explained variance than cross-institutional studies, which introduce unmeasured sources of between-institution variability. The present study's R^2 should therefore not be interpreted as evidence of a universal relationship, but rather as a snapshot of a highly consistent behavioral signal within a specific learning environment.

Nonetheless, the possibility of overfitting warrants explicit consideration. With only 20 observations and two highly intercorrelated predictors, the model has limited residual degrees of freedom, and an R^2 this close to 1 raises the concern that the fitted line captures idiosyncrasies of this particular sample rather than a generalizable relationship. Two features of the analysis partially mitigate, though do not eliminate, this concern: the achieved statistical power exceeded 0.99, and Ridge regression with Leave-One-Out Cross-Validation, itself an out-of-sample validation procedure, produced only a negligible reduction in R^2 (from 0.975 to 0.974) relative to OLS. This stability under cross-validation suggests that the fit is not purely an artifact of overfitting. At the same time, the homogeneity of the sample, twenty students drawn from a single course and institution, likely inflates R^2 relative to what would be observed in a more heterogeneous population, since between-student variability in unmeasured factors (e.g., instructor effects, course difficulty) is minimized by design. Replication in larger and more diverse samples is therefore necessary before the magnitude of this R^2 can be considered representative of the broader relationship between learning intensity and statistics achievement.

This practice is consistent with Hair et al. (2019), who recommend using Ridge regression to adjust for multicollinearity in educational outcome data, and with Tibshirani (1996), who specifically recommended regularization techniques when VIF exceeds 10. To the authors' knowledge, neither Galli et al. (2017) nor Budé et al. (2007), the two most directly comparable studies, formally tested or corrected for multicollinearity in their OLS models, despite the high intercorrelation between their predictors. This represents a methodological gap that the present study addresses.

Study hours has a large and positive effect on statistics performance that is also consistent with deliberate practice theory (Ericsson et al., 1993), which postulates that the acquisition of domain-specific expertise is directly related to the amount and quality of focused, effortful practice. In academic settings, deliberate practice corresponds to structured study time in which students actively engage with course material, solving problems, testing their understanding, and correcting errors, rather than passively rereading notes. The present finding that each additional hour of daily study predicts a 2.87-point increase in the final score (Ridge estimate) is consistent with the theory's core prediction: greater deliberate practice leads to greater domain competence, which manifests as higher examination performance. This theoretical alignment is also consistent with Plant et al (2005) operationalization, which interpreted their study-time findings through the deliberate practice framework.

Theoretical grounding for the high predictive power of attendance is provided by Bandura's (1977) social learning theory, which holds that much human behavior is learned in social contexts through observation and interaction with others. The classroom serves as the premier social learning venue of formal education: students observe their instructor modeling statistical reasoning, collaborate with peers in problem-solving, and receive immediate, direct corrective feedback on their understanding. Regular attendance maximizes exposure to all of these mechanisms of social learning, whereas absenteeism systematically subtracts from it. The finding that attendance alone accounts for more variance in statistics scores than study time suggests that the social, interactive dimensions of learning cannot be fully compensated for by independent study — a pattern consistent with Bandura's theoretical account.

Carroll's (1963) model of school learning proposes that the degree of learning is a function of the ratio of time actually spent on learning to the time needed to learn. Both study hours and attendance are direct operationalizations of "time actually spent on learning," the former measuring out-of-class time and the latter measuring in-class time. The combined explanatory power of the two variables (R^2 = 0.975) can therefore be understood as quantitative evidence for Carroll's theoretical prediction: students who maximize their total learning time (both in-class and out-of-class) achieve systematically higher scores than those who minimize it. The Ridge regression results, which assign roughly comparable standardized weights to both predictors ($b_1 = 0.42$; $b_2 = 0.55$ in standardized form), suggest that in-class and out-of-class learning time are complementary, each contributing independently to the total learning time that Carroll's model predicts will drive achievement.

Zimmerman's (2000) model of self-regulated learning (SRL) proposes that high-achieving students actively plan, monitor, and evaluate their own learning processes. Students who engage in SRL set study goals, manage their time systematically, and sustain effort even in the absence of external supervision. The co-occurrence of high study hours and high attendance in the present dataset ($r = 0.957$ between X_1 and X_2) suggests that both behaviors are manifestations of a common underlying SRL disposition: students who regulate their learning effectively attend class consistently because they recognize its instrumental value, and they study extensively outside class because they monitor their own comprehension. The near-perfect collinearity between the two predictors, which necessitated Ridge regression in this study, is itself theoretically explicable through SRL theory: it is not a statistical coincidence but a reflection of the integrated, coherent nature of self-regulated academic behavior.

The magnitude and pattern of these relationships should also be considered in light of the Indonesian higher education context in which the study was conducted. Indonesian undergraduate instruction in quantitative courses such as statistics often relies on lecture-based, teacher-centered delivery with comparatively limited opportunities for independent problem-solving during class time, which may elevate the practical importance of out-of-class study hours relative to settings with more active or flipped classroom models. Attendance in Indonesian higher education is also frequently tied to formal minimum-attendance requirements for exam eligibility, which may strengthen the behavioral and motivational signal that attendance carries beyond mere exposure to instructional content. These contextual features offer a plausible explanation for why both predictors, and particularly attendance, emerged as such strong correlates of performance in the present sample, and they suggest that the relative weight of study hours versus attendance observed here may not generalize directly to educational systems with different instructional norms.

