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Determinants of Students' Satisfaction in Online Distance Learning: A Multiple Linear Regression

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Abstract: This study aims to determine which factors (student-student interaction, student-content interaction, and student-instructor interaction) significantly influence students' satisfaction in online distance learning. An online survey was conducted among students of Universiti Teknologi MARA Kelantan Branch, Kota Bharu Campus from semester 3 to semester 7. The data collected was analyzed by using multiple linear regression analysis. The findings reveal that student-student interaction, student-content interaction, and student-instructor interaction emerged as the significant factor that contributed to students' satisfaction in online distance learning. The insights gained from this research can guide educators and institutions in enhancing their teaching strategies and course designs, ultimately leading to more engaging and effective learning experiences for students in both online distance learning and blended learning environments

Keywords: Multiple linear regression, Satisfaction in online learning, student-content interaction, student-instructor interaction and student-student interaction

1 Introduction

Technology has fundamentally transformed the teaching and learning landscape, shifting it from a traditional, fixed, face-to-face model to a flexible online environment. Changes in the mode of the teaching-learning process in higher education institutions have influenced student satisfaction. The definition of satisfaction in online distance learning is complex and multidimensional and includes many factors, such as communication, student participation in online discussions, flexibility, workload, technology support, instructor pedagogical skills, and feedback [1], [2].

Online learning satisfaction refers to evaluation opinions and feeling experiences of learners toward the quality of online learning service provided by online learning providers, which is a cumulative psychological response to online learning contents and learning environment, formed after a rational and emotional comparison between the actual perceived online learning effect and expectations of the perception [3].

Students' interactions with other students, instructors and content play a significant role in satisfaction. Therefore, satisfaction with the learning experience increases as multiple types of interactivities are used within the learning context [4]. According to Virtanen et al. [5], the success of online learning platforms has generally been determined by student satisfaction. Although the governments, universities and service providers have made significant investments in new technologies, the full benefit and value of online learning platforms have not yet been realised [6], [7], nor have students yet been as satisfied as expected [8]–[12]. Hence, this necessitates the implementation of continuous investigations on determinants of student satisfaction [13], [14].

Numerous studies have measured determinants of students' satisfaction towards online learning. According to some of the key determinants student satisfaction towards online learning include the student engagement [15]–[18], learner-learner interaction [19], [20], learner-instructor interaction and learners' interaction with content [21], [22].

Therefore, this study aimed to identify the determinants of students' satisfaction in online distance learning by including several predictors (learner-content, learner-instructor, and learner-learner interaction) as suggested by previous studies.

2 Methodology

This section details the methodology of the research, covering the conceptual model, target population, study and sampling designs, sample size, instrument, data collection, and data analysis.

A Conceptual Model

The primary aim of this study is to test the following hypotheses, which are derived directly from the conceptual framework (Figure 1) linking the three interaction types (student-student interaction, student-content interaction, and student-instructor interaction) to student satisfaction in online distance learning:

H_{11}: Student-content interaction significantly influences students' satisfaction in online distance learning.

H_{12}: Student-student interaction significantly influences students' satisfaction in online distance learning.

H_{13}: Student-instructor interaction significantly influences students' satisfaction in online distance learning.

