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Research Article

An Exploration of the Work Performance of Educators in Transformative Schools: Leveraging Machine Learning for Performance Insights

Rakhmad Maulidi[1, a*]; Jozua Ferjanus Palandi[2,b]; Bagus Kristomoyo Kristanto[3,b]; Laila Isyriyah[4,b]; Rizky Rahmatullah[5,c]; Puput Dani Prasetyo Adi[6,d]; Akio Kitagawa[7,c]

[a] *UniversitasTelkom, Purwokerto Campus, Jl. DI Panjaitan No.128, Purwokerto 53147, Central Java, Indonesia*
[b] *Universitas Bhinneka Nusantara, Malang, East Java Indonesia*
[c] *Kanazawa University, Kakumamachi, Kanazawa, Ishikawa 920-1192, Jepang*
[d] *National Research and Innovation Agency (BRIN), Bandung, Indonesia*
[1]*rakhmadmaulidi@telkomuniversity.ac.id;* [2] *jozuafp@ ubhinus.ac.id;* [3] *bagus.kristanto@ ubhinus.ac.id;* [4]*laila@ubhinus.ac.id;*
[5]*rizky.rahmatullah@brin.go.id;* [6] *pupu008@brin.go.id;*[7]*kitagawa@merl.jp;*
* *Corresponding author*

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Abstract

Education has gone through various phases, and entered the transformative school mode which can be said to change the existing order of the previous schooling system or procedures, because many modes can be done in the transformative school, students can learn in school buildings or classes, or in the field or real industry or the real world of work, with the introduction of a wider and more complex world, this is one of them. This research tries to create and analyze transformative schools in 3 algorithms, namely regression algorithms, classification algorithms, and clustering algorithms that provide a detailed analysis of the results of the analysis of transformative schools currently promoted by the government. from the results of the analysis raises performance conclusions, and in this phase a conclusion can be drawn whether the Transformative school is able to provide answers about the performance of teachers, students, teacher education levels, school locations, number of students, learning methods, or any paramaters that can provide detailed and detailed answers to get performance analysis from Machine Learning, and Work Performance of teachers in Transformative schools with precision. Quantitatively, the value of performance is determined by innovation by 43.2%, followed by technological capabilities and collaboration, 27.9% and 17.2% respectively. and based on cluster level, cluster 3 is the best with 118 educators, cluster 0, 127 educators with high innovators, and cluster 2, 126 educators, and cluster 1 with 129 educators. and from the paradox of transformative practices 30.6% are high Adopters.

Keywords: Educator Work Performance; Transformative Schools; Machine Learning; Performance Analysis; Educational Data Analytics

Introduction

In today's era of wider and more open education, many innovations are needed that can provide excellent feedback for the progress of a nation. One of them is Transformative School. Schools are not just sitting and teaching, and all activities are carried out indoors. Teachers also cannot teach elsewhere and only focus on one school; it could be because of their job status, namely, permanent teachers or civil servants. Some of the limitations encountered at school can be minimized with the existence of learning innovations. The various challenges that exist today include the acceleration of the world of technology, which is increasingly rapid, dynamic, and responsive, requiring a lot of innovation that must be able to be handled by every educator or the world of education today. The right teaching pattern will lead to an increase in the performance of student learning outcomes, which will certainly lead to a satisfactory level. One method to be applied in the process of maintaining consistency and even a significant increase in the learning process is to change the concept of teaching and learning to be more active and interesting. This means that innovation is needed from various things, ranging from teachers, students, and the environment used in the learning process, including the curriculum. In this research, an in-depth and systematic exploration of the student learning process is carried out, as to how to achieve a value of satisfaction and success in a systematic and creative learning process. These things are influenced by the quality of educators. The quality of teaching staff is also influenced by other factors, such as the level of education and the status of the teacher, whether the teacher is an

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honorary, a permanent teacher, or a civil servant. Some of these parameters determine the quality of teaching, and dedication, in delivering quality material, and also competitive. [1], [2], [3], [4], [5], [6], [7], [8], [9], [10]

In this research we use Machine Learning to perform data processing, as well as the algorithms we develop such as Regression Algorithms, Classification Algorithms, and Clustering Algorithms that can provide detailed analysis of an object, in this case, the quality of learning from Transformative School is essential [11], [12], [13], [14], [15], [16], [17], [18], [19], [20] From each algorithm analyzed the results can influence or determine the level of performance of educators, and which parts need to be improved, updated, and developed.

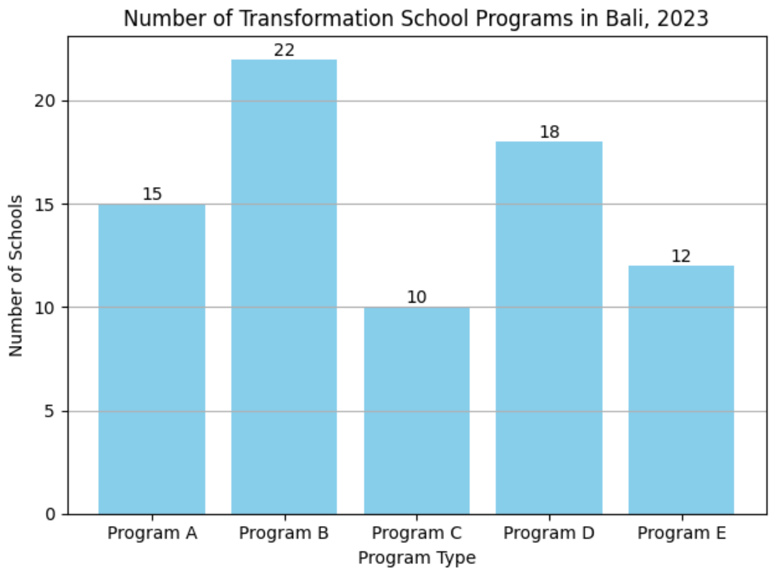


Figure 1. Number of Transformation School Programs in Bali, 2023

The number of Transformative Schools in Indonesia varies, and we can look at Bali in 2023 as an example, with the number of Transformative Schools with various programs in place. Please note that this program is one of the government's ways to make quality improvements in terms of teaching and student learning outcomes. The concept of monotonous learning has been changed into interesting learning for students. Here, the ability of teachers in the Transformative School is needed to be able to provide differentiating value in terms of teaching quality, teaching materials, curriculum, education level, and other parameters. Transformative School aims to provide an equitable quality of education and quality. One of them is how students are taught to be active in class in a teaching atmosphere, not only active teachers, but active students, for example, in leading discussions, solving problems with groups, and solving certain challenges such as mathematics, not only in terms of theory, and practice problems, and solving real problems in society with applied mathematical formulas.