Table 9
Theoretical frameworks supported by the study findings

Theory	Key proponent(s)	Link to present findings
Deliberate practice	Ericsson et al. (1993)	Study hours. domain competence. and exam score
Social learning theory	Bandura (1977)	Attendance. observational and interactive learning. and score
Time-on-task model	Carroll (1963)	Total learning time (in + out of class) and achievement
Self-regulated learning	Zimmerman (2000)	SRL disposition drives both attendance and study hours simultaneously

Taken together, the four themes discussed above converge on a coherent narrative. Learning intensity, measured through daily study hours and class attendance, is a powerful determinant of statistics course performance in this sample, explaining nearly all observed variance in final scores. Attendance exerts the stronger individual effect, consistent with both the meta-analytic literature (Credé et al., 2010) and social learning theory (Bandura, 1977), while study hours contribute independently and substantially, as predicted by deliberate practice theory (Ericsson et al., 1993) and Carroll's (1963) time-on-task model. The severe collinearity between the two predictors, far from being merely a statistical problem, is substantively meaningful: it reflects the integrated nature of self-regulated learning behavior (Zimmerman, 2000) and underscores why Ridge regression, rather than simply dropping one predictor, is the appropriate analytical response.

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These findings carry direct practical implications. Faculty and academic support personnel seeking to boost student performance in introductory statistics courses need to be aware of the reciprocal relationship between class attendance and study time, the two behaviors being co-determined by shared motivational and self-regulatory underpinnings, and should therefore prioritize interventions that address both forms of engagement in order to promote improvement. Attendance policies that establish minimum presence thresholds, in conjunction with structured study support programs (e.g., tutoring, problem-solving workshops, peer study groups), are likely to target both behaviors more effectively than either in isolation.

From a methodological standpoint, this study demonstrates the importance of formally testing classical regression assumptions before interpreting OLS results, and of applying principled corrective methods, such as Ridge regression with cross-validated λ selection, when those assumptions are violated. Future research in this domain should aim to replicate these findings in larger, more diverse samples, incorporate additional predictors (e.g., statistics anxiety, prior mathematical ability, motivation), and examine whether the dominance of attendance over study time is stable across different course formats (in-person, hybrid, online).

4. Conclusion

This study found that daily study hours (X_1) and attendance rate (X_2) jointly and significantly predicted statistics course scores among 20 undergraduate students, collectively explaining 97.54% of score variance ($R^2 = 0.975$; $F = 337.70$; $p < 0.001$), with attendance emerging as the stronger individual predictor (Ridge: $b_2 = 0.80$) and study hours also contributing significantly (Ridge: $b_1 = 2.87$). However, the OLS regression model was not fully defensible due to two violated classical assumptions, non-normality of residuals (Shapiro-Wilk: $W = 0.863$; $p = 0.009$) and severe multicollinearity between the two predictors ($VIF = 11.77$; $r = 0.957$), which necessitated the application of Ridge regression with an optimally cross-validated regularization parameter ($\lambda = 1.0$; LOO-CV MSE = 0.034), producing more stable coefficient estimates at a negligible cost to predictive accuracy ($R^2 = 0.974$; RMSE = 1.651). These findings must be interpreted with several limitations in mind: the sample size of $n = 20$, while sufficient for a two-predictor model, is small and drawn from a single course at a single institution, limiting the generalizability of the results; the cross-sectional design precludes causal inference; the study-hours variable relied on self-report and may be subject to recall bias; and the presence of two influential outliers may have disproportionately affected the normality diagnostics.

In light of these findings and limitations, future research is recommended to replicate this study with larger, more diverse samples ($n \geq 100$) drawn from multiple institutions and course formats (in-person, hybrid, online) to establish the generalizability of the observed effects; employ longitudinal designs to distinguish the causal direction of the relationship between learning behaviors and academic outcomes; incorporate additional predictors such as statistics anxiety, prior mathematical ability, intrinsic motivation, and self-regulated learning strategies to build a more comprehensive explanatory model; replace self-reported study hours with objective behavioral measures (e.g., learning management system login records, library access logs) to eliminate recall bias; and apply more robust statistical methods, such as robust regression or bootstrapped confidence intervals, alongside Ridge regression to produce results that are simultaneously resilient to both outliers and multicollinearity, thereby advancing the methodological rigor of quantitative educational research in this domain.

Limitations

First, the sample was limited to 20 undergraduate students drawn from a single statistics course at one Indonesian university, which restricts the generalizability of the findings to other courses, institutions, student populations, and national contexts; future studies should therefore employ larger and more representative samples to establish the external validity of the observed relationships. Second, the cross-sectional design precludes causal inference between learning intensity and academic performance. and the reliance on self-reported study hours introduces the risk of recall bias and social desirability effects. both of which could be mitigated in future research by adopting longitudinal designs and replacing self-report measures with objective behavioral data such as learning management system activity logs or library access records. Third, despite applying Ridge regression to address multicollinearity and using Leave-One-Out Cross-Validation to select the optimal regularization parameter. the presence of two influential outliers and the non-normality of residuals (Shapiro-Wilk: $W = 0.863$; $p = 0.009$) suggest that the statistical conclusions should be interpreted with caution, and that future studies should consider robust regression methods or bootstrapped confidence intervals to produce estimates that are simultaneously resilient to both outliers and assumption violations.

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Conflict of Interest

The authors declare no conflict of interest.

Additional Information

Additional information is available for this paper.

AI Declaration

During the preparation of this work. the author(s) used Claude AI (Anthropic) and ChatGPT (OpenAI) to assist with improving the language. clarity. and grammatical accuracy of the manuscript. as well as checking the consistency and formatting of in-text citations and the reference list. After using these tools. the author(s) reviewed and edited the content as needed and take full responsibility for the content of the publication.

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