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Student Clustering Based on Subject Grades: A K-Means Approach to Clustering Study Groups

Rosita[1], Fitria[2]

[1,2]Department of Informatics Management, Universitas Negeri Surabaya, Indonesia
[1]rositarosita@unesa.ac.id, [2]fitriafitria@unesa.ac.id

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ABSTRACT

Student clustering based on academic scores is a strategic approach to improve learning effectiveness in vocational education. This study implemented the K-Means algorithm to group Vocational High School (SMK) students into three main clusters: Guidance Group (low scores), Potential Group (medium scores), and Excellence Group (high scores). The data used included scores from 12 subjects in the Computer Network and Telecommunication Engineering expertise program. The analysis results showed that clustering was able to identify student learning patterns and provide recommendations for appropriate learning strategies for each cluster. Cluster 1 requires intensive guidance, Cluster 2 can be directed to academic challenges, and Cluster 3 requires enrichment programs to optimize its potential. This study shows that data-driven approaches, such as clustering, provide significant benefits in supporting personalized learning and preparing students for the needs of the workforce.

1. INTRODUCTION

Education is one of the main components in improving the quality of human resources. This is in line with the goals of the 2030 Agenda for Sustainable Development [1], particularly Goal 4, which aims to ensure inclusive and equitable quality education and support lifelong learning for all. In the context of vocational education, one of the main challenges is designing effective learning strategies to encourage student development in accordance with the needs of the world of work. Vocational education focuses not only on mastering theory, but also on practical skills that prepare students to face the dynamics of the world of work. This education emphasizes technical and practical skills, while developing cultural human competencies in local, national, and global contexts, so that students are ready to directly enter the world of work [2], [3].

To meet these needs, a data-driven approach is needed that can accurately identify student characteristics, so that educators can develop learning strategies that suit the needs of each learning group. In recent years, advances in big data technology have had a major impact on the world of education, especially in the aspect of monitoring and improving the quality of teaching which is now increasingly being applied [4], [5]. Clustering, as one of the data analysis techniques, has been proven to have an important role in supporting educational development. The K-means algorithm, which is one of the unsupervised learning methods, is widely used to group data based on sample similarities by separating them into several different clusters [6]. The K-means method functions to group data points into certain clusters based on their similar characteristics, where the number of clusters, namely k, is determined by the user [7].

Research conducted by [8] shows that the K-Means algorithm can be used to classify students based on specific performance categories, such as excellent, good, and poor. The results of this study prove that clustering not only helps in analyzing student performance, but also supports improving the quality of teaching through the implementation of more targeted strategies. Similarly, a study conducted by [9] found that combining the K-Means algorithm with regression methods was able to identify factors that influence school dropout and predict dropout rates with a high degree of accuracy. This shows that clustering-based analysis has the ability to reveal deep insights into student learning patterns. The results of these studies confirm that clustering has great potential for use in personalized learning, especially in understanding student patterns and needs through data analysis.

Approaches such as clustering can help analyze students based on their grade patterns. This research aims to:
1. Grouping students based on their grades across 12 subjects using K-Means
2. Providing educators with insight into student groups that require a more personalized learning approach

In addition, this study identified three main clusters for use in the student learning group category, namely as follows:
- Cluster 1: Students with low scores are placed in the guidance group category
- Cluster 2: Students with high scores are placed in the superior group category
- Cluster 3: Students with superior scores are placed in the potential group category

Multidimensional data from student grades will be processed to identify distinct learning patterns in each cluster. The primary contribution of this research is its focus on the context of vocational education, where learning is designed to meet the specific needs of the workplace. Through the analysis of learning patterns in each cluster, this research is expected to serve as a reference for educators in providing specialized attention to specific student groups.

Thus, this research not only enriches the literature on the application of the K-Means algorithm in education but also provides practical benefits in improving the quality of learning at the vocational education level. The implementation of this cluster-based learning strategy is expected to help students reach their maximum potential according to the identified learning categories, thus better preparing them and helping educators design effective teaching strategies and data-driven classroom policies.

This article is structured as follows: Section 2 provides a literature review; Section 3 describes the data, methods, and concepts used; Section 4 presents the results and discussion; and finally, Section 5 concludes.