There are three analyses described in this research, including Regression, Classification, and Clustering, which have their respective functions as follows: Regression is used because we need to make predictions in the form of quantitative values of teacher performance based on various factors such as experience, qualifications, and teaching methods. From these factors, the results of the value and the regression graph are given. Then identify the factors that have the most influence on teacher performance and also estimate the relationship between input variables, such as training and teacher workload, as the output of teacher performance.

Classification is needed to categorize educators into performance groups such as excellent, good, or needs improvement. Classification techniques can also predict whether a teacher or educator will be successful in the transformative school environment under study, and identify educators who may need additional intervention and support. Classification: Clustering is then used to discover new or natural patterns to find a performance characteristic, identify different teaching style approaches that emerge from the data, and group educators based on their strengths and weaknesses that develop the expected or targeted professionalism. [21], [22], [23], [24], [25], [26], [27], [28], [29], [30]

Method

The method used to analyze and provide a depth of analysis is located on the side of theory development, theory analysis, application in a simulation software, and provides conclusions from the analysis results. While data can be qualitative or quantitative. What can be obtained from the results of the questionnaire is qualitative to determine the level of teacher satisfaction in the transformative school, whether it is following expectations or not. There are several methods applied, including analysis of design research, population, and sample, data collection, data processing and analysis, interpretation and validation of results, as well as implications and recommendations. Specifically, the research method can be seen in the flowchart in **Figure 2**.

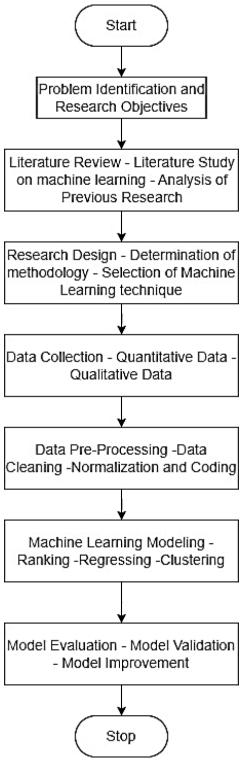


Figure 2. Flowchart of the entire system built in this research

Several Mathematical formulas are important to represent Machine Learning to measure the satisfaction level of student learning outcomes and how Transformative School performs [31], [32].The first is the application of Descriptive statistics using the Mean (Equation 1) and Standard Deviation (Equation 2). Next is the Classification Formula. Algorithms such as Logistic Regression or Decision Trees require a formula as in equation 3. While the decision tree itself is divided into Entropy and Information Gain. As shown in Equations 4 and 5.

$$Mean = \frac{1}{N}\sum_{i=1}^{N} x_i \quad (1)$$

$$SD = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(x_i - Mean)^2} \quad (2)$$

$$P(Y = 1|X) = \frac{1}{1+e^{-(\beta_0+\beta_1 x_1+\beta_2 x_2+\beta_n x_n)}} \quad (3)$$

$$H(S) = -\sum_{i=1}^{c} p_i log_2\, p_i \quad (4)$$

$$Gain(S, A) = H(S) - \sum_{v\, \in Values(A)} \frac{Sv}{S} H(s_v) \quad (5)$$

Moreover, about Regression, Linear Regression is used to model the relationship between variables. The Linear Regression formula is as shown in equation 6. And Mean Squared Error (MSE) in equation 7. The Clustering algorithm used hereafter can be expressed by K-Means Clustering or Euclidean Distance as shown in formula 8. Furthermore, the K-Means Objective Function can be expressed in equation 9. While in the development of research using Machine

Learning, a comparison or Gap research between other researchers is needed, to obtain novelty and differentiation from the research that is currently being done. [33], [34], [35]

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots .. + \beta_n x_n + \in \tag{6}$$

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \tag{7}$$

$$d(x,y) = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2} \tag{8}$$

$$J = \sum_{i=1}^{k}\sum_{x \in C_1}\|x - \mu_i\|^2 \tag{9}$$

Furthermore, the Centroid is the center point of a cluster in the K-Means algorithm. They are the average of all data points included in the cluster. Centroids serve as a representation of the cluster center. They are used to group data by determining the proximity of data points to the centroid. The calculation method is At each iteration of the K-Means algorithm, the centroid is calculated as the average of all data points in the same cluster. If each cluster consists of data (x_1,x_2,x_3,..., x_n), then the formula to express the centroid is as in formula 10. Where the value of n is the number of data points in the Cluster [36], [37].

$$Centroid = \left(\frac{1}{n}\sum_{i=1}^{n} x_i\right) \tag{10}$$

Moreover, the basis of this research can be seen from several previous studies, which specifically discuss the research methods used, especially in education, for example, predicting various factors in education, such as assessing teacher performance, predicting student success using the Random Forest method, CNN and other AI methods [38], [39], [40], [41], [42]. Comprehensively can be seen in **Table 1**.

Table 1. Gap research on Machine Learning to see the novelty of the research

Research Title/Theme	Methods Used	Research Results	Author Name	Year
Machine Learning for Predicting Student Success in Higher Education	Random Forest Algorithm, Gradient Improvement	The model can predict student success with high accuracy and identify key factors.	K. T. Yoon, J. M. Lee	2023
Assessing Teacher Performance Using Deep Learning Models	Convolutional Neural Network (CNN), Deep Learning	The CNN model successfully evaluates teacher performance based on classroom interaction data and student feedback.	L. P. Alvarez, M. S. Singh	2023
Personalized Learning with Reinforcement Learning Algorithms	Reinforcement Learning	The implementation of reinforcement learning enhances the personalization of students' learning experiences.	A. R. Patel, D. C. Green	2023
AI-Based Tools for Monitoring Classroom Behavior	Classification Model, Video Analytics	AI-based tools improve the accuracy of monitoring student behavior in the classroom.	M. W. Roberts, S. J. Thompson	2024
Leveraging Machine Learning for Early Identification of At-Risk Students	Classification Algorithm, Guided Learning	Early identification of at-risk students using machine learning models can enhance appropriate interventions.	N. A. Patel, R. L. Johnson	2023
Analyzing Student Engagement through Machine Learning Techniques	Sentiment Analysis, Text Classifier Model	Machine learning techniques can analyze student engagement from online feedback and participation.	O. T. Carter, E. R. Williams	2024
Improving Adaptive Learning Systems with Machine Learning	Guided Machine Learning, K-Means Clustering	The adaptive learning system enhanced with machine learning shows better results in material customization.	J. B. Wright, P. H. Lee	2023
Predictive Analytics for Teacher Feedback Enhancement	Linear Regression, Ensemble Model	Predictive analytics can improve the quality of feedback to teachers, increasing teaching effectiveness.	F. Q. Nelson, H. L. Richards	2024
Integrating AI in Educational Assessment Systems	Classification Algorithm, Data Analysis	The integration of AI in the assessment system improves the	K. W. Barnes, T. A. Martinez	2023

