Perbanas International Conference on Economics, Business, Management, Accounting and IT (PROFICIENT) 2026
"Integrity-Driven Innovation: Reimagining Business, Finance, and Digital Transformation for Sustainable Impact"

Proceedings of the Perbanas International Seminar on Economics, Business, Management, Accounting and IT [June 2026] [ISSN 3047-0951]

Analysis of Learning Quality Factors on Student Learning Experiences Across Study Programs at University X Using Multiple Linear Regression

Rina Hudaini[1,a)], Widya Ayu Purwati[2,b)], Mohammad Harits Akbar[3,c)], Muhammad Henriansyah[4,d)] , Alrafiful Rahman[5,e)]

[1,2,3,4,5]*Data Science Study Program, Faculty of Information Technology, Perbanas Institute Jakarta*

[a)]Corresponding author: rina.hudaini04@perbanas.id
[b)] widya.ayu09@perbanas.id
[c)]mohammad.harits01@perbanas.id
[d)] muhammad.henriansyah02@perbanas.id
[e)] alrafiful.rahman@perbanas.id

Abstract. *This study examines the influence of six learning quality indicators technology access, content quality, teaching quality, resource availability, interaction and collaboration, and learning experience on overall student satisfaction across study programs at University X. Employing a quantitative approach, data were collected from 98 students representing 18 different study programs through a structured questionnaire using a Likert scale. Multiple linear regression was selected as the analytical method due to its capacity to simultaneously model relationships between multiple independent variables and a single continuous dependent variable, offering interpretable coefficient estimates and effect size quantification through the coefficient of determination (R^2). Descriptive statistics, outlier detection, and heatmap-based per-program analysis were performed prior to regression modelling. Results indicate that the model explains 87.3% of the variance in student satisfaction, with Interaction and Collaboration, Teaching Quality, and Content Quality, emerging as the three strongest predictors. Technology Access, despite receiving the highest aggregate score, demonstrated the smallest regression coefficient, suggesting that high infrastructure availability alone does not guarantee proportional satisfaction. Notable variation in scores across study programs further indicates heterogeneity in students' learning experiences. These findings provide data-driven insights for institutional policy-making aimed at improving the overall quality of education at University X.*

Keywords: higher education, learning quality, multiple linear regression, Student satisfaction, technology access, teaching quality

INTRODUCTION

The quality of higher education has been a central concern for universities, policymakers, and students worldwide. In an era marked by rapid technological change and increasing competition among academic institutions, universities are under mounting pressure to deliver learning experiences that meet or exceed students' expectations(Slade & Prinsloo, 2013). Student satisfaction serves as a key metric for evaluating institutional performance, reflecting not only the perceived quality of teaching and facilities but also the broader academic environment, including peer interaction and resource availability (Douglas et al., 2006).

Previous studies have established that student satisfaction is a multidimensional construct influenced by a range of academic and non-academic factors (Tinto, n.d.). Among these factors, teaching quality, course content, and the availability of learning resources have been consistently identified as significant

Proceedings of the Perbanas International Seminar on Economics, Business, Management, Accounting and IT
[June 2026] [ISSN 3047-0951]

determinants (Marsh, n.d.). More recently, the emergence of digital learning platforms has introduced technology access as an additional dimension that may affect how students engage with educational content and, consequently, their overall satisfaction (Selim, 2007).

Despite a growing body of literature on student satisfaction, most existing studies focus on single indicators or apply qualitative approaches that limit generalizability. There remains a gap in research that simultaneously and quantitatively evaluates the relative contribution of multiple learning quality factors particularly across diverse study programs within a single institution. Understanding which factors most strongly predict satisfaction enables universities to allocate resources strategically and tailor interventions to specific academic programs.

University X presents a unique case for such analysis. With 18 diverse study programs ranging from engineering and informatics to humanities and social sciences, the institution exhibits considerable variation in infrastructure, pedagogical approaches, and student demographics. This diversity makes it an ideal setting for examining whether learning quality indicators affect student satisfaction uniformly or differentially across programs.

This study aims to: (1) describe the overall distribution of learning quality indicator scores across the student population; (2) examine per-program variation in these indicators; and (3) determine the relative predictive strength of each indicator on student satisfaction using multiple linear regression. The novelty of this study lies in its simultaneous quantitative modelling of six learning quality dimensions technology access, content quality, teaching quality, resource availability, interaction and collaboration, and learning experience within a unified regression framework, offering a level of analytical granularity that remains underexplored in the Indonesian higher education literature (Puspitasari & Wahyuni, 2022). The findings are expected to contribute both to the academic literature on student satisfaction and to evidence-based institutional decision-making at University X.