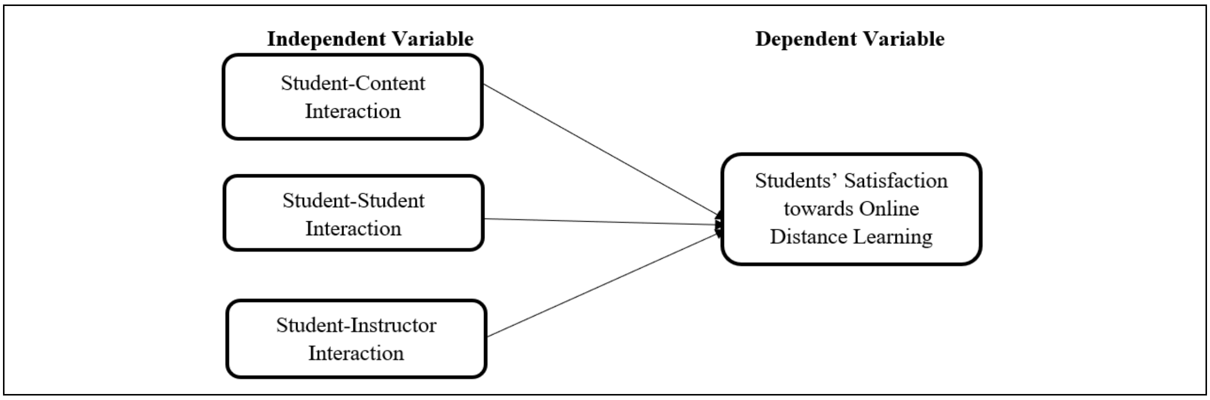


Figure 1: Conceptual Model

B Target Population and Study Design

A cross-sectional study design was adopted to examine the variables of interest among students at Universiti Teknologi MARA (UiTM) Kelantan Branch, Kota Bharu Campus, between March and August 2024. The target population included all 1,117 undergraduate students from semesters 3 to 7. The sample frame of the study was exclusively limited to individuals within the following six-degree programs: BA242, BA249, BA250, BA240, CS241, and CS291.

C Sampling Design and Sample Size Determination

A proportionate stratified random sampling method was employed to ensure representativeness across the different academic disciplines. The student population (semesters 3–7) was segmented into six distinct strata corresponding to the included courses (BA240, BA242, BA249, BA250, CS241, and CS291). A simple random sample was then selected from each stratum, with the size of each sample being directly proportional to the stratum's size relative to the total population.

The population for this study is 1117 students from UiTM Kelantan Branch, Kota Bharu Campus. However, only 287 students were selected as the samples to answer the questionnaires. The sampling frame for this study was obtained from the Academic Affairs Office. In order to obtain the required sample size, this study involved three steps which were firstly determined minimum sample size, secondly obtained number of samples for each course and lastly used randomized random number to obtain required respondents for each course.

First step:
Sample size was determined by using a software namely Raosoft (Raosoft, 2004). Steps to generate this sample size were as followed:

1. There are 1117 students in UiTM Cawangan Kelantan Kampus Kota Bharu. This samples were calculated as below using Raosoft.

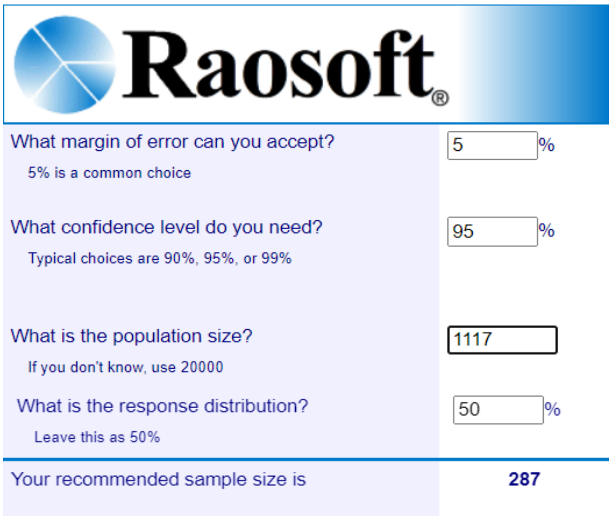


Figure 2: Raosoft Software

2. The sample required was 287. Due to the possibility of dropouts or sampling errors, a 10% increase had been decided (Suresh & Chandrashekara, 2012). As a result, the total sample size for this study are 316 students.

Second Steps:
As this study adopted Proportionate Stratified Random Sampling. Hence, the number of samples for each course pursued needed to be calculated.
(Sample size of the strata = size of entire sample / population size * layer size)

Table 1: The number of samples for each course

Course	Number of People in Strata	Number of People in Sample
BA240	195	316/1117*195= 55.16 ≈ 55
BA242	344	316/1117*344= 97.31 ≈ 97
BA249	198	316/1117*198= 56.01 ≈ 56
BA250	170	316/1117*170= 48.09 ≈ 48
CS241	201	316/1117*201= 56.86 ≈ 57
CS291	9	316/1117*9= 2.55 ≈ 3

Thus, the sample size now was estimated to be 316 students.

Third step:
In order to obtain required respondents for each course pursued, this study used research randomizer software in Figure 3.2. All six courses were involved. This software generated 55 random numbers for BA240. Next, 97 random numbers for BA242. Then, 56 random numbers for BA249. Moreover, BA250 has 48 random numbers. CS241 has 57 random numbers. Lastly, CS291 has 3 random numbers. It pursued each course, and the respondents were randomly selected.