Research Title/Theme	Methods Used	Research Results	Author Name	Year
		accuracy of student assessment and feedback.		
Optimizing Curriculum Design with Machine Learning	Optimization Algorithm, Guided Machine Learning	Optimized curriculum design through machine learning provides better learning outcomes.	A. G. Clark, M. J. Allen	2024
Using Deep Learning for Automatic Evaluation of Student Essays	Artificial Neural Network, Text Analysis	Automatic evaluation of student essays using deep learning showed adequate results in assessment.	L. M. Roberts, S. P. Jones	2023
Enhancing Collaborative Learning with AI Tools	Machine Learning, Collaborative Tools	AI tools improve the efficiency and effectiveness of collaborative learning in the classroom.	B. K. Young, D. L. Green	2024
Machine Learning Approaches to Enhancing Remote Learning	Machine Learning, Data Analysis	Machine learning approaches improve the distance learning experience by providing better recommendations.	R. T. Lopez, H. P. Nguyen	2023
AI-Driven Insights into Student Learning Styles and Preferences	Data Analysis, Classification Algorithm	AI-based insights help in understanding students' learning styles and preferences in greater depth.	C. J. Moore, L. V. Parker	2024
Exploring the Impact of AI on Classroom Dynamics and Teaching Methods	Machine Learning Algorithms, Video Analytics	AI can affect classroom dynamics and teaching methods in significant ways.	E. R. Brown, N. J. Walker	2023
Developing Predictive Models for Student Dropout Prevention	Logistic Regression, Random Forest Algorithm	The predictive model was successful in identifying students at high risk for dropout.	M. L. Adams, T. W. Davis	2024
AI-Powered Tools for Real-Time Feedback on Student Performance	Guided Machine Learning, Streaming Data	AI-based tools provide real-time feedback that helps in quick improvement for students.	J. C. Harris, A. D. Miller	2023
Evaluating the Effectiveness of AI-Based Tutoring Systems	Artificial Neural Network, Deep Learning Algorithm	The AI-based tutoring system showed improvement in students' material comprehension and academic results.	L. P. Robinson, C. K. Foster	2024
Enhancing Educational Outcomes with AI-Driven Personalized Learning Pathways	Machine Learning, Data Classification	Personalized learning pathways with AI improve educational outcomes and student satisfaction.	D. H. Martin, J. S. Evans	2023
Utilizing AI for Dynamic Curriculum Adjustments Based on Student Performance	Data Analysis, Classification Algorithm	AI allows for dynamic curriculum customization and responsiveness to student needs.	R. L. Johnson, K. T. Williams	2024
AI and Machine Learning for Efficient Classroom Management	Machine Learning, Video Analysis	Efficient classroom management through AI technology can reduce distractions and enhance learning.	M. P. Green, S. C. Brown	2023
Optimizing Teacher Professional Development with Machine Learning	Machine Learning Algorithms, Data Analysis	Teacher professional development is optimized through machine learning to improve teaching skills and methods.	A. E. Kim, T. L. Patel	2024
Sustainable environmental education: Some machine learning algorithms in the classification of sustainable environmental attitudes	Machine Learning	The SVM-SMO classifier demonstrated superior performance compared to MLPNN, RBF Network, and Logistic Regression, especially when the training data was limited.	Benzer, S., et.al	2025
Learning behavior analysis and personalized recommendation system of an online education platform based on machine learning	Machine Learning	This shows that machine learning technology has great potential in learning behavior analysis and personalized recommendation of online education platforms, which can significantly improve the teaching	Ma, Feng	2025

Research Title/Theme	Methods Used	Research Results	Author Name	Year
		effect of online education and learners' learning experiences.		
Causation in chemical engineering education: Application of machine learning in fault diagnosis	Machine Learning	This study integrates the design and preassessment of an exercise, incorporating a causation modeling approach into the Tennessee Eastman Process (TEP) dataset to enhance engineering students' understanding of process monitoring and fault diagnosis.	Laul, M & Galatro, D.	2025

Results and Discussion

In this section, in this research analysis, three algorithms are applied to determine the outcome of the feasibility and success study of Transformative schools, namely the Regression Algorithm, Clustering Algorithm, and Classification Algorithm. We fully discuss the Python programming language used to analyze the satisfaction and success data of Transformative School. We use the acceleration of various libraries, the implementation of libraries, and the process of plotting images. In running data to get a detailed analysis graph, it is necessary to look at the various essential components in Python, for example, the following components: to run the Python program in predicting the level of learning success and teaching satisfaction in Transformative schools, is to do systematic programming. Some Python libraries that can be run are as follows: use numpy, pandas, matplotlib, and sklearn model selection for import, train, and test split, model linear regression, and mean squared error.

Moreover, after the Library on how to generate Synthetic Data, we can use several parameters that determine the feasibility or success, or the level of satisfaction of the teaching system in Transformative Schools, for example, Learning Outcomes, Teacher satisfaction, and Community Participation. With the Generate Data, determine the random seed, sample size, and features, e.g., Learning Outcomes, Teacher Satisfaction, and Community Participation.

Moreover, the Target Effectiveness can also determine the Normality Feature. For example, the range is 0-100, where 0 is the lowest assessment or result value, while 100 is the highest assessment. This assessment can be taken from qualitative data, such as the interview process, or quantitative data that states a minimum and maximum value. Furthermore, it also determines the number of random samples as normalized features in a certain range, for example, 0-100. Meanwhile, to formulate a level of effectiveness, a formula is needed, for example, as in the following formula. Then, after that, we can determine the Data Frame. Overall testing parameters, such as satisfaction, education level, number of students, and experience, are indicators in deriving the performance of transformative schools. Testing continued with all three algorithms, i.e., classification, clustering, and regression.