LITERATURE REVIEW

Student Satisfaction in Higher Education

Student satisfaction is broadly defined as students' subjective evaluations of their educational experiences relative to their expectations (Pascarella & Terenzini, 2005). Research consistently shows that satisfaction is positively associated with student retention, academic performance, and post-graduation outcomes (Tinto, n.d.). Elliot and Healy (Elliot & Healy, 2001) argued that satisfaction should be treated as a strategic outcome, as it reflects the institution's success in meeting the diverse needs of its student population. Studies indexed in Scopus have further demonstrated that satisfaction is shaped by both tangible factors such as physical facilities and library resources and intangible factors such as faculty responsiveness and peer relationships (Alves & Raposo, 2007).

Learning Quality Dimensions

The concept of learning quality in higher education encompasses multiple dimensions. Ramsden (Ramsden, 2003) identified teaching quality as one of the most influential factors shaping students' approaches to learning. Content quality encompassing curriculum relevance, depth, and alignment with real-world applications has similarly been found to positively predict student engagement and satisfaction (Biggs & Tang, 2011). Resource availability, including access to laboratories, libraries, and digital tools, constitutes another critical dimension (Kuh, 2005).

Interaction and collaboration between students and faculty, as well as among peers, has gained increased attention in contemporary educational research. Studies on active learning environments indicate that collaborative activities enhance knowledge construction and students' sense of belonging, both of which are associated with higher satisfaction levels (Vygotsky, n.d.). The learning experience dimension integrates these elements holistically, capturing students' overall perceptions of the educational process.

Proceedings of the Perbanas International Seminar on Economics, Business, Management, Accounting and IT
[June 2026] [ISSN 3047-0951]

Technology Access in Higher Education

The role of technology in higher education has been extensively studied, particularly following the accelerated adoption of digital platforms during and after the COVID-19 pandemic (Hodges et al., 2020). Research published in IEEE Transactions on Education has shown that technology access facilitates flexible learning, enhances student engagement, and supports instructional variety. However, several studies caution against an overemphasis on technology at the expense of pedagogical quality, noting that access to technology without adequate instructional design yields limited benefits for satisfaction or learning outcomes (Selim, 2007).

Multiple Linear Regression in Educational Research

Multiple linear regression (MLR) is a widely employed statistical technique for examining the simultaneous effects of several independent variables on a continuous dependent variable (Hair et al., 2019). In educational research, MLR has been applied to predict academic performance, student attrition, and satisfaction from sets of institutional and individual-level predictors (Delen et al., 2020). The method offers several advantages in this context: it provides interpretable regression coefficients that indicate the direction and magnitude of each predictor's effect while holding other variables constant; it quantifies overall model fit through R^2, enabling assessment of how well the predictor set explains outcome variance; and it can accommodate multiple predictors drawn from survey-based Likert data, which are widely used in educational assessment (Field, 2018).

The choice of MLR in the present study is further justified by the nature of the research questions, which require estimating the relative contribution of each learning quality indicator to satisfaction. Alternative methods such as structural equation modelling, while capable of handling latent variables, require larger sample sizes and more complex model specification. Decision-tree-based methods, though powerful for prediction, offer less interpretability at the coefficient level. MLR thus represents an appropriate and parsimonious analytical choice given the study's objectives and dataset characteristics (Cohen et al., 2003).

Prior studies have employed MLR to identify key predictors of student satisfaction in higher education settings across Southeast Asia and other regions, yielding actionable insights for institutional improvement (Annamdevula & Bellamkonda, 2016). Research indexed in Sinta-level journals has similarly applied regression approaches to evaluate learning quality in Indonesian universities, validating the method's suitability for the current institutional context (Puspitasari & Wahyuni, 2022).

METHODS

Research Design

This study employed a quantitative cross-sectional research design to examine the influence of learning quality factors on student satisfaction across study programs at University X. A quantitative approach was selected because it enables the analysis of relationships between multiple learning quality indicators and student satisfaction using numerical data.

The study utilized a secondary dataset obtained from Kaggle, consisting of student responses collected through a structured questionnaire. To achieve the research objectives, Multiple Linear Regression (MLR) was employed as the primary analytical method to evaluate the influence of learning quality indicators on student satisfaction. The research framework adopted in this study is presented in Figure 1.

