JPPIPA 10(1) (2024)

Jurnal Penelitian Pendidikan IPA

Journal of Research in Science Education

http://jppipa.unram.ac.id/index.php/jppipa/index

Lecturer Performance Prediction Based on Student Evaluation Data Using a Hybrid K-Means and Random Forest Model

Heri Subangkit[1*], Taqwa Hariguna[1], Dhanar Intan Surya Saputra[1]

[1] Faculty of Computer Science, Amikom University, Purwokerto, Indonesia.

Received: November 01, 2025
Revised: December 26, 2025
Accepted: January 25, 2026
Published: January 31, 2026

Corresponding Author:
Heri Subangkit
24MA41D036@students.amikompurwokerto.ac.id

DOI: 10.29303/jppipa.v12i1.14163

Abstract: Using a quantitative correlational design, this predictive research was based on secondary EDOM data. The first episode of the school year 2024/2025 served as the data collection period. The target population of this research are the lecturer subjected to students' evaluations from Universitas Al-Irsyad Cilacap. After processing the data and cleaning and aggregating, a total of 594 records of the lecturer were analyzed with a census technique. K-Means was used to detect the presence of latent patterns of performance in the teaching, professional, personality and social dimensions of the lecturer. The Random Forest model was used to predict the performance category of the lecturer from both the baseline and hybrid models. The results of the study showed that the hybrid models were able to predict with a high measure of accuracy, and of the two, the hybrid model was the most robust when compared to the baseline model with a manual high-defined grouping of performance levels. The baseline model was able to completely and perfectly classify the group, the hybrid model with high performance was able to analyze the data in a general way, revealing a structure of performance that was hidden in the data. This means that, there is greater analytical value to the data. This analysis of EDOM data is of high analytical value. The developing of the hybrid model of lecturer performance analysis provides a positive contribution in data-driven quality assurance and decision-making to higher education. Objectives were met.

Keywords: Evaluation of teaching; Hybrid machine learning; K-Means clustering; Lecturer performance; Random Forest

Introduction

Teacher performance significantly impacts the quality of instruction and effectiveness of higher education institutions. In addition to providing course content, teachers have the additional responsibility of guidance and creating opportunities for meaningful interaction with students, which ultimately impacts student success. Therefore, student evaluations of teaching (SET) are one of the main tools used by higher education institutions to evaluate teacher performance (Sánchez et al., 2021). The SET is also known in Indonesia as EDOM or *Evaluasi Dosen oleh Mahasiswa*. Through the SET/EDOM process, quantitative data are collected that reflect students' perceptions of their teachers' pedagogical skills, professionalism, personality, and interpersonal skill set (Uttl, 2023). Although the data collected through the SET/EDOM process are extremely valuable, they are often utilized only for descriptive summary purposes (i.e., the average score), and very little effort is made to analyze the data to discover the underlying performance trends for individual teachers (Nancy, 2019).

Research shows a consistent correlation between the caliber of the lecturers and the quality of education offered. Education human resource management systems, including motivation of the lecturers, staff development, and systemized and ongoing evaluation of the performance of the lecturers, are necessary conditions that will lead to increased effectiveness of the lecturers and improved learners' outcomes (Muhamad, 2023). As Idrus et al. (2022) state, the lecturers'

How to Cite:
Subangkit, H. S., Taqqa, T. H., & Saputra, D. I. S. (2026). Lecturer Performance Prediction Based on Student Evaluation Data Using a Hybrid K-Means and Random Forest Model. *Jurnal Penelitian Pendidikan IPA*, *12*(1), 352-358. https://doi.org/10.29303/jppipa.v12i1.14163

performance in unison is a determinant of the quality of the institution and impacts learners' satisfaction and academic success. This is supported by (Warizal et al., 2023), who state that there exists a strong relationship between education quality and lecturer performance. This shows the relevance of performance evaluation based on facts and objective measurements in the education of lecturers and the enhancement of higher education systems.