2. RELATED WORK

Various previous studies have shown that clustering in education provides various benefits, especially in supporting personalized learning. By grouping students based on similar grade patterns or characteristics, educators can develop more effective and targeted learning strategies. For example, [10] used machine learning technology to analyze teaching in university classes by utilizing multidimensional data, such as student attendance, academic performance, and grades. This study applied cluster analysis and association rule mining techniques, which were proven effective in improving the quality of teaching in the classroom. [11] also used various clustering methods, such as K-means, DBSCAN, Hierarchical, and Affinity Propagation Clustering, to group teaching strategies and classroom policies. In addition, research [9] found that the K-Means algorithm, when combined with regression methods, was able to effectively identify factors causing dropout and predict student dropout rates with good accuracy.

A study conducted by [8] used the K-Means algorithm (KMA) to analyze student performance reports, which successfully classified students into three performance categories: excellent, good, and poor. Through cluster analysis of student grades over four semesters, this study significantly improved the accuracy of grade prediction as well as the quality of teaching. Meanwhile, a study by [12] utilized the KMA algorithm to cluster student heart rate data, with the aim of evaluating teaching effects through analyzing changes in student emotions. The results of this study provide important insights into how to assess teaching quality. Furthermore, a study conducted by [13] developed a teaching reform evaluation methodology using the K-Means algorithm to cluster teaching effects, involving 26 Euclidean distance-based evaluation indicators. The study demonstrated that the K-Means algorithm is effective for data classification in an educational context.

This research aligns with previous studies that emphasize the benefits of clustering in education for personalized learning. The main contribution of this research is its specific application to Vocational High School students majoring in Computer Network Engineering and Telecommunications, utilizing multidimensional data from 12 subjects. Not only focusing on dividing students into specific clusters, this research will also provide an analysis of student learning patterns in each cluster, which is expected to serve as a reference for educators in designing more effective learning strategies. Thus, in addition to enriching the literature related to the application of K-Means in education, this research also provides practical benefits in improving the quality of learning at the vocational education level.

3. RESEARCH METHODS

To address the research objectives, the researchers used the data presented in Section 3.1. Section 3.2 provides a brief overview of the analytical methods used, which are then combined as described in Section 3.3. Finally, Section 3.4 explains the visualizations used.

3.1. Data

The data used in this study are the results of collecting student scores from 12 subjects taught in the Computer Network Engineering and Telecommunications expertise program at Rajasa Vocational High School Surabaya. These subjects include (1) Islamic Religious Education, (2) Pancasila Education, (3) Indonesian, (4) English, (5) Local Content in Regional Languages, (6) Mathematics, (7) History, (8) Science Project, (9) Physical Education, Sports, and Health, (10) Informatics, (11) Fine Arts, and (12) Basic Computer Network Engineering and Telecommunications. The research sample consisted of 35 tenth grade students where these scores reflect their academic performance in the even semester of the 2020/2023 academic year. This data was then analyzed to identify certain patterns or groupings of students into three categories to help educators in identifying groups of students who require special attention.

3.2. K-Means Clustering

One method frequently used in data analysis is clustering, which aims to group objects based on their similar characteristics. In this context, K-Means is the most well-known and widely used clustering technique due to its simplicity of implementation and flexibility in various data analysis cases. Clustering, in general, is a method for dividing objects in a dataset into several groups or clusters that have similarities [14]. Meanwhile, K-Means is one of the most popular and easy-to-implement unsupervised machine learning techniques [15], [16], [17], [18], [9]. The K-means algorithm begins by randomly selecting a number of initial clusters or groups along with their centroid values, then iteratively minimizing the total distance between each point and its respective cluster centroid, and grouping them [19], [20].

3.3. Concept of K-Means Clustering Algorithm

3.3.1. Inisitialize the initial centroid

In this study, we collected grade data from 35 students across 12 subjects, divided into three categories, or k = 3 clusters. Therefore, in the initial centroid initialization step, three centroids were randomly selected from the data.

3.3.2. Calculate the distance between each data point and the centroid to determine the closest cluster

In this step, calculate the distance using the Euclidean distance from each data point to each centroid.

3.3.3. Assign Data Points to the Nearest Centroid

Each data point is placed into a cluster based on its closest centroid. By calculating this distance, temporary clusters can be determined.

3.3.4. Update Centroid

Update the centroid position for each cluster by calculating the average value of the data included in that cluster.