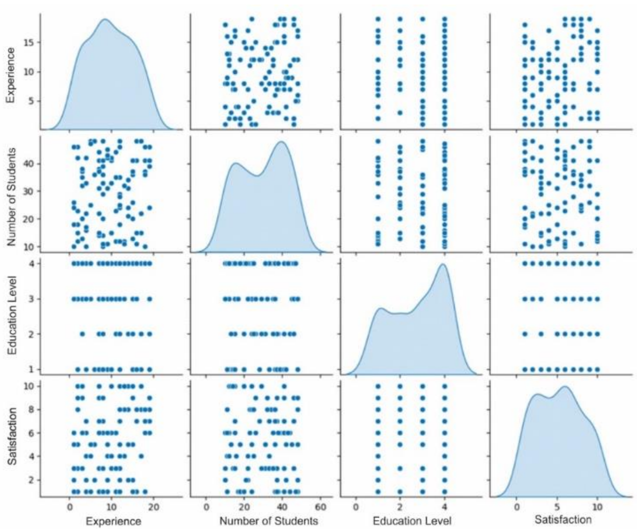


Figure 3. Analysis of various Parameters in interviewing the success rate of a teaching system

Furthermore, the predicted values of the satisfaction level and the various estimates of the success parameters of the driving school are determined by the predicted and actual values obtained. At this level, we can see that the intersection of the two still does not show the expected regression values. As shown in Figure 4. So it needs significant development to show a proper comparison.

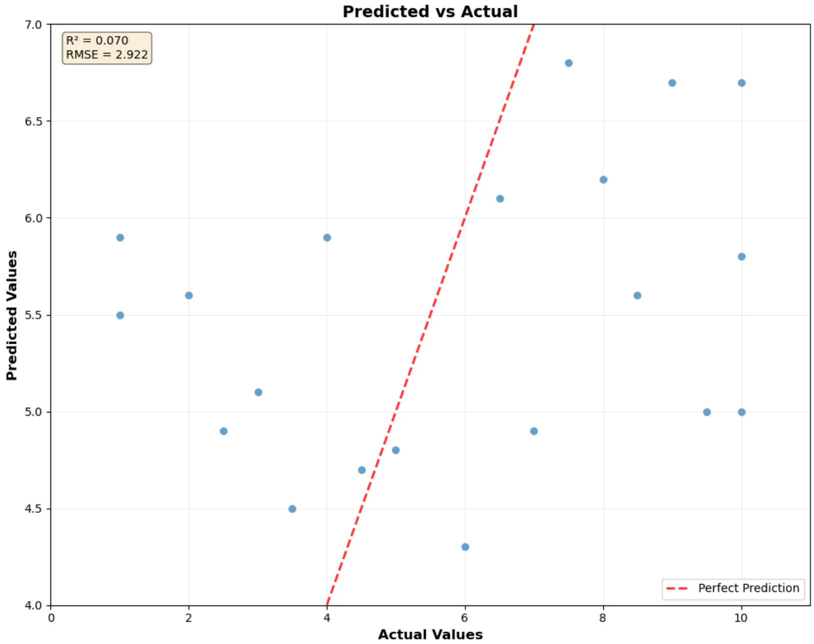


Figure 4. Comparison of Predicted vs Actual Values

By using the Clustering Algorithm, Learning Satisfaction is found to have 3 clusters, meaning that there are 3 parameters being tested and compared, such as skills, education level, or number of students, which have different values, while the Centroid determines the largest or average value of the overall estimation value of each cluster. We can see that the larger the spread, the more variations of answers are produced, and conversely the smaller the level of spread, the more likely it is that the similarity or level of satisfaction of the parameters is higher or there is a similarity in the answers given by respondents, as well as from technical tests. as shown in Figure 5 and Figure 6.