Lecturer–student engagement alongside institutional factors also matters for teaching effectiveness. Previous evidence illustrates the contributions of classroom conversations, lecturer feedback, academic direction, and student involvement to enhanced learning (Baashar et al., 2023; Hong et al., 2023). Active lecturer response to student questions and feedback fosters student learning and satisfaction (ELsaeed & Mahmoud, 2022; Siregar et al., 2023). Also, learning environments that combine technology with pedagogical strategies not only enhance learning but also promote sustained engagement (Donham et al., 2022; Goyal et al., 2023; Li, 2023). This means that lecturer–student interaction is an evaluative dimension that can be rigorously analyzed through student evaluations.

Although SET/EDOM enhances transparency and student participation, several studies have identified inherent limitations related to subjectivity, bias, and variability across disciplines. While transparent evaluation systems promote accountability, subjective perceptions and inconsistent evaluation criteria may reduce the reliability and objectivity of performance assessments (Ceelen et al., 2022; Wut et al., 2022). These limitations become more pronounced when EDOM data are analyzed solely with descriptive or threshold-based approaches, which may fail to capture latent, multidimensional patterns embedded in complex evaluation data. As a result, reliance on average scores alone may oversimplify the assessment of lecturer performance and limit the potential of EDOM as a decision-support tool.

Studies such as those in (Hariguna et al., 2024) show that hybrid machine learning can capture more complex interactions, leading to better accuracy across more dimensions of the dataset. This is because the most recent applied machine learning results point to more dependence on a hybrid model approach to complex and high-dimensional data structures (Saputra et al., 2025). This data is often the most realistic data analysis cases that require better feature representation and predictive accuracy. Thus, it is now clear that the more complex machine learning frameworks are needed to go beyond basic evaluations.

To support this view, educational analytics have been seeking less traditional evaluation methods and have increasingly adopted data mining and machine learning techniques. Among the techniques, K-Means clustering has been most widely used to group entities based on their similarity across several performance measures, thereby revealing the hidden structures of complex datasets. Clustering techniques in the lecturer evaluation context enable the institutions to figure out those performance patterns that remain invisible even when one uses descriptive analyses. Dewi et al. (2022) proved that the implementation of the Knowledge Discovery in Database (KDD) framework and K-Means clustering on EDOM data was very effective in grouping lecturers based on competencies in teaching, professional, personality, and social areas, which brought the internal quality assurance processes a lot of new insights. Unfortunately, the research has only an exploratory focus and did not extend the clustering results to predictive modeling or classification of lecturer performance categories.

Such use of K-Means clustering in educational contexts is also indicative of its efficacy in identifying underlying performance patterns among students, institutions, and educators (Faisal et al., 2022; Liu et al., 2023). However, a common methodological limitation of such studies is that clustering results are treated as endpoints in most cases and not incorporated into predictive models for proactive, evidence-based decision-making.

Meanwhile, Random Forest has shown remarkable predictive performance across different educational areas, such as student achievement forecasting and teacher quality assessment. Its strength for handling high-dimensional and non-linear data leads the PSWQ to be appropriate in analyzing complex educational datasets (Doz et al., 2023; Kim et al., 2025; Maulana et al., 2023). However, to our knowledge, the RF has still been used directly with raw features or handcrafted ones in most applications, and it is unclear how we can exploit structures that might have significant relations among patterns when available.

Recent studies show that combining unsupervised clustering with supervised classification makes it easier to analyze complex, multidimensional data, even with these limitations. Hybrid models that use both K-Means clustering and Random Forest classification can identify hidden data structures by clustering them and then exploiting those structures to make predictions more accurate. (Sehhati et al., 2022) demonstrated that incorporating K-Means clustering results into a Random Forest model improved its classification accuracy by enhancing feature representation and reducing noise in high-dimensional datasets. Anand et al. (2023) similarly asserted that hybrid clustering–classification methodologies yield greater prediction robustness than independent classifiers, especially in scenarios characterized by heterogeneous data patterns and class overlap. These results highlight the methodological benefits of hybrid frameworks in connecting exploratory pattern discovery with predictive modeling.