3.3.5. Repeat until the cluster is stable

After the centroids are updated, recalculate the distances between the data and the centroids, adjust the cluster assignments if necessary, and update the centroids. Repeat this step until the cluster assignments or centroid positions no longer change. Repeating steps 3.3.3 and 3.3.4 is done until convergence is achieved, convergence occurs when the centers stop showing substantial changes or when a predetermined maximum number of repetitions is reached, so that the algorithm produces k final clusters, by placing each data point into the cluster corresponding to the nearest centroid [21].

4. RESULT AND DISCUSSION

4.1. Student Grouping Results

The application of the K-means Clustering method produces the number of main clusters with the centroid showing the average profile for each group. As shown in Figure 1, the graph shows the WSS (Total Within-Cluster Sum of Squares) value on the vertical axis and the number of clusters k on the horizontal axis. It can be seen that the WSS value decreases drastically between k = 1 to k = 3. At k = 3, the decrease in WSS begins to plateau (no longer significant), this point is called the elbow point. After k = 3, the decrease in WSS is not significant even though the number of clusters increases. Based on the Elbow Method graph, 3 clusters is the most optimal number.

This is in accordance with the research objective to group students into Guidance Groups (Remedial), Potential Groups, and Superior Groups. In accordance with the specified parameters (centers = 3), the data has been grouped into 3 clusters. From the analysis results, the cluster size is obtained, namely in cluster 1 there are 5 students, cluster 2 there are 22 students and cluster 3 there are 8 students. Furthermore, from this analysis, the average variable in each cluster is also known, as shown in Table 1.

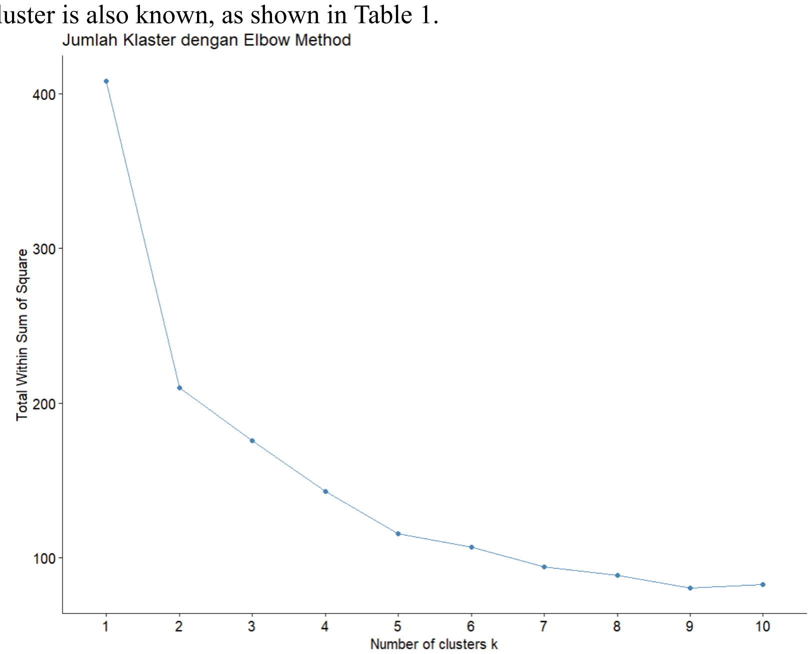

Figure 1 Number of Clusters with Elbow Method

Based on Table 1, the average of each variable in each cluster (Cluster Means) shows that Cluster 1 has a significant negative value in almost all subjects. This indicates that students in Cluster 1 have lower-than-average scores, thus requiring additional guidance or remedial work. Cluster 2 has positive values in almost all subjects, indicating that students in this cluster have high performance and are included in the superior group. Meanwhile, Cluster 3 has varied scores, with some subjects still below average but not extreme. This indicates that students in this cluster have average performance (potential) and need to strengthen the focus on weaknesses.