Proceedings of the Perbanas International Seminar on Economics, Business, Management, Accounting and IT
[June 2026] [ISSN 3047-0951]

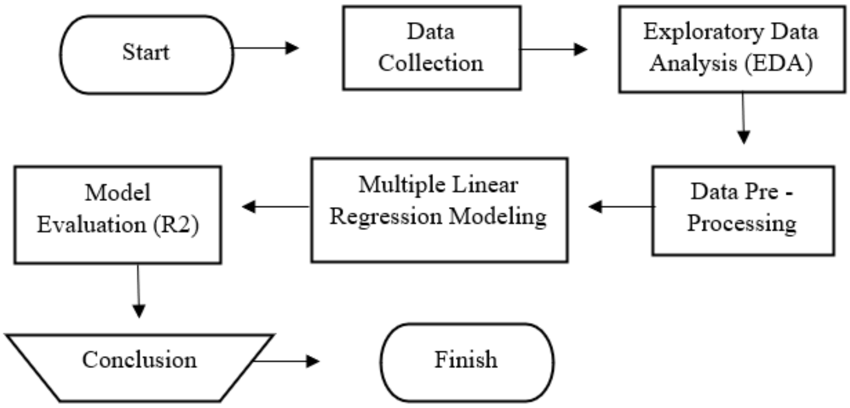


FIGURE 1. Research Framework

Research Dataset

The dataset used in this study consists of 98 student responses obtained from a publicly available dataset on Kaggle. Each record represents an individual respondent and contains demographic information, evaluations of learning quality indicators, and overall student satisfaction. The dataset includes responses from students across 18 study programs. As a secondary dataset, the data were collected and published by the original dataset provider and subsequently used for analysis in this study.

TABLE 1. Student Review Dataset

No	Nama	Jenis Kelamin	Program Studi	AKSES TEKNOLOGI	KUALITAS MATERI	KUALITAS PENGAJARAN	KETERSEDIAAN SUMBER DAYA	INTERAKSI DAN KOLABORASI	PENGALAMAN PEMBELAJARAN	KEPUASAN
1	Junlias Safika Nugraha	Perempuan	Akuntansi	5	3	3	3	3	3	3
2	La Ode Alvin Rahmat Saputra	Laki-Laki	Teknik Informatika	5	4	3	4	4	4	4
3	latifa khairiyah	Perempuan	Akuntansi	4	3	3	3	3	3	3
4	asrifa dwi permata	Perempuan	Manajemen	3	4	4	4	4	4	3
5	Yosh	Perempuan	Manajemen	5	4	3	4	3	4	3
6	KLAUDIA PATULAK PANGINAN	Perempuan	Akuntansi	4	4	3	4	3	4	3
7	Wilda Rahma Riskika	Perempuan	Teknik Informatika	4	4	4	3	4	4	3

Table 1 presents a sample of the dataset used in this research. The dataset includes information such as gender, study program, technology access, content quality, teaching quality, resource availability, interaction and collaboration, learning experience, and student satisfaction.

As the study utilizes a secondary dataset obtained from Kaggle, the data collection procedure, sampling process, and instrument assessment were determined by the original dataset provider. Consequently, this study focuses on data preprocessing, statistical analysis, and interpretation of the available observations..

The independent variables (predictors) consist of six learning quality indicators:

1. Technology Access (X1): availability and quality of digital tools, internet, and learning management systems.
2. Content Quality (X2): relevance, depth, and currency of course materials.
3. Teaching Quality (X3): clarity, expertise, and effectiveness of instruction.
4. Resource Availability (X4): access to libraries, laboratories, and academic support services.

5. Interaction and Collaboration (X5): frequency and quality of student-faculty and peer interaction.
6. Learning Experience (X6): overall perceived quality of the academic learning environment.

The dependent variable is Student Satisfaction (Y), operationalised as students' global rating of their satisfaction with education at University X.

Data Preprocessing

Prior to statistical analysis, the dataset underwent a preprocessing stage to ensure data quality and consistency. The preprocessing procedures included checking for missing values and detecting duplicate data using Python.

```
Missing Values per Kolom:
No                          0
Nama                        0
Jenis Kelamin               0
Program Studi               0
AKSES TEKNOLOGI             0
KUALITAS MATERI             0
KUALITAS PENGAJARAN         0
KETERSEDIAAN SUMBER DAYA    0
INTERAKSI DAN KOLABORASI    0
PENGALAMAN PEMBELAJARAN     0
KEPUASAN                    0
dtype: int64

Jumlah Duplikat:
0
No                          0
AKSES TEKNOLOGI             0
KUALITAS MATERI             0
KUALITAS PENGAJARAN         0
KETERSEDIAAN SUMBER DAYA    0
INTERAKSI DAN KOLABORASI    0
PENGALAMAN PEMBELAJARAN     0
KEPUASAN                    0
dtype: int64
```

FIGURE 2. Check for data duplication and missing values

As shown in **Figure 2**, all variables contained no missing values, indicating that the dataset was complete and no imputation or data deletion procedures were required. Furthermore, duplicate detection revealed no duplicate data in the dataset, confirming that each respondent was represented only once in the analysis.