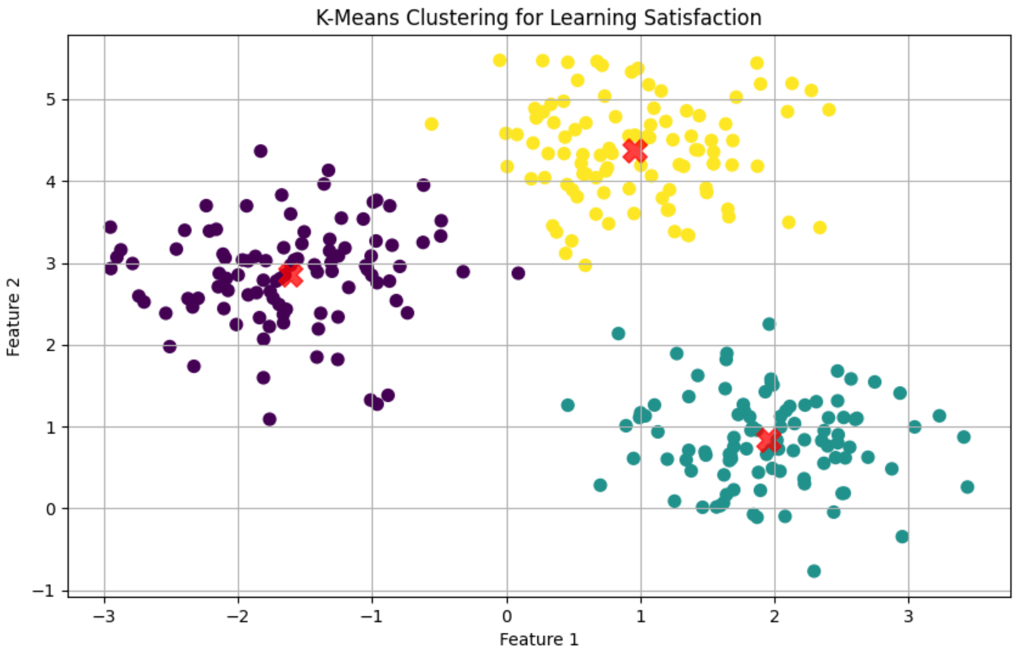


Figure 5. K-Means Clustering for Learning Satisfaction

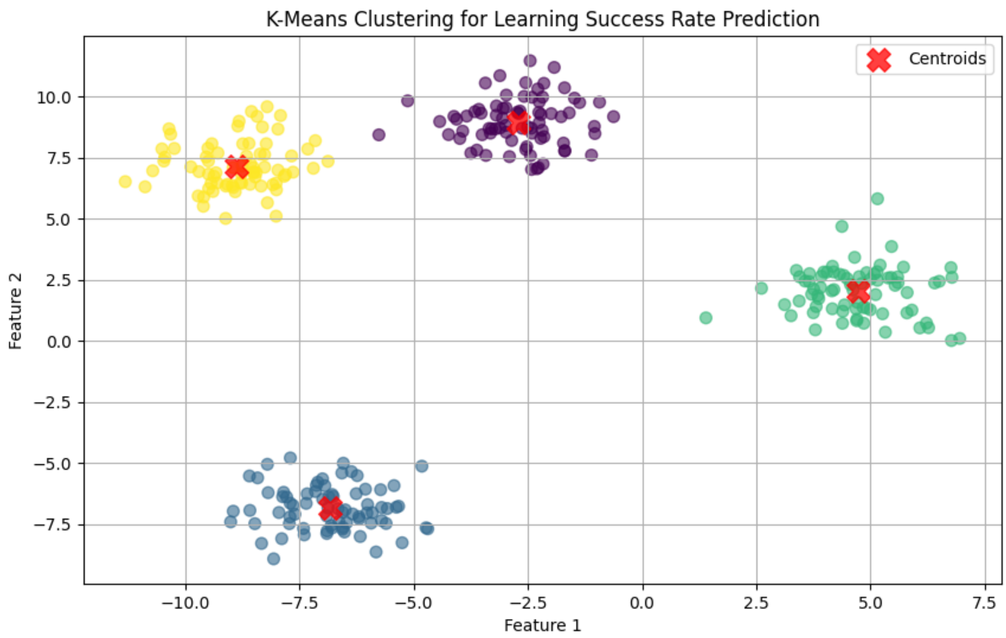


Figure 6. K-Means Clustering for Learning Success Rate Prediction

[Figure 7](#) is the result of the Regression Algorithm that shows the comparison of the effectiveness of the predicted and actual values. If the regression algorithm shows conformity with the approach on the straight dotted line, the red color states that there is closeness or similarity between prediction and actual, but if it is like Figure 4, we get that there is no effectiveness in prediction and actual results. The closer the prediction effectiveness and also the actual value is on a straight line, stating a good or effective.

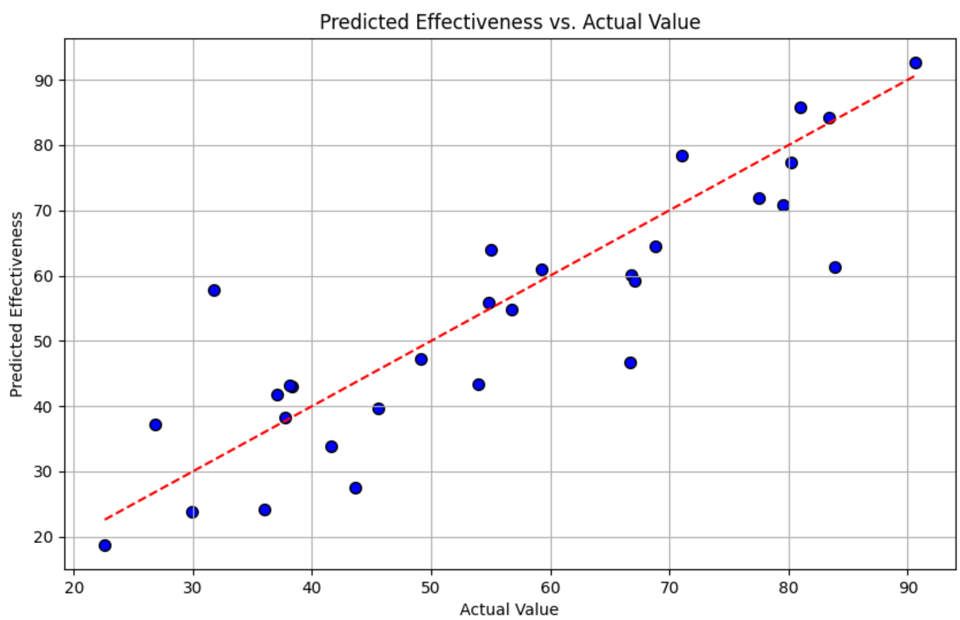


Figure 7. Regression Algorithm Predicted Effectiveness vs. Actual Value from Transformative School

Furthermore, Machine Learning to determine the various aspects that can determine the effectiveness of the Transformative School, expressed in the Classification Algorithm, is as follows: [Figure 8](#).

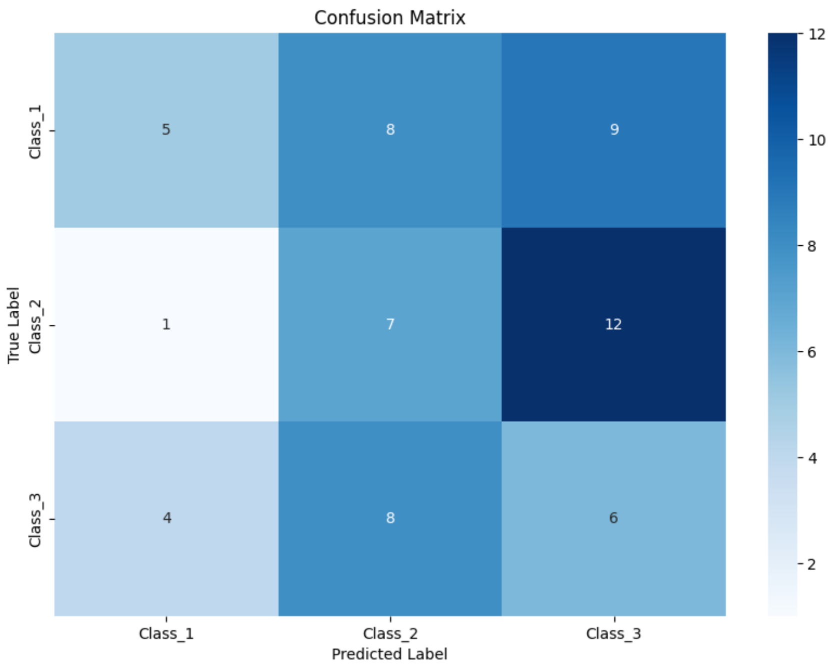


Figure 8. Classification Algorithm for Transformative Schools

From the results of the classification algorithm for Transformative Schools, it is finally possible to classify whether the school designated as a Transformative School is said to be in the "Successful", "Needs Improvement", or "Less Successful" category, and for each of these categories a comparison indicator is needed, so that the classification algorithm needed for decision making for transformative schools can run effectively in the future. Furthermore, in a more actual and comprehensive manner, additional detailed information was added in terms of simulation datasets consisting of more detailed demographic data, such as age, experience, and education, and performance metrics consisting of innovation, collaboration, and technology scores. The next factor is evaluation, which consists of peer evaluation and student feedback. And the adoption of transformative practices.