Table 1. Average of Each Variable in Each Cluster

Subjects	Cluster 1 (Bimbingan)	Cluster 2 (Unggul)	Cluster 3 (Potensial)
PAI	-1.32	0.35	-0.14
PNCSL	-2.03	0.51	-0.13
BIN	-1.68	0.57	-0.55
BING	-.1.69	0.50	-0.32
MTK	-.1.69	0.48	-0.27
BDAE	-1.88	0.39	0.09
SJRH	-1.15	0.63	-1.00
IPAS	-2.04	0.54	-0.21
PJOK	-1.62	0.30	0.17
INF	-1.42	0.36	-0.10
SNRP	-1.53	0.62	-0.75
KEJUR	-1.56	0.37	-0.04

In measuring the variation of data in each cluster, the Within-cluster sum of squares shows the results of measuring the variation of data in each cluster, namely cluster 1 obtained 58.03, cluster 2 obtained 72.88, and cluster 3 obtained 33.56. In addition, between_ss or total_ss = 59.7%. This means that 59.7% of the variation in the data can be explained by the division into 3 clusters. With a percentage of 59.7%, it can be said that the grouping is quite informative and the quality of the grouping can be considered quite good. The following in table 2 are the results of cluster grouping.

Table 2. Group Results Based on Clusters

ID	Cluster	Cluster Label
Siswa 1	2	Unggul
Siswa 2	1	Bimbingan
Siswa 3	2	Unggul
Siswa 4	3	Potensial
Siswa 5	2	Unggul
Siswa 6	3	Potensial
Siswa 7	2	Unggul
Siswa 8	3	Potensial
Siswa 9	1	Bimbingan
Siswa 10	2	Unggul
Siswa 11	3	Potensial
Siswa 12	2	Unggul
Siswa 13	1	Bimbingan
Siswa 14	2	Unggul
Siswa 15	2	Unggul
Siswa 16	2	Unggul
Siswa 17	2	Unggul
Siswa 18	2	Unggul
Siswa 19	3	Potensial
Siswa 20	3	Potensial
Siswa 21	2	Unggul
Siswa 22	1	Bimbingan
Siswa 23	3	Potensial
Siswa 24	2	Unggul
Siswa 25	2	Unggul
Siswa 26	3	Potensial
Siswa 27	2	Unggul
Siswa 28	2	Unggul
Siswa 29	2	Unggul
Siswa 30	2	Unggul
Siswa 31	2	Unggul
Siswa 32	1	Bimbingan
Siswa 33	2	Unggul
Siswa 34	2	Unggul
Siswa 35	2	Unggul

The visualization of the K-Means Clustering results in Figure 2 shows that the data is grouped into three clusters marked with different colors, namely cluster 1 marked in red with a circle symbol, cluster 2 marked in green with a triangle symbol, and cluster 3 marked in blue with a square symbol. Cluster 1 is located on the right and appears to have a fairly large area but has fewer members than the other clusters. This indicates that the variation of the data in this cluster is higher. Cluster 2 has a more elongated area with a fairly dense data distribution. This cluster appears to have the largest number of members compared to the other clusters. Cluster 3 is located in the middle with a smaller area, indicating that the data in this cluster is more concentrated and has lower variation. The centroid of each cluster is also shown as a larger symbol in each cluster. This centroid represents the average position of cluster members in the visualized dimension. The horizontal axis Dim1 shows that 64% of the data variation is explained by this dimension. Meanwhile, the vertical axis Dim2 shows that 8.1% of the data variation is explained by this dimension.