Speaking to the analysis of lecturer-student interaction patterns, existing research in EDOM has mainly focused on descriptive analysis and standalone clustering. However, classification is often poorly integrated with clustering-based patterns. It is difficult to find a unified analytical framework that can comprehensively analyse latent lecturer-student interaction structures and leverage classification to predict lecturer performance.

The problem of getting to know them, and in turn, getting to know how they interact with their students, becomes a major hurdle when analysing the performance of lecturers in higher education. This problem is addressed in the present study with a hybrid machine learning framework that employs K-Means clustering and Random Forest classification.

The proposed framework uses multidimensional EDOM indicators across pedagogical, professional, personality, and social domains to provide a comprehensive understanding of the interaction patterns between a lecturer and their students. Plugging the results of the cluster analysis into a predictive model is the study's goal. Making the forecast more accurate and providing a more objective, systematic analysis of the lecturer's performance.

The ultimate aim is to make the analysis of EDOM data in higher education more efficient, and to provide the impetus for a more data-driven approach to quality assurance.

Method

Research Design

This study employed a quantitative research design with a correlational–predictive approach. The design was selected to analyze measurable relationships between lecturer performance indicators and lecturer–student interaction patterns derived from Student Evaluation of Teaching (EDOM) data. Rather than examining causal interventions, the study focused on identifying latent performance patterns and predicting lecturer performance categories using a hybrid machine learning framework. This approach is appropriate for handling large-scale numerical data and evaluating predictive model performance in an objective and systematic manner.

Population and Sample

The study included all lecturers at Universitas Al-Irsyad Cilacap. These lecturers received student evaluations using the *Evaluasi Dosen oleh Mahasiswa* (EDOM) tool during the odd semester of the 2024/2025 academic year. Initially, the study focused on EDOM data gathered at the item-response level. This data shows how individual students rated their lecturers on various performance indicators logged in the institutional quality assurance system.

The dataset included 17,777 EDOM records that represented student evaluations of teaching, professional skills, personality, and social abilities. However, these individual records were not the main focus of the analysis. This study aimed to evaluate lecturer performance instead of examining individual student responses.

After the data preprocessing stage, which included cleaning the data, removing incomplete records, and calculating scores, the EDOM data were summarized at the lecturer level. Aggregation involved calculating the average score for each performance dimension for each lecturer. As a result, the dataset was reduced from 17,777 item-level records to 594 lecturer-level records, which became the final dataset for analysis.

The study used a census method. All lecturers with complete and valid EDOM data were included as research samples. As a result, the final sample consisted of 594 lecturers. This group represented the entire population that met the necessary standards for data completeness and representativeness. The criteria for inclusion in the sample were: lecturers had complete EDOM data across all evaluated indicators, including pedagogical, professional, personality, social, and interaction-related items; each lecturer had enough student respondents to meet the minimum requirement for reliable and representative aggregated evaluation scores.

Data Collection Instrument

Data were collected using *the Evaluasi Dosen oleh Mahasiswa (EDOM)* instrument. This tool is regularly administered as part of the university's internal quality check process. It includes several items that measure lecturer performance in four main areas: pedagogical competence, professional competence, personality, and social competence. Each item was rated on a five-point Likert scale, from 1 (strongly disagree) to 5 (strongly agree).

The EDOM instrument was developed by the institution and applied consistently across all study programs. In this study, the collected data were treated as secondary data from official institutional records.

Validity and Reliability

In order to assess the reliability of the instrument, the internal consistency of the EDOM items was measured using Cronbach's Alpha. Acceptable reliability was established with Cronbach's Alpha coefficient of greater than 0.70. The constructs were theoretically aligned and the EDOM indicators were in accordance with the established dimensions of lecturer performance in higher education evaluation frameworks. Utilization of secondary data in this study from an evaluation system of the particular institution meant that there was no item-level modification or revalidation.