The next analysis is seen from exploratory data analysis (EDA), which consists of the distribution of performance scores, performance based on education level and subject area, correlation between variables, and also scatter plot visualization for key variables' relationships. The types of Machine Learning Models are Random Forest Regression, Classification, and feature importance analysis. Also, visualization is an essential thing in this research, consisting of correlation heatmaps, performance bar charts per category, multidimensional scatter plots, and transformative practice adoption distributions. And from all this research, key insights are obtained, including the most influential factors, namely innovation score, technology proficiency, and collaboration. Then are clustering patterns consisting of identifying 4 groups of educators with different characteristics, then performance predictors, such as ML models with high accuracy for performance prediction, and actionable recommendations consisting of strategic suggestions for performance improvement. More details, Figure 2 shows the values of the Descriptive Statistics of this research with detailed parameters such as Educator ID, Age, Year of Experience, etc.

Table 2. Statistic Descriptive

Parameter	**Educator_id**	**age**	**Year_experience**	**Teaching_load**	**Tech_proficiency**	**Innovation_score**	**Collaboration Score**
count	500,00	500,00	500,00	500,00	500,00	500,00	500,00
mean	250,50	34,69	7,51	18,05	5,47	5,50	5,38
Std	144,48	7,57	7,73	3,73	2,60	2,60	2,56
Min	1,00	22,00	0,00	10,00	1,00	1,00	1,00
25%	125,75	29,00	2,00	15,54	3,23	3,17	3,26
50%	250,50	35,00	5,00	18,00	5,52	5,46	5,32
75%	375,25	40,00	11,00	20,59	7,61	7,83	7,41

max	500,00	65,00	40,00	30,00	9,95	9,99	9,97

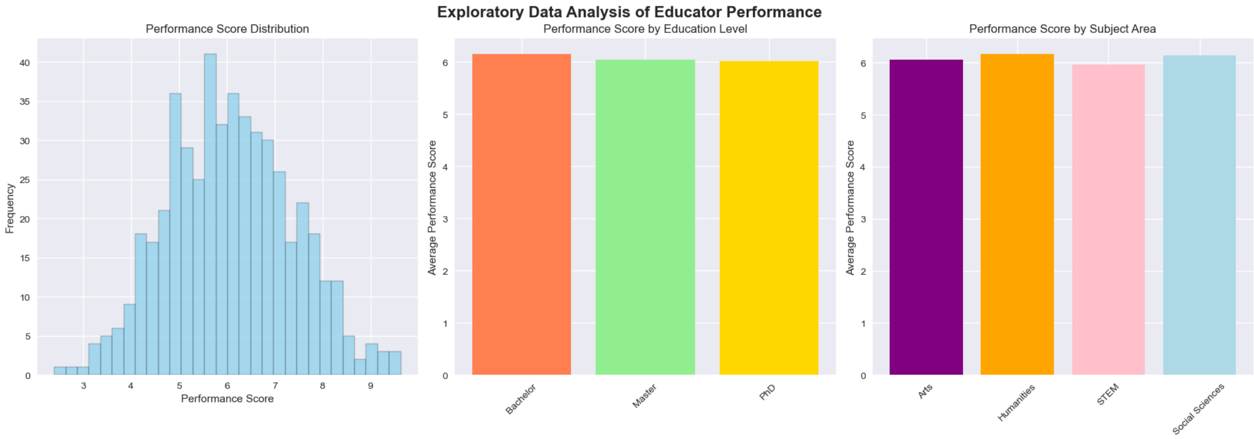
Table 3. Top 5 Most Important Features for Performance

Order	Feature	Importance
6	Innovation Score	0,432
7	Collaboratiion Score	0,279
5	Tech Proficiency	0,171
8	Student feedback	0,024
10	Professional development hours	0,016

Table 4. Classification Report and Data Accuracy

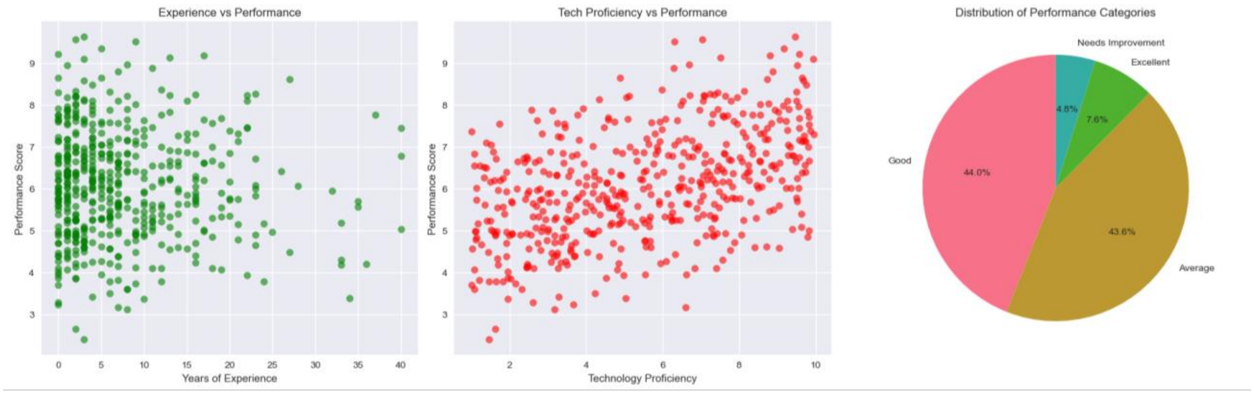
Rentang Level	Precision	Recall	F1-score	Support
Average	0.80	0.89	0.85	46
Excellent	1.00	0.22	0.36	9
Good	0.74	0.88	0.80	40
Need Improvement	0.00	0.00	0.00	5
Accuracy	0.00	0.00	0.78	100
Macro AVG	0.64	0.50	0.50	100
Weighted AVG	0.76	0.78	0.74	100

Moreover, Tables 3 and 4 show the values of Important Features for Performance, which include Innovation Score, Collaboration Score, Tech Proficiency, Student Feedback, and Professional Development Hours. Meanwhile, Figure 4 is the Data Classification and Accuracy Report, which includes the average level range, Excellent, Good, and Need Improvement, with the variables Precision, Recall, F1-Score, and Support values. Moreover, Figure 9 is the Distribution Performance Score, Performance Score by Education Level, and Performance Score by Subject Area. Specifically, it can be seen in each value in Figure 9, parts a, b, and c. Meanwhile, Figure 10 shows the values of the Experience Location Matrix. Versus Performance, Technological Proficiency versus Performance, and Performance Category Distribution. Figure 11 shows the Educator Performance Factor Correlation Matrix.