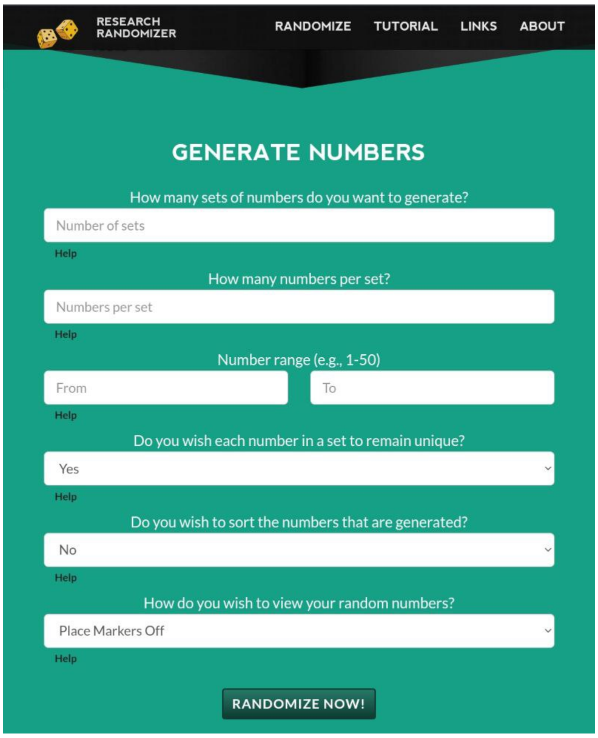


Figure 3: Research Randomizer Software

D Research Instrument and Data Collection Method

A semi-structured questionnaire served as the research instrument for this study. It was organized into five sections: demographic profile, self-efficacy, self-readiness and employment intention. Participants rated each item in every section on a 10-point scale. A summary of the number of items and the scales used for each section can be found in Table 2.

Table 2: Summary of the Number of Items for each Section

Section	Number of Items	Scale
A: Demographic	3	Not Applicable
B: Student-student interaction	8	A 10-point Likert response range from strongly disagree to strongly agree
C: Student-content interaction	8	
D: Student-instructor interaction	9	
E: Students' satisfaction in online distance learning	8	

Data for this study were collected using a self-administered questionnaire created on the Google Forms platform. The online questionnaire was shared with selected participants via WhatsApp, which was chosen as it is a widely used communication tool among students. Completing the questionnaire took approximately 10 to 15 minutes. Participation was entirely voluntary, allowing respondents to fill out the questionnaire at their convenience and in a location of their choice.

E Method of Data Analysis

i. Descriptive Analysis

The demographic profile of the study's respondents was summarized using descriptive statistics. Specifically, pie charts were utilized to provide a clear quantitative description of the distribution of respondents based on gender and their course of study.

ii. Reliability Analysis

Reliability analysis was conducted to assess the internal consistency of the scales used in this study. The Cronbach's alpha coefficient is a commonly employed statistical tool for evaluating the reliability of these scales. A Cronbach's alpha value below 0.6 indicates insufficient internal consistency, while values between 0.6 and 0.7 are deemed acceptable, and values above 0.8 are considered good.

iii. Multiple Linear Regression Analysis

Multiple linear regression analysis was employed to determine which factors (student-student interaction, student-content interaction, and student-instructor interaction) significantly influence students' satisfaction in online distance learning. The multiple linear regression model used in this study is represented by Equation 1.

$$Y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \beta_3 X_{i3} + \varepsilon_i \qquad (1)$$

Where,

Y_i is the value of students' satisfaction towards online distance learning.
X_1 is the value of student-content interaction in the i^{th} trial.
X_2 is the value of student-student interaction in the i^{th} trial.
X_3 is the value of student-instructor interaction in the i^{th} trial.
$\beta_0, \beta_1, \beta_2, \beta_3$ are unknown constants (regression coefficients) or parameters
$\varepsilon_i \sim NID(0, \sigma^2)$

To evaluate how well the linear regression model fits the observed data, the coefficient of determination (R-squared) was used. This value, which lies between 0 and 1, quantifies the model's predictive power. A higher R-squared suggests a better fit, as it indicates that the regression line explains a greater percentage of the total variability in the response variable

The adequacy of the linear regression model was evaluated by systematically testing its underlying statistical assumptions prior to predicting the dependent variable. This assessment focused on three key areas: normality, homoscedasticity, and multicollinearity. The normality assumption was verified using the normal probability plot (Figure 3(a)), While the homoscedasticity was assessed via the scatterplot of residuals versus predicted values (Figure 3(b)); if this plot shows a random, even scatter (i.e., no distinct pattern), the assumption of consistent error variance is considered met.