Data Preprocessing

Before the model construction, data processing involved data pre-processing in order to check data quality, relevance, and usability for the analysis. Data pre-processing involved data cleaning, data normalization, and aggregating item-level data into lecturer averages. Data pre-processing led to the creation of a data structure that comprises four numeric variables of performance in pedagogics, profession, personality, and social ability of each of the lecturers.

Data Analysis Technique

K-Means Clustering

K-Means clustering was used to group instructors according to different behavioural patterns demonstrated across all four performance metrics in the EDOM data set. As such, the defined number of clusters was three depicting different behavioural patterns, namely low, moderate and high performance. Outcomes of the clustering were understood by looking at the centroid value for each cluster, indicating the mean performance traits for each cluster. The labels of the cluster were then converted to digits, which were used in the predictive models for added functionality.

Random Forest Classification

Predicting lecturer performance categories using the Random Forest classification algorithm was conducted using two modeling approaches: a baseline Random Forest model which solely used the original EDOM performance features; a hybrid Random Forest model that added the results of the K-Means clustering as an extra input feature.

A stratified split was used to divide the dataset into training and testing subsets in order to maintain the class distribution. Metrics of accuracy, precision, recall, and F1-score were used to assess model performance to give a holistic evaluation of predictive performance, particularly with regard to imbalanced data conditions.

Software and Tools

The utilized the Python programming language for all data preprocessing tasks, including clustering, classification, and evaluations. For the analysis, I chose the most common Machine Learning libraries such as` pandas for data handling, `scikit-learn` for clustering and classification, and `matplotlib` and `seaborn` for visualization. I chose Python for its reproducibility and flexibility, as well as for the rich ecosystem it provides in support of Machine Learning research.

Ethical Considerations

This reseach followed ethical guidelines. To protect the identity and confidentiality of lecturers, all the EDOM data were anonymized before analysis. The data were accessed from the institutional records with the necessary permissions, and the data were used strictly for educational and research purposes. Since the study used secondary data and involved no direct contact with any participants, informed consent was obtained at the institutional level, and all research activities were conducted in accordance with relevant ethical guidelines.

Result and Discussion

Dataset Characteristics

This study utilized Evaluation of Lecturers by Students (EDOM) data consisting of 594 lecturer records after preprocessing and aggregation. Each record included four numerical performance dimensions, namely pedagogical, professional, personality, and social. An overall average score was calculated from these dimensions to derive lecturer performance categories.

The distribution of performance categories was highly imbalanced, with most lecturers classified as having high performance. Due to the extremely limited number of low-performance observations, the low category was merged into the moderate category to ensure statistical stability during model training and evaluation.

Table 1. Features of the Dataset

Description	Value
Total Lecturers	594
Performance dimensions	Pedagogical, Professional, Personality, Social
Clustering approaches	Manual (rule-based), K-Means
Performance categories	High, Moderate
Class imbalance	High-dominant

Random Forest Baseline Results

For a fair comparison with the hybrid model, the Random Forest baseline used a manually defined cluster feature that was based on rule-based thresholds. The manual grouping was based on the average EDOM score. Lecturers were categorized into low, moderate, or high performance groups according to established cutoff thresholds.

The baseline model incorporated five input features: four EDOM dimensions and one manually defined cluster feature. The classification results indicated that the manually constructed cluster provided robust deterministic information consistent with the target variable. However, this strict agreement indicates that the baseline model relies more heavily on predefined scoring criteria than on uncovering latent performance patterns within the data.

Outcomes of K-Means Clustering

Using K-Means clustering to uncover latent performance patterns across lecturers without using any set thresholds, all four EDOM dimensions were used. The clustering method made three groups, which were then split into low, medium, and high performance levels based on the average scores of each group.

K-Means clustering, on the other hand, used data to construct groupings that demonstrated how similar teachers were in different areas of their work. We translated the cluster labels that came out of this into numbers and put them to the hybrid classification model as a new feature.