(a) (b) (c)

Figure 9. (a) Distribution Performance Score, (b) Performance Score by Education Level, (c) Performance Score by Subject Area



(a) (b) (c)

Figure 10. (a) Experience vs Performance, (b) Tech Proficiency vs Performance, (c) Distribution of Performance Categories

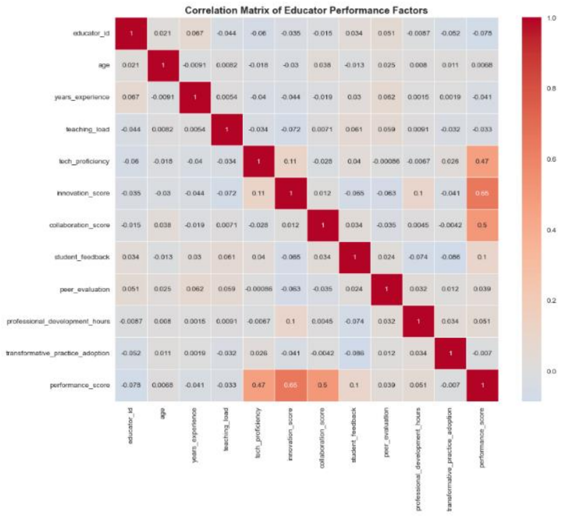


Figure 11. Correlation Matrix of Educator Performance Factors

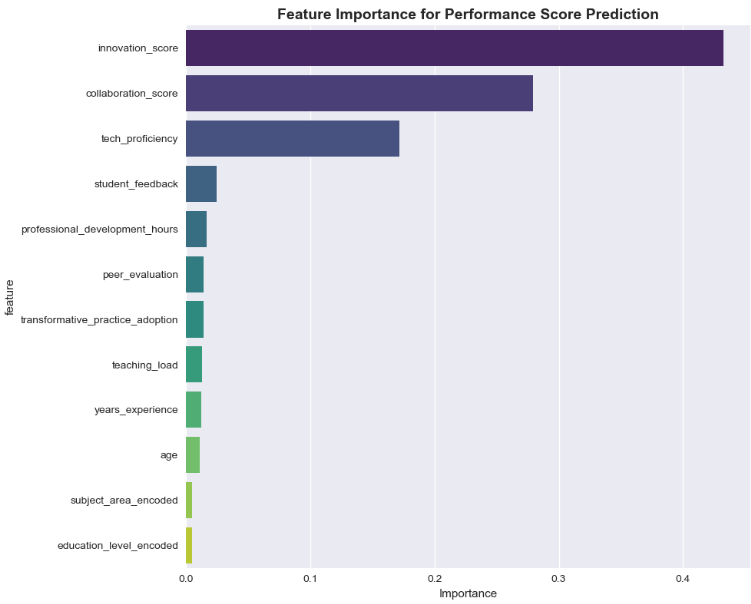
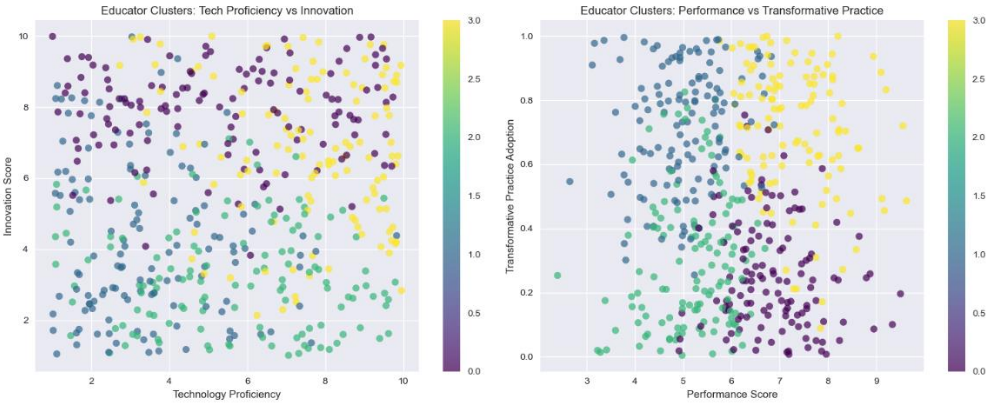


Figure 12. Feature Importance for Performance Score Prediction

Figure 12 shows the values of the Important Scores for Performance Prediction, which are dominated by the Innovation Score, Collaboration Score, and Technological Proficiency, with values greater than 0.1 importance value. The rest, with values less than 0.1 significance, include student feedback, professional development hours, peer evaluation, adoption of transformative practices, teaching load, years of experience, age, encoded field of study, and encoded education level. Next is Clustering Analysis, consisting of Educator Clusters, namely Tech Proficiency vs Innovation and Performance vs Transformative Practice, as shown in Figure 13.



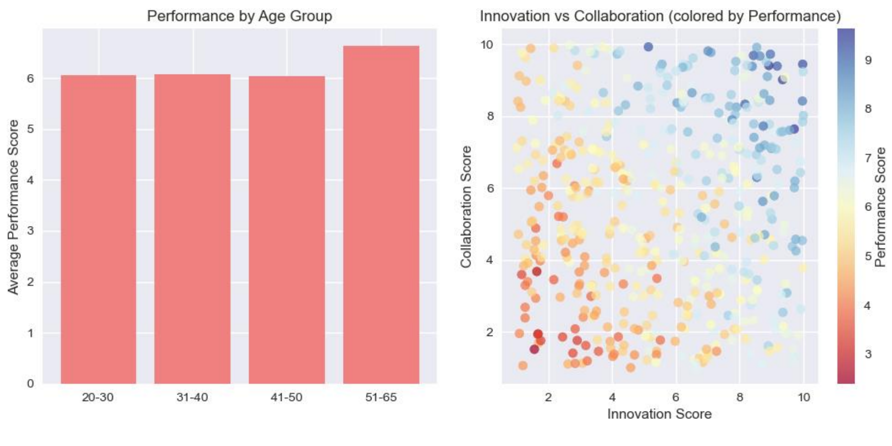
(a) (b)

Figure 13. (a) Educator Clusters: Tech Proficiency vs Innovation (b) Educator Cluster: Performance vs Transformative Practice