Given the inclusion of multiple independent variables in the model, an essential step was to assess the potential for multicollinearity, a condition where predictor variables are highly correlated with one another. Such strong correlations can inflate the standard errors and compromise the stability and interpretation of the regression coefficients. This condition was diagnosed using the Variance Inflation Factor (VIF). A common rule of thumb dictates that if the VIF value exceeds 10, the model is deemed to have a severe multicollinearity issue, requiring corrective action.

The multiple linear regression analysis systematically determines the collective and individual influence of the independent variables on the dependent variable. After establishing that all prerequisites, including model adequacy (normality, homoscedasticity, and no multicollinearity via VIF) and goodness of fit (R-squared) are satisfied, the analysis proceeds with the overall F-test (ANOVA) to assess model significance.

If p-value of the F-test is below the 0.05 threshold, confirming the regression model is significance, the individual t-tests are then examined to identify which specific predictor variables (student-student interaction, student-content interaction, and student-instructor interaction) contribute significantly to the outcome (students' satisfaction in online distance learning). Finally, the regression coefficients (beta) are interpreted to quantify the magnitude and direction of each significant predictor's effect on the dependent variable, allowing for the construction of a predictive equation.

3 Finding

A Descriptive Analysis

Figure 4 shows the descriptive analysis for the demographic part of the respondents involved in the study. The respondent demographic data reveals a predominant participation by female students (73.84%), significantly outweighing male students (26.16%). The participants were drawn from several courses, with the largest group coming from BA242 (31.10%), followed by BA250 (19.48%), and BA249 (18.31%). The smallest representation was from CS291 (0.87%). Regarding their academic standing, the respondents were primarily concentrated in the later stages of their studies, with the highest proportion in Semester 6 (34.88%), followed by Semester 4 (29.36%), and Semester 5 (21.80%).

B Reliability Analysis

A reliability analysis was conducted to assess the internal consistency of the scales used in this study (Table 3). The results, summarized in Table 3, show that the Cronbach's Alpha values for all constructs are exceptionally strong. Specifically, the coefficients ranged from 0.928 (Student-content interaction) to 0.963 (Students' satisfaction). Since all computed values significantly exceed the minimum acceptable standard of 0.6, it is concluded that the set of items within each construct exhibits a high degree of reliability and is internally consistent for measuring the designated variables