Results of the Random Forest Hybrid

The Random Forest hybrid model added the K-Means cluster labels as a fifth input feature to the four initial EDOM dimensions. The hybrid model got about 0.994 accuracy on the test dataset.The confusion matrix showed only one incidence of misclassification, in which a professor who was doing well was expected to be doing okay. The hybrid model was not as accurate as the baseline model, but it was more robust because it didn't rely as much on manually set criteria and used unsupervised clustering information.

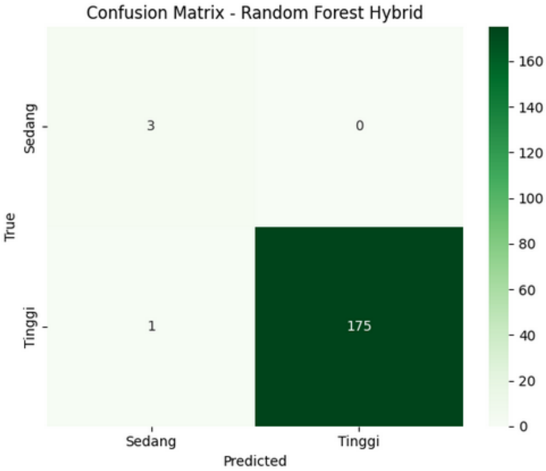

Figure 1. (Confusion Matrix of the Hybrid Model)

Last Model Comparison

When you compare the baseline and hybrid models side by side, you can see that the hybrid approach has a methodological edge. Both models used the same number of input features, which made the comparison fair. The baseline model used rule-based manual clustering, while the hybrid model used data-driven clustering through K-Means.

The baseline model got 100% accuracy, which could mean that it overfitted because manual clustering criteria are deterministic. The hybrid model, on the other hand, was a little less accurate but gave a more realistic and generalizable way to make predictions by finding hidden performance structures that weren't clearly specified by score criteria.

Table 2. Data of baseline and hybrid models

Model	Cluster Source	Number of Features	Accuracy	Macro F1	Interpretation
Random Forest Baseline	Manual (Rule-based)	5	1.000	1.000	Deterministic, potential overfitting
K-Means + Random Forest (Hybrid)	K-Means	5	0.994	0.93	More robust and generalizable

The results of this study demonstrate that incorporating clustering information can influence the robustness of lecturer performance prediction models. Manual clustering yields highly accurate results but inherently includes pre-existing assumptions that may limit generalizability. The hybrid model, on the other hand, uses unsupervised learning to discover hidden performance trends, which makes the evaluation process more flexible and based on data.These results suggest that hybrid learning frameworks that combine both supervised and unsupervised methods may provide more reliable insights for institutional quality assurance systems. The hybrid model isn't more accurate than the baseline model, but it's more resilient and doesn't rely on deterministic rules as much, which makes it better for real-world use.

Incorporating unsupervised clustered information in the classification not only improved performance with the baseline model but also made the hybrid method rational, as the baseline model relied on manual performance categorizations. While baseline achieved perfect classification consistency, the hybrid model achieved more realism as well as more generalizable performance as it unearthed unrecognized elements of the data, as well as reduced the dependence on pre-defined scoring systems.

This study underscores the merit of combining unsupervised and supervised learning methodologies to add analytical depth to EDOM data. Furthermore, the model can help universities establish transparent, data-informed quality assurance and performance evaluation systems for their teaching staff. On the other hand, the study illustrates that the use of features generated from clustering can improve predictive abilities and, in doing so, integrates the use of machine learning in educational data mining and the provision of the hybrid approach. Perhaps future studies will help improve generalizability of the model in the use of additional contextual data and cross-institutional datasets.

Conclusion

This research developed a combination of clustering and classification methodologies that utilize the K-Means and Random Forest algorithms to examine and forecast the performance of instructors based on Students' Evaluation of Teaching (EDOM) data. The study indicates that the performance of instructors can be effectively evaluated using a range of indicators that assess the instructors' pedagogy, professionalism, personality, and social attributes. The K-Means clustering algorithm successfully detected the hidden patterns of performance that were obtained from the interactions of the instructors and students, and the Random Forest classification algorithm was able to predict the data with a considerable degree of accuracy.