The results of the pre-processing stage indicated that the dataset was free from completeness and data redundancy issues. Therefore, all 98 observations were retained and deemed suitable for further analytical procedures, including exploratory data analysis and multiple linear regression modeling.

Statistical Analysis

Statistical analysis was conducted using Python with the Pandas, NumPy, Matplotlib, Seaborn, and Scikit-learn libraries. The analysis consisted of three stages: descriptive statistical analysis, exploratory data analysis (EDA), and regression modelling.

Descriptive statistical analysis was performed to summarize the characteristics of the dataset and provide an overview of student perceptions regarding learning quality indicators and overall satisfaction. The analysis included the calculation of the mean, standard deviation (SD), minimum value (Min), maximum value (Max), and quartiles (Q1, Q2, and Q3) for each variable. In addition, a program-level analysis was conducted by grouping respondents according to their study programs and calculating the average scores of each learning quality indicator.

Proceedings of the Perbanas International Seminar on Economics, Business, Management, Accounting and IT
[June 2026] [ISSN 3047-0951]

Prior to regression modelling, Exploratory Data Analysis (EDA) was conducted to examine data distributions, relationships among variables, and variations across study programs. The EDA results were visualized using heatmaps, bar charts, and boxplots to facilitate interpretation and comparison across study programs.

Subsequently, Multiple Linear Regression (MLR) was applied using the Linear Regression algorithm from the Scikit-learn library to evaluate the influence of learning quality indicators on student satisfaction. MLR is a widely used statistical method for examining the simultaneous effects of multiple independent variables on a dependent variable and estimating the contribution of each predictor (Hair et al., 2019; Field, 2018). The general regression model is expressed as follows:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \epsilon \qquad (1)$$

where Y represents the dependent variable, namely student satisfaction; $\beta_0$denotes the intercept; $\beta_i$represents the regression coefficients; $X_i$denotes the learning quality indicators; and εrepresents the error term. The regression model was used to estimate the contribution of each learning quality indicator to student satisfaction. The model fit was subsequently evaluated using the coefficient of determination (R^2), which is expressed as follows:

$$R^2 = 1 - \frac{□□_{□□□}}{□□_{□□□}} \quad (2)$$

where $□□_{□□□} = \sum_{i=1}^{n} \left(y_i - \hat{y}_i\right)^2$ and $□□_{□□□} = \sum_{i=1}^{n} \left(y_i - \underline{y}\right)^2$

where SS_{res} denotes the residual sum of squares and SS_{tot} represents the total sum of squares. Higher R^2values indicate that a greater proportion of variance in student satisfaction can be explained by the independent variables, reflecting stronger explanatory power of the regression model. The findings obtained from both descriptive analysis and regression modelling were subsequently interpreted to identify the most influential learning quality factors affecting student satisfaction across study programs at University X (Hair et al., 2019; Cohen et al., 2003).

Python was selected as the analytical environment due to its extensive capabilities for data preprocessing, statistical analysis, and visualization through widely used scientific computing libraries. In particular, the Scikit-learn library was employed to implement the Multiple Linear Regression model because it provides efficient, reliable, and reproducible machine learning and statistical modelling functions. Furthermore, Scikit-learn offers built-in tools for model fitting, coefficient estimation, and performance evaluation, making it well suited for educational data analysis and predictive modelling tasks. The use of Python and Scikit-learn enabled a systematic and transparent analytical workflow throughout the study.

RESULTS AND DISCUSSION

Descriptive Statistics

Table 1 presents the descriptive statistics for all study variables. Technology Access recorded the highest mean score (M = 4.32, SD = 0.84), indicating generally positive perceptions of digital infrastructure. Student Satisfaction had the lowest mean (M = 3.47, SD = 1.08), suggesting considerable room for improvement. All variables had scores ranging from 1 to 5, and standard deviations between 0.84 and 1.17 indicate moderate variability across respondents. The 0.85-point gap between Technology Access (M = 4.32) and Student Satisfaction (M = 3.47) indicates that high infrastructure availability does not automatically translate into proportional satisfaction gains. The elevated standard deviations for Interaction and Collaboration (SD = 1.17) and Student Satisfaction (SD = 1.08) further signal high inter-student variability, justifying both the regression approach and the program-level analysis that follows.