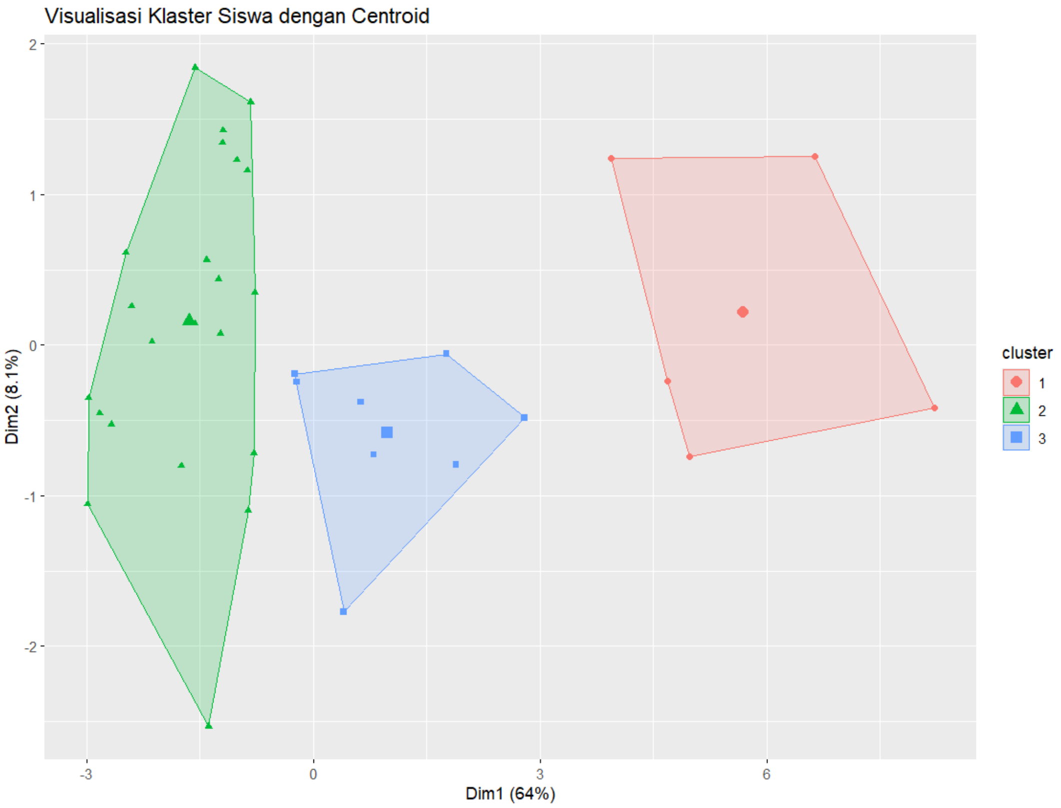

Figure 2. Visualization of Clustering Results

Based on the visualization results, it can be concluded that clustering successfully divided the data into three groups with separate distributions and clear centroids. Cluster 1 has greater internal variation, while Cluster 3 appears more compact. Most of the data variation can be explained by the first dimension (Dim1), which dominates the explanation of total variation.

4.2. Clustering for Vocational Education

4.2.1. The relationship between value patterns and clustering

a. Students in Cluster 1 (Guidance Group)

Students in this cluster had significantly negative scores in almost all subjects, indicating low performance compared to the average. This cluster had the fewest members, at 5 students, but had quite high data variation with a Within-Cluster Sum of Squares (WSS) of 58.03. Students in this cluster require additional guidance or remedial programs to improve their understanding of the material and basic skills. Recommended learning approaches include more structured instruction, the provision of supporting modules that facilitate understanding of basic concepts, and intensive mentoring through peer tutors or support teachers. Furthermore, it is important to provide additional motivation to students in this cluster to increase their motivation in the learning process.

b. Students in Cluster 2 (Superior Group)

This cluster comprises 22 students, the largest among the other clusters. Students in this group have positive grades in almost all subjects, demonstrating superior and consistent academic performance. This cluster has a dense data distribution with a WSS of 72.88, reflecting a group of students who are actively engaged and ready to accept more complex learning challenges. Recommended approaches include providing accelerated programs, participation in academic and non-academic competitions, and opportunities to lead collaborative projects in class. Furthermore, students in this cluster can also be directed to contribute as mentors or peer tutors to students in other clusters, which not only helps other students but also improves their leadership skills.

c. Students in Cluster 3 (Potential Group)

Students in this cluster have varying scores, with some subjects performing below average, but not extremely so. This cluster consists of eight students with lower internal variation than other clusters (WSS of 33.56). Students in this group show significant potential for growth with appropriate intervention, particularly in strengthening weaknesses in specific subjects. This group requires enrichment programs designed to maximize their potential.

Enrichment programs can include project-based learning activities, specific skills training relevant to industry needs, or academic challenges designed to broaden horizons and enhance problem-solving skills. By providing additional support in the form of enrichment programs, students in this cluster can develop further and achieve higher academic performance.