Acknowledgments
The authors would like to express their sincere gratitude to to all parties who have helped carry out this research directly or indirectly so that this article can be completed.

Author Contributions
Conceptualization and Methodology, H.S.; Validation, and Formal analysis, T. H. Verification, and Editing, D. I. S. S; All authors have read and agreed to the published version of the manuscript.

Funding
This research received no external funding.

Conflicts of Interest
The authors declare no conflict of interest

References

Anand, M., Shaukat, I., Kaler, H., Narula, J., & Singh Rana, P. (2023). Hybrid Model for the Customer Churn Prediction. *SCRS Proceedings of International Conference of Undergraduate Students*, 85–94. https://doi.org/10.52458/978-81-95502-01-1-9

Baashar, A., Raju Suresh Kumar, S. M. I. A., Alyousif, S. M., Alhassan, A. I., & Townsi, N. (2023). Impact of Audience Response System in Enhancing Teaching of Anatomy and Physiology for Health Sciences Students at King Saud Bin Abdulaziz University for Health Sciences. *Advances in Medical Education and Practice*, *14*(April), 421–32. https://doi.org/10.2147/AMEP.S397621

Ceelen, L., Khaled, A., Nieuwenhuis, L., & de Bruijn, E. (2022). Understanding students' participation in physiotherapy and nursing work settings. *Advances in Health Sciences Education*, *28*(1), 65–85. https://doi.org/10.1007/s10459-022-10142-6

Dewi, N. L. P. P., Purnama, I. N., & Utami, N. W. (2022). Penerapan Data Mining Untuk Clustering Penilaian Kinerja Dosen Menggunakan Algoritma K-Means (Studi Kasus: STMIK Primakara. *Jurnal Ilmiah Teknologi Informasi Asia*, *16*(2), 105–12. https://doi.org/10.32815/jitika.v16i2.761

Donham, C., Pohan, C., Menke, E., & Kranzfelder, P. (2022). Increasing Student Engagement through Course Attributes, Community, and Classroom Technology: Lessons from the Pandemic. *Journal of Microbiology & Biology Education*, *23*(1). https://doi.org/10.1128/jmbe.00268-21

Doz, D., Cotič, M., & Felda, D. (2023). Random forest regression in predicting students' achievements and fuzzy grades. *Mathematics*, *11*(19), 4129. https://doi.org/10.3390/math11194129

ELsaeed, Z. Z., & Mahmoud, S. A. (2022). Lecturers' teaching competence and nursing students' engagement in the use of on-line learning. *Tanta Scientific Nursing Journal*, *27*(4), 84–102. https://doi.org/10.21608/tsnj.2022.267249

Faisal, M., Nurdin, F., & Fitri, Z. (2022). Information and Communication Technology Competencies Clustering for Students for Vocational High School Students Using K-Means Clustering Algorithm. *International Journal of Engineering, Science and Information Technology*, *2*(3), 111–20. https://doi.org/10.52088/ijesty.v2i3.318

Goyal, M., Agarwal, M., & Goel, A. (2023). Interactive Learning: Online Audience Response System and Multiple Choice Questions Improve Student Participation in Lectures. *Cureus*, *15*(7). https://doi.org/10.7759/cureus.42527

Hariguna, T., Sarmini, & Azis, A. (2024). Health and Socio-Demographic Risk Factors of Childhood Stunting: Assessing the Role of Factor Interactions Through the Development of an AI Predictive Model. *Journal of Applied Data Sciences*, *5*(4), 2175–86. https://doi.org/10.47738/jads.v5i4.612

Hong, L., Ma, Y., Yang, X., & Tang, R. (2023). Research on the Influencing Factors of Teaching Interaction on Deep Learning of Graduate Students in Smart Classroom Environment. *2022 3rd International Conference on Artificial Intelligence and Education (IC-ICAIE 2022)*, 778–84. https://doi.org/10.2991/978-94-6463-040-4_118