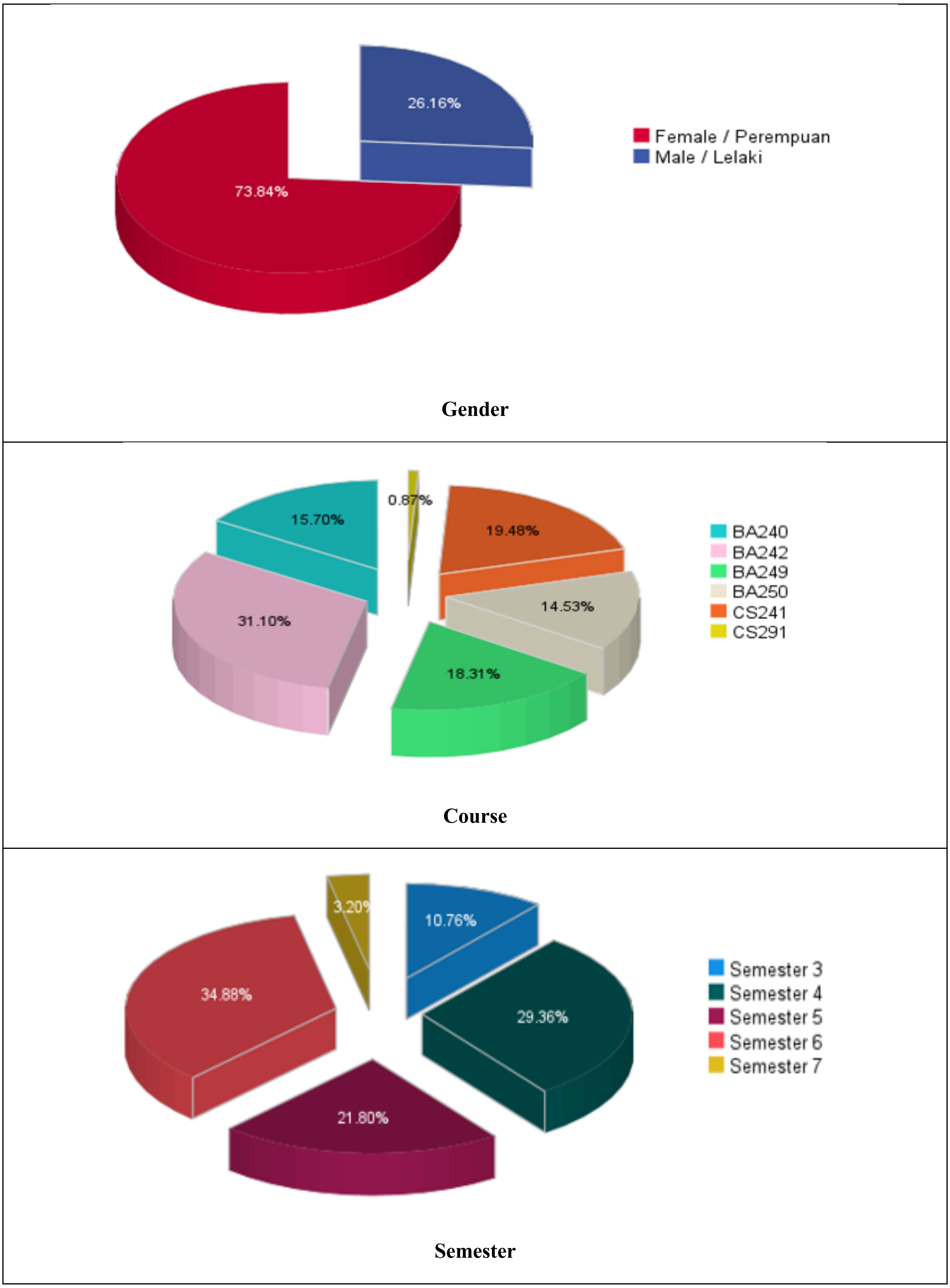


Figure 4: Distribution of Respondents according to Gender, Course and Semester

Table 3: Summary of Reliability Analysis for each Construct

Construct	Number of Items	Cronbach’s Alpha Coefficient
Student-student interaction	8	0.949
Student-content interaction	8	0.928
Student-instructor interaction	9	0.938
Students’ satisfaction in online distance learning	8	0.963

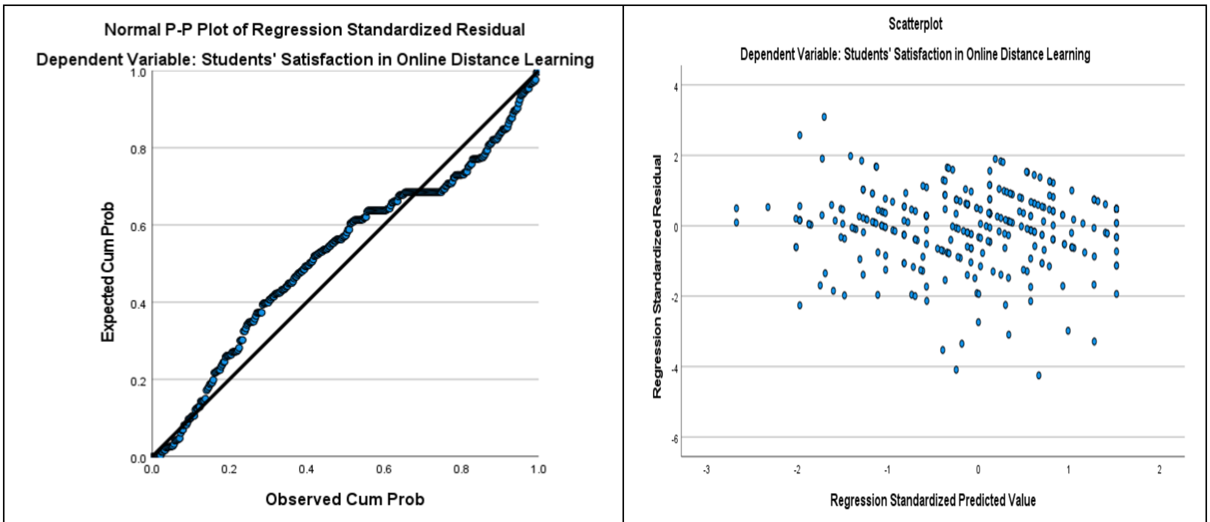
C Multiple Linear Regression Analysis

The Goodness of Fit of the regression model was assessed using the R-square coefficient (Table 4). As indicated in the analysis, the independent variables (student-student interaction, student-content interaction, and student-instructor interaction) collectively explain 53.1% of the variation observed in students' satisfaction in online distance learning (the dependent variable). Consequently, 46.9% of the variance remains unexplained by the current model and is therefore attributed to other factors not included in this study.