Proceedings of the Perbanas International Seminar on Economics, Business, Management, Accounting and IT
[June 2026] [ISSN 3047-0951]

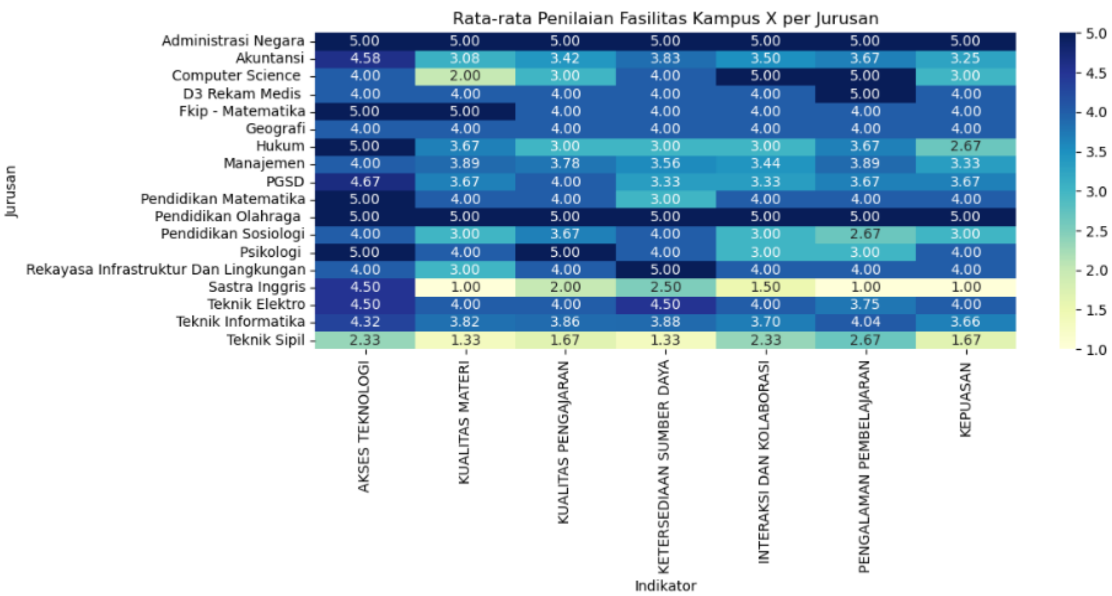
TABLE 2. Descriptive Statistics of Study Variables

Variable	Mean	SD	Min	Max	Median
Technology Access	4.32	0.84	1	5	4.50
Content Quality	3.59	1.11	1	5	4.00
Teaching Quality	3.70	1.04	1	5	4.00
Resource Availability	3.76	1.07	1	5	4.00
Interaction & Collaboration	3.57	1.17	1	5	4.00
Learning Experience	3.83	1.08	1	5	4.00
Student Satisfaction	3.47	1.08	1	5	3.00

Per-Program Analysis

Figure 2 presents a heatmap of mean indicator scores grouped by study program. Considerable heterogeneity is evident across programs. Programs such as Administrasi Negara and Pendidikan Olahraga achieved uniformly high scores (mean = 5.00) across all indicators, including satisfaction. In contrast, Teknik Sipil and Sastra Inggris recorded the lowest scores across most indicators, with satisfaction means of 1.67 and 1.00, respectively. Teknik Informatika, the largest represented program (n = 22), showed moderate scores across all dimensions, with a mean satisfaction of 3.66.

Programs with uniformly high scores (e.g., Administrasi Negara, Pendidikan Olahraga) tend to have smaller sample sizes, which likely enables closer faculty-student relationships and stronger peer cohesion, directly reinforcing the top two regression predictors. Conversely, Sastra Inggris (satisfaction M = 1.00) and Teknik Sipil (M = 1.67) may reflect structural issues such as perceived curriculum misalignment or limited peer interaction opportunities. Teknik Informatika's moderate scores (satisfaction M = 3.66, n = 22) suggest convergence toward the institutional mean as enrollment increases. These inter-program differences confirm that uniform institutional policies are insufficient; targeted, program-specific interventions are required.



Proceedings of the Perbanas International Seminar on Economics, Business, Management, Accounting and IT
[June 2026] [ISSN 3047-0951]

FIGURE 3. Heatmap of Mean Learning Quality Indicator Scores per Study Program

Aggregate Indicator Totals

Figure 3 displays the total aggregate scores for each indicator across all 98 respondents. Technology Access achieved the highest total score (423), followed by Learning Experience (375), Resource Availability (368), Teaching Quality (363), Content Quality (352), Interaction and Collaboration (350), and Student Satisfaction (340). The relatively lower aggregate for Satisfaction compared to the individual indicator totals is noteworthy and motivates the regression analysis below.