Idrus, A., Abidin, D., Saputra, N., Rahman, A., & Shobri, M. (2022). Implementation of Minister of Education and Culture Policy Number 84 of 2013 Article 11. *Munaddhomah*, *3*(2), 175–82. https://doi.org/10.31538/munaddhomah.v3i2.248

Kim, E. J., Kim, S. K., Jung, S. H., & Ryu, Y. S. (2025). Predictive Factors of Adolescents' Happiness: A Random Forest Analysis of the 2023 Korea Youth Risk Behavior Survey. *Child Health Nursing Research*, *31*(2), 85–95. https://doi.org/10.4094/chnr.2024.049

Li, H. (2023). The Influence of Online Learning Behavior on Learning Performance. *Applied Science and Innovative Research*, *7*(1). https://doi.org/10.22158/asir.v7n1p69

Liu, Y., Fan, S., Xu, S., Sajjanhar, A., Yeom, S., & Wei, Y. (2023). Predicting Student Performance Using Clickstream Data and Machine Learning. *Education Sciences*, *13*(1). https://doi.org/10.3390/educsci13010017

Maulana, A., Idroes, G. M., Kemala, P., Maulydia, N. B., Sasmita, N. R., Tallei, T. E., Sofyan, H., & Rusyana, A. (2023). Leveraging Artificial Intelligence to Predict Student Performance: A Comparative Machine Learning Approach. *Journal of Educational Management and Learning*, *1*(2), 64–70. https://doi.org/10.60084/jeml.v1i2.132

Muhamad, L. F. (2023). Human Resource Management Strategies in Improving Lecturer Performance in Higher Education. *Indo-MathEdu Intellectuals Journal*, *4*(2), 728–42. https://doi.org/10.54373/imeij.v4i2.283

Nancy, H. (2019). A Descriptive Study of Teachers' Instructional Use of Student Assessmetn Data. In *VCU Scholars Compass (Virginia Commonwealth University*. Virginia Commonwealth University. https://doi.org/10.25772/d1xg-kx34

Sánchez, T., León, J., Corbí, R. G., & Costa, J. L. C. (2021). Validation of a Short Scale for Student Evaluation of Teaching Ratings in a Polytechnic Higher Education Institution. *Frontiers in Psychology*, *12*. https://doi.org/10.3389/fpsyg.2021.635543

Saputra, A. N. A., Saputro, R. E., & Saputra, D. I. S. (2025). Enhancing Sentiment Analysis Accuracy Using SVM and Slang Word Normalization on YouTube Comments. *Sinkron*, *9*(2), 687–99. https://doi.org/10.33395/sinkron.v9i2.14613

Sehhati, M., Tabatabaiefar, M., Gholami, A., & Sattari, M. (2022). Using Classification and K-Means Methods to Predict Breast Cancer Recurrence in Gene Expression Data. *Journal of Medical Signals and Sensors*, *12*(2), 122–26. https://doi.org/10.4103/jmss.jmss_117_21

Siregar, G., Bismala, L., Hafsah, H., Handayani, S., Manurung, Y. H., Andriany, D., & Hasibuan, L. S. (2023). Unveiling Determinant of Student Engagement. *Journal of Education and Learning*, *17*(2), 174–82. https://doi.org/10.11591/edulearn.v17i2.20747

Uttl, B. (2023). Student Evaluation of Teaching (SET): Why the Emperor Has No Clothes and What We Should Do About It. *Human Arenas*, *7*(2), 403. https://doi.org/10.1007/s42087-023-00361-7

Warizal, W., Gursida, H., & Sasongko, H. (2023). The Relationship Between The Quality of Education and The Performance of Lecturers In Waqf-Based Private Universities in West Java. *Journal of World Science*, *2*(7), 1030–35. https://doi.org/10.58344/jws.v2i7.374

Wut, T. M., Xu, J., Lee, S. W., & Lee, D. (2022). University Student Readiness and Its Effect on Intention to Participate in the Flipped Classroom Setting of Hybrid Learning. *Education Sciences*, *12*(7). https://doi.org/10.3390/educsci12070442