Table 4: Goodness of Fit

R-Square
0.531

The assumptions of normality and homoscedasticity were visually inspected using the residual plots in Figures 5(a) and 5(b). For normality, the Normal Probability Plot (Figure 5(a)) shows the standardized residuals closely following the fitted line, confirming that the error terms are normally distributed. Regarding homoscedasticity (constant variance), the scatterplot of residuals versus predicted values (Figure 5(b)) demonstrates a random and evenly dispersed pattern. The absence of a discernible trend confirms that both critical assumptions are satisfied for this regression analysis.



(a) Normal Probability Plot **(b) Scatter Plot of Residual vs Predicted**

Figure 5: Normality and Homoscedasticity Assumptions

Another method employed to examine the constancy of error variance is the Breusch-Pagan test. Based on the Table 5, Studentized Breusch-Pagan test results indicates a significance value of 0.08134 which are greater than alpha which is 0.05. Therefore, the error variance is constant, and the homoscedasticity assumption is fulfilled.

Table 5: Studentized Breusch-Pagan Test

Breush-Pagan Test	Df	Sig.
6.7212	3	0.08134

The presence of multicollinearity among the independent variables was evaluated using the Variance Inflation Factor (VIF). As presented in Table 6, the VIF values for all predictor variables (student-student interaction, student-content interaction, and student-instructor interaction) were substantially below the common threshold of 10. This confirms the absence of high correlation among the predictors, ensuring that the regression estimates are reliable and unbiased.

Table 6: Multicollinearity Assumption

Construct	VIF
Student-student interaction	2.426
Student-content interaction	2.929
Student-instructor interaction	2.917

The overall statistical significance of the multiple linear regression model was determined using the ANOVA F-test, as shown in Table 7. The calculated p-value is < 0.001, which is substantially below the predetermined significance level of alpha (0.05). This result allows for the rejection of the null hypothesis, confirming that the model is statistically significant. We therefore conclude that the three predictor variables—student-student interaction, student-content interaction, and student-instructor interaction—collectively account for a significant amount of the variance in students' satisfaction in online distance learning.

Table 7: Test for Significance of Regression Model

Model	Sum of Square	DF	Mean Square	F Statistics	Sig.
Regression	593.517	3	197.836	117.760	<.001
Residual	524.070	312	1.680		
Total	1117.586	315			

All three independent variables were found to be statistically significant predictors of students' satisfaction in online distance learning (Table 8). As shown by the p-values (Sig.), the influence of Student-content interaction (p < 0.001), Student-student interaction (p < 0.001), and Student-instructor interaction (p < 0.001) are all well below the 0.05 significance threshold. Student-instructor interaction has the highest coefficient value (0.327). This means it has the strongest practical influence on predicting students' satisfaction compared to the other two interaction types.

Table 8: Test for Significance of Individual Predictor Variable

Variable	Coefficient Value	T Statistics	Sig.
Constant	0.205	0.550	0.583
Student-content interaction	0.322	4.787	<.001
Student-student interaction	0.271	3.772	<.001
Student-instructor interaction	0.327	4.489	<.001

The fitted regression model is as follows:

$$\hat{Y}_{satisfaction\_in\_online\_distance\_learning} = 0.205 + 0.322_{student-content\_interaction} + 0.271_{student-student_{interaction}} + 0.327_{student-instructor\_interaction} \tag{3}$$

4 Conclusion

The multiple linear regression analysis effectively investigated the factors influencing students' satisfaction in online distance learning, utilizing a sample drawn through proportionate stratified random sampling. The rigorous methodological assessment, including the confirmation of reliability (Cronbach's alpha ranging from 0.928 to 0.963), satisfaction of core assumptions (normality and homoscedasticity), and absence of multicollinearity (VIF values well below 10), ensures the stability and validity of the findings. The overall model was found to be statistically significant ($p < 0.001$), with the three interaction variables collectively explaining a substantial portion of the variance in students' satisfaction. Individually, all three factors including Student-instructor interaction (beta = 0.327), Student-content interaction (beta = 0.322), and Student-student interaction (beta = 0.271), were significant positive predictors of satisfaction, with Student-instructor interaction demonstrating the strongest influence.

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