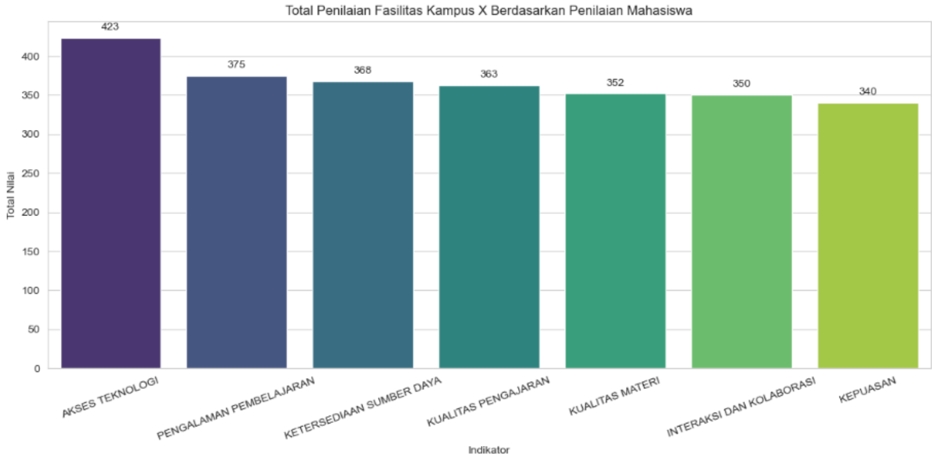
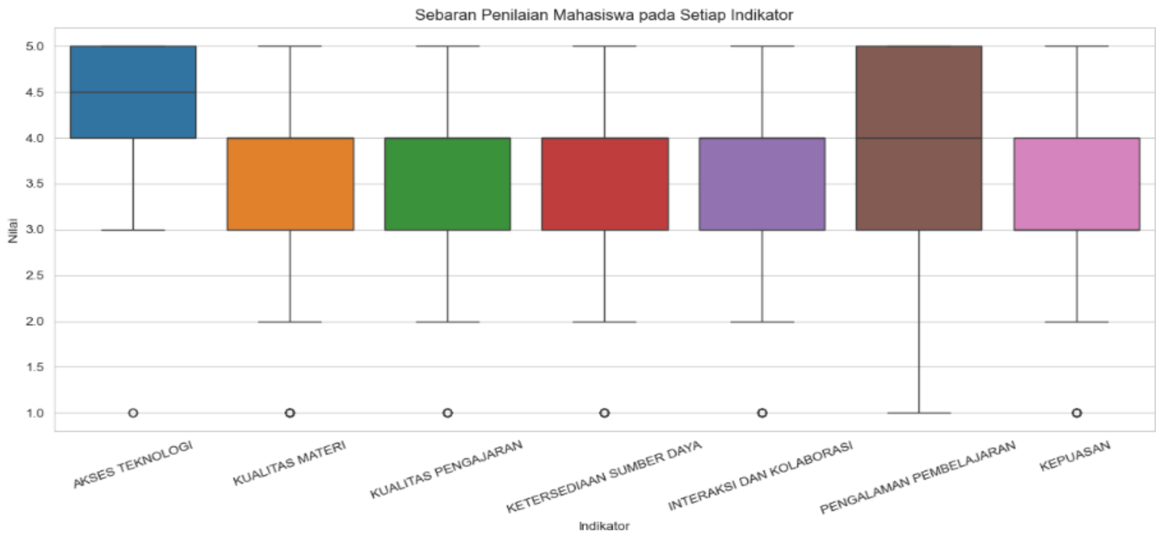


FIGURE 4. Total Aggregate Scores per Learning Quality Indicator

Score Distribution

Figure 4 presents box plots for each indicator, illustrating score distributions and potential outliers. Technology Access exhibits the highest median (4.5) and a narrow interquartile range, reflecting relatively consistent high ratings. In contrast, Interaction and Collaboration and Content Quality show wider distributions, including observations at the minimum score of 1, indicating that some students perceived these dimensions very poorly. Student Satisfaction also shows a wide spread, with a median of 3.0, consistent with the descriptive statistics.



Proceedings of the Perbanas International Seminar on Economics, Business, Management, Accounting and IT
[June 2026] [ISSN 3047-0951]

FIGURE 5. Box Plot Distribution of Scores Across All Learning Quality Indicators

Multiple Linear Regression Results

Table 3 presents the results of the multiple linear regression analysis. The model achieved an R^2 of 0.873, indicating that 87.3% of the variance in student satisfaction is explained by the six predictor variables collectively. This represents an excellent model fit for social science research, where R^2 values above 0.70 are generally considered strong (Hair et al., 2019). The negative intercept ($\beta_0 = -0.689$) confirms that student satisfaction is not self-sustaining — it is entirely conditional on the combined presence of all six learning quality indicators. No single dimension in isolation is sufficient to generate satisfaction; the predictors must act collectively.