4.2.2. Opportunities for application in learning strategies

The results of this clustering provide valuable insights for educators in designing more adaptive and data-driven learning strategies. The clustering results can be implemented in various ways, including:

a. Create a More Personal Teaching Plan

Clustering allows educators to understand the specific needs of each group of students based on their grade patterns. With this information, educators can develop more personalized and relevant teaching plans. For example, guidance group or cluster 1 focuses on developing a remedial learning program specifically designed to help students grasp basic concepts that are still difficult. The teaching plan should be more intensive with an individual or small group approach. Meanwhile, the superior group or cluster 2 challenges students through technology-based projects, problem-based learning (PBL) activities, or advanced skill development to maximize their potential. Finally, the potential group or cluster 3 provides additional learning that focuses on reinforcing concepts in subjects where students are still weak and encouraging exploration to develop potential.

b. Developing an Evaluation Strategy Based on Specific Needs

Learning evaluation can be tailored to the needs of each cluster. For students in the guidance group or cluster 1, regular formative evaluations are implemented, providing quick and clear feedback so they can correct mistakes early. For students in the superior group or cluster 2, evaluation strategies can include project-based assessments, collaborative assignments, or challenging academic competitions to gauge deeper understanding. For the potential group or cluster 3, a combination of formative and summative evaluations can be used to monitor student progress and identify areas for further improvement.

c. Allocating Learning Resources Effectively

The implementation of clustering allows schools and educators to allocate learning resources, such as time, teaching staff, and learning aids, more effectively. Students in guidance group or cluster 1 prioritize teacher time allocation, more interactive teaching media, and additional supporting resources such as remedial modules and tutorial-based technology. Students in the superior group or cluster 2 allocate more complex learning resources such as access to technology simulations, digital laboratories, and more challenging enrichment materials. Meanwhile, students in the potential group or cluster 3 can focus resources on boosting student learning motivation by providing additional training, group tutoring, and the use of technology that facilitates in-depth concept exploration.

4.3. Limitations and Implications

This study has several limitations that should be considered. First, the sample size was relatively small, involving only 35 students, so the results may not be widely generalizable to a larger population. This small sample size may also affect the reliability of the statistical analysis and clustering results. Second, this study only used academic grades as the basis for clustering, without considering other factors that also influence learning, such as student motivation, learning behavior, attendance levels, or psychosocial conditions. These factors could provide more comprehensive insights into the dynamics of student learning. Third, the K-Means algorithm used in this study has inherent limitations, such as its inability to handle non-linear data or clusters with unbalanced sizes and shapes. Furthermore, the algorithm's clustering results are highly dependent on the initial centroid initialization, which could potentially produce suboptimal solutions if initialization is performed randomly.

The implications of this research underscore the importance of using multidimensional data in personalized learning, particularly in the context of vocational education. By considering various aspects of the data, including academic grades, motivation, practical skills, and even non-academic indicators such as interests and career inclinations, this data-driven approach can help educators design learning strategies that are more adaptive and relevant to individual students' needs. For further development, it is recommended that future research utilize more sophisticated methods, such as fuzzy clustering algorithms, which are capable of handling data with unclear or overlapping cluster boundaries. Furthermore, the use of artificial intelligence-based methods, such as artificial neural networks or decision tree algorithms, can help identify more complex patterns in the data and provide more accurate and robust results.

5. CONCLUSION

This study successfully applied the K-Means algorithm to group students based on their academic scores into three clusters with unique characteristics. This clustering provides valuable insights for personalized learning strategies in vocational education. Students in the Guidance Cluster require intensive approaches, such as additional tutoring or remedial programs. Students in the Potential Cluster require reinforcement in specific subjects through project-based learning or specialized training programs. Students in the Excellence Cluster can be optimized through acceleration programs and involvement in collaborative projects. The results of this study support the importance of using multidimensional data to understand student needs and design more adaptive learning strategies.

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AUTHOR BIOGRAPHY

	**Rosita** is a lecturer in the Department of Informatics Management, Surabaya State University, Indonesia. She earned a Bachelor of Education (S.Pd.) from Surabaya State University in Information Technology Education. She also earned a Master of Education (M.Pd.) from Surabaya State University in Vocational Technology Education. Her primary research interests are the Development of Computer-Based Learning Media and Innovative Technology-Based Learning Models. She can be contacted via email at rositarosita@unesa.ac.id.
	**Fitria** is a lecturer in the Department of Informatics Management, Surabaya State University, Indonesia. She earned a Bachelor of Education (S.Pd.) from Makassar State University in Informatics and Computer Engineering. She earned a Master of Education (M.Pd.) from Makassar State University in Technology and Vocational Education. She also earned a Doctorate (Dr.) from Makassar State University in Vocational Engineering Education. Her primary research interests are the Development and Implementation of Online Learning Models. She can be contacted via email at fitriafitria@unesa.ac.id.