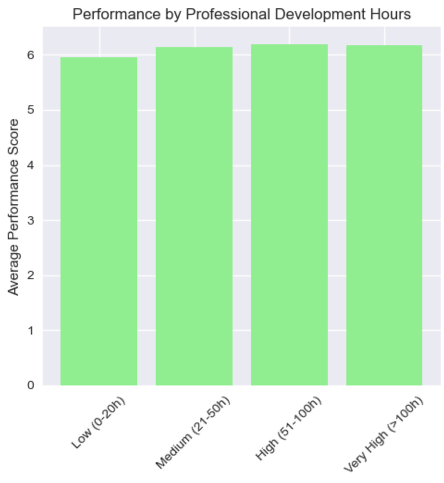
Table 5. Cluster Characteristics

Cluster	**Tech Proficiency**	**Innovation Score**	**Collaboration Score**	**Performance Score**	**Transformation Practice Adoption**
0	5.407823	7.876887	5.726574	6.869896	0.253488
1	3.463086	4.237234	4.710947	5.027220	0.715427
2	5.686036	3.219349	4.551211	5.185966	0.300223
3	7.528301	6.761251	6.641531	7.319352	0.710908

In addition, Table 5 shows the Cluster Characteristics values consisting of Clusters 0, 1, 2, and 3. These characteristics include the variables of Technological Capability, Innovation Score, Collaboration Score, Performance Score, and Application of Transformation Practices. Specifically, Figure 14 displays Performance based on Age Group, Comparison of Innovation versus Collaboration, and Performance based on Professional Development Hours. Meanwhile, Figure 15 shows the results of the analysis of the variables Teaching Load vs. Performance, Student Feedback vs. Peer Evaluation, and Distribution of Transformative Practice Adoption.

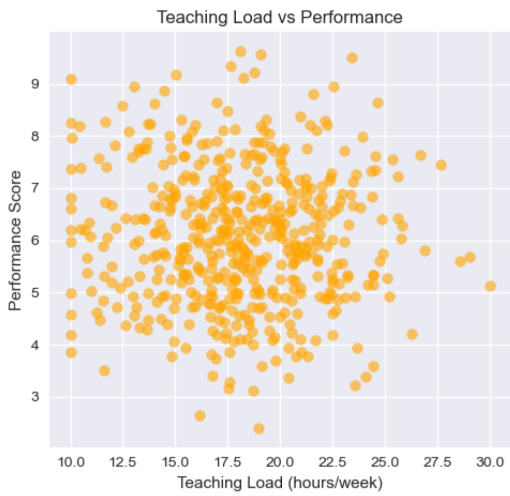


(a) (b)

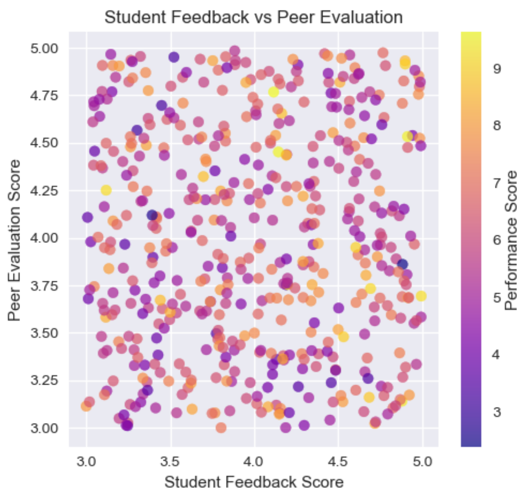


(c)

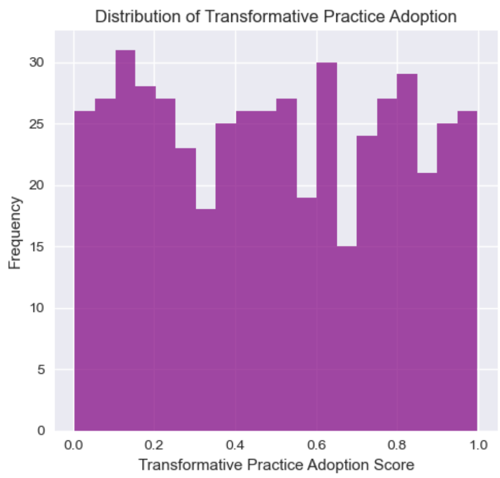
Figure 14. (a) Performance by Age Group, (b) Innovation vs Collaboration (Colored by Performance), (c) Performance by Professional Development Hours



(a)



(b)



(c)

Figure 15. (a) Teaching Load vs Performance, (b) Student Feedback vs Peer Evaluation, (c) Distribution of Transformative Practice Adoption

From the Key Insights and recommendations data, some analysis is obtained, namely Performance Drivers, among others, have Innovation Score value most important factor of 0.432, Technology Proficiency is the Second most important at 0.279, and Collaboration Score Third most important by 0.172. For performance distribution, Good by 44%, Average by 43.6%, Excellent by 7.6%, and Need Improvement by 4.8%. As for Cluster Analysis Insights consists of Cluster 0, 127 educators, Average Performance. Average Performance: 6.87, Tech: 5.41, Innovation: 7.88, Cluster 1: 129 educators, Average Performance: 5.03, Tech: 3.46, Innovation: 4.24, Cluster 2: 126 educators, Average Performance: 5.19, Tech: 5.69, Innovation: 3.22, Cluster 3: 118 educators, Average Performance: 7.32, Tech: 7.53, Innovation: 6.76. Cluster Analysis Overview consists of: Cluster 0: 127 educators, Average Performance: 6.87, Technology: 5.41, Innovation: 7.88, Cluster 1: 129 educators, Average Performance: 5.03, Technology: 3.46, Innovation: 4.24, Cluster 2: 126 educators, Average Performance: 5.19, Technology: 5.69, Innovation: 3.22, Group 3: 118 educators, Average Performance: 7.32, Technology: 7.53, Innovation: 6.76. The final analysis is the Application of Transformative Practices, which consists of: 153 educators (30.6%) are high adopters, the average performance of high adopters is 6.09, and the average performance of low adopters is 6.13.

Conclusion

Machine Learning can evaluate and understand the process of understanding how the implementation of the transformative school model can be implemented and how effectively this implementation can be done and analyzed. Machine Learning in this research applies three algorithms, namely Classification Algorithm, Clustering Algorithm, and Regression Algorithm, and analyzes in detail how these three algorithms provide specific results about the pattern of the Transformative School. In the Clustering Algorithm, the process of sorting parameters based on clusters is determined by how similar the values can be so that the spread of each cluster is not so wide. One of the indicators used is the Centroid, where the Centroid is a point that is used as a reference point for the value obtained from a comparison of existing parameters, for example, the parameters of education level and age, the closer it is to the average of the overall respondents in qualitative research will prove that it is the location of the centroid and it becomes a measuring point for how the other distribution, the distribution of data talks about the inequality of perception, so the more spread the data is, it needs to be clarified again what mistakes or incompatibility.

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