TABLE 3. Multiple Linear Regression Results (Dependent Variable: Student Satisfaction)

Variable	Coefficient (β)	Rank	Interpretation	Reference
(Intercept)	-0.689	—	Baseline	-
Technology Access (X1)	0.081	6th	Weakest effect	(Flora et al., 2025)
Content Quality (X2)	0.230	3rd	Strong effect	(Flora et al., 2025)
Teaching Quality (X3)	0.234	2nd	Strong effect	(Flora et al., 2025)
Resource Availability (X4)	0.185	4th	Moderate effect	(Flora et al., 2025)
Interaction & Collaboration (X5)	0.252	1st	Strongest effect	(Flora et al., 2025)
Learning Experience (X6)	0.136	5th	Moderate effect	(Flora et al., 2025)
R^2 (Model Fit)	**0.873**	—	**87.3% variance explained**	**(Gambino & McCoach, 2025)**

Interaction and Collaboration ($\beta = 0.252$) is the strongest predictor, consistent with Vygotsky's sociocultural theory that knowledge is co-constructed through social engagement. In a multi-program institution like University X, students experiencing richer collaborative dynamics, through group projects, active discussion, or accessible faculty mentorship, report meaningfully higher satisfaction. Teaching Quality ($\beta = 0.234$) ranks second, closely trailing Interaction and Collaboration. This near-parity suggests the two dimensions are mutually reinforcing: instructional effectiveness and social learning quality together form the primary satisfaction drivers, replicating Marsh's global findings in a Southeast Asian multi-program context. Content Quality ($\beta = 0.230$) ranks third. Its coefficient proximity to the top two predictors positions these three variables as a core satisfaction cluster, collectively dominating the model's explanatory power and reflecting students' sensitivity to curriculum relevance and alignment with real-world outcomes, as established by Biggs and Tang's constructive alignment framework.

Resource Availability ($\beta = 0.185$) demonstrated a moderate effect, suggesting that physical and digital resource provision meaningfully contributes to satisfaction, though not as directly as pedagogical quality. Learning Experience ($\beta = 0.136$) had a smaller but still positive effect, indicating that students' holistic perception of the academic environment is a distinct predictor beyond individual indicator components.

Notably, Technology Access ($\beta = 0.081$) recorded the highest aggregate score yet the smallest regression coefficient, a result explained by a ceiling effect. With most students already rating technology highly and consistently (M = 4.32, SD = 0.84), the variable carries insufficient variance to generate strong predictive power. Technology access at University X has evidently reached a baseline adequacy that students take for granted, producing diminishing returns in satisfaction. This directly corroborates Selim (2007) and Means et al., both of whom found that technology infrastructure without accompanying pedagogical quality yields limited satisfaction gains. Accordingly, further investment in technology procurement is unlikely to improve satisfaction; resources should instead be redirected toward faculty development, curriculum enhancement, and collaborative learning facilitation, the three highest-coefficient predictors.

This result echoes findings from the IEEE education literature, which warns that technology infrastructure, while necessary, is insufficient on its own to drive meaningful improvements in student learning and satisfaction (Means et al., n.d.). The data thus reinforce a pedagogically grounded approach to quality improvement over a purely infrastructure-driven one.

CONCLUSIONS

This study investigated the influence of six learning quality indicators on student satisfaction across 18 study programs at University X using multiple linear regression. The model achieved an R^2 of 0.873, demonstrating strong explanatory power. Among the predictors, Interaction and Collaboration, Teaching Quality, and Content Quality were identified as the three most influential factors, while Technology Access, despite recording the highest aggregate score (M = 4.32), yielded the smallest regression coefficient ($\beta = 0.081$), attributable to a ceiling effect in which near-universal satisfaction with technology infrastructure leaves insufficient variance to drive further gains in overall satisfaction. The negative intercept ($\beta_0 = -0.689$) further confirms that student satisfaction does not arise from any single factor; it is contingent on the simultaneous contribution of all six learning quality dimensions acting collectively.

These findings highlight a critical discrepancy between perceived infrastructure quality and its actual impact on satisfaction. The results suggest that University X should prioritise investments in faculty development, curriculum enhancement, and the creation of collaborative learning environments over further technology procurement. Additionally, the substantial variation in satisfaction scores across study programs, ranging from a mean of 1.00 in Sastra Inggris to 5.00 in Administrasi Negara, underscores that uniform institutional policies are insufficient. Program-specific interventions, particularly targeting peer interaction structures and curriculum relevance in low-scoring programs, are necessary to address the root causes of dissatisfaction.

Future research should examine the temporal dynamics of these factors for instance, how satisfaction evolves across academic years and explore moderating variables such as gender, year of study, and mode of instruction (face-to-face vs. online). Longitudinal designs and larger samples drawn from multiple universities would further strengthen the generalizability of the findings.

Acknowledgments

The authors would like to acknowledge the use of Artificial Intelligence (AI) tools as supportive instruments in this study. AI was utilized to assist in searching for relevant academic journals, improving language clarity, refining grammar, and supporting the organization of research materials. However, all analyses, interpretations, and final conclusions were conducted and reviewed by the authors.

References

Alves, H., & Raposo, M. (2007). Conceptual model of student satisfaction in higher education. *Total Quality Management & Business Excellence*, *18*(5), 571–588. https://doi.org/10.1080/14783360601074315

Annamdevula, S., & Bellamkonda, R. S. (2016). The effects of service quality on student loyalty: The mediating role of student satisfaction. *Journal of Modelling in Management*, *11*(2), 446–462. https://doi.org/10.1108/JM2-04-2014-0031

Biggs, J., & Tang, C. (2011). *Teaching for Quality Learning at University* (4th ed.). Open University Press / McGraw-Hill.

Cohen, J., Cohen, P., West, S. G., & Aiken, L. S. (2003). *Applied Multiple Regression/Correlation Analysis for the Behavioral Sciences* (3rd ed.). Lawrence Erlbaum Associates.

Delen, D., Topuz, A. C., & Eryarsoy, E. (2020). Development of a Bayesian belief network–based DSS for predicting and understanding freshmen student attrition. *European Journal of Operational Research*, *281*(3), 575–587. https://doi.org/10.1016/j.ejor.2019.03.037

Douglas, J., Douglas, A., & Barnes, B. (2006). Measuring student satisfaction at a UK university. *Quality Assurance in Education*, *14*(3), 251–267. https://doi.org/10.1108/09684880610678568

Elliot, K. M., & Healy, M. A. (2001). Key factors influencing student satisfaction related to recruitment and retention. *Journal of Marketing for Higher Education*, *10*(4), 1–11. https://doi.org/10.1300/J050v10n04_01

Field, A. (2018). *Discovering Statistics Using IBM SPSS Statistics* (5th ed.). SAGE Publications.

Flora, D. B., Crone, G., & Bell, S. M. (2025). Effect Size Interpretation in Structural Equation Models. *Structural Equation Modeling*. https://doi.org/10.1080/10705511.2025.2459768

Gambino, A. J., & McCoach, D. B. (2025). r2_mlm: A Command for Computing R-squared Measures for Models Fit by Mixed. *The Stata Journal*.

Ginkel, J. R., & Karch, J. D. (2025). R Package for Calculating Estimators of the Proportion of Explained Variance and Standardized Regression Coefficients in Multiply Imputed Datasets. *Applied Psychological Measurement*. https://doi.org/10.1177/01466216251316275

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate Data Analysis* (8th ed.). Cengage Learning.

Hodges, C., Moore, S., Lockee, B., Trust, T., & Bond, A. (2020). The difference between emergency remote teaching and online learning. *EDUCAUSE Review*, *27*, 1–9.

Kuh, G. D. , K. J. , S. J. H. , & W. E. J. (2005). *Student Success in College: Creating Conditions That Matter.* Jossey-Bass.

Marsh, H. W. (n.d.). Students' evaluations of university teaching: Research findings, methodological issues, and directions for future research. *International Journal of Educational Research*, *11*(3), 253–388. https://doi.org/10.1016/0883-0355(87)90001-2

Means, B., Toyama, Y., Murphy, R., Bakia, M., & Jones, K. (n.d.). Evaluation of evidence-based practices in online learning: A meta-analysis and review of online learning studies. *IEEE Transactions on Education*.

Pascarella, E. T., & Terenzini, P. T. (2005). *How College Affects Students: A Third Decade of Research* (Vol. 2, p.).

Puspitasari, D., & Wahyuni, S. (2022). Analisis kepuasan mahasiswa terhadap kualitas layanan akademik menggunakan regresi berganda. *Jurnal Pendidikan dan Kebudayaan (Sinta*, *7*(1), 45–58. https://doi.org/10.24832/jpnk.v7i1.2145

Ramsden, P. (2003). *Learning to Teach in Higher Education* (2nd ed.).

Selim, H. M. (2007). Critical success factors for e-learning acceptance: Confirmatory factor models. *Computers & Education*, *49*(2), 396–413. https://doi.org/10.1016/j.compedu.2005.09.004

Slade, S., & Prinsloo, P. (2013). Learning analytics: Ethical issues and dilemmas. *American Behavioral Scientist, 57*(10), 1510–1529. https://doi.org/10.1177/0002764213479366

Tinto, V. (n.d.). *Leaving College: Rethinking the Causes and Cures of Student Attrition*. University of Chicago Press.

Vygotsky, L. S. (n.d.). *Mind in Society: The Development of Higher Psychological Processes*. Harvard University Press.