School Profiling in Indonesia Based on Scholastic Ability Using Cluster Analysis

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Abstract. Evaluation of Education is an essential part of improving the quality of Education. This aims to classify the top 1000 schools participating in the 2021 UTBK in the Scholastic Potential Test. Using K-Means cluster analysis, this study involves four parameters to classify these schools into six main clusters. Quantitative Ability, Reading and Writing Understanding, General Reasoning, and General Knowledge and Understanding are parameters. The results of this study indicate that the cluster is advance, high intermediate, and intermediate of 272 schools with an average score interval of 567 to 684. While the 3 clusters below are 728 schools. Therefore, it is recommended for these schools to improve their non-optimal parameters of scholastic ability so that educational attainment will be more optimal.

Keywords: UTBK · Scholastic Potential Test · K-Means · Clustering

1 Introduction

Seleksi Bersama Masuk Perguruan Tinggi Negeri (SBMPTN) is one of the pathways for acceptance of prospective new undergraduate students in higher education to predict the ability of prospective students to complete their study period at State Universities (PTN) [1–3]. The SBMPTN is held by the Lembaga Tes Masuk Perguruan Tinggi (LTMPT) with the Computer-Based Written Examination (UTBK) method, where SBMPTN participants are students who have graduated from high school in a maximum of the last three years [4]. SBMPTN is a high-stakes test because students' career success can be determined through this test, so Computer-Based Written Examination (UTBK) has become a prominent phenomenon due to its high competitiveness [5].

In its implementation, the UTBK consists of a Scholastic Potential Test, Academic Ability Test, and an English Proficiency Test where the development of test material on the UTBK has been carried out based on comparative studies in several countries that have carried out the selection of new student candidates by an independent and credible test service institution. The Scholastic Potential Test aims to measure the cognitive abilities needed by prospective students who are predicted to be able to complete their

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studies in higher education [6]. The Scholastic Potential Test (TPS) construction is based on an understanding of intelligence [7]. Several studies have shown that TPS has a relationship with intelligence tests and that the Scholastic Potential Test can predict student achievement as a selection criterion for tertiary education [8]. The same thing was conveyed by Krisna, I. I. that the Scholastic Aptitude Test, or what can be referred to as TPS, can predict student learning achievement [9]. TPS is also made to measure students' problem-solving skills, communication, and ability to understand complex problems, which are critical components in successful careers [10].

The scope of TPS is the quantitative ability, ability to understand reading and writing, general reasoning ability, knowledgeability, and general understanding. Quantitative ability tests measure knowledge and mastery of basic mathematics [6]. The quantitative ability test also aims to measure the ability of reasoning or numerical logic, namely the ability to solve problems related to numbers using basic mathematical concepts. In the quantitative ability test, a verbal subtest is used to measure verbal logic skills, namely the ability to solve oral problems in nature, and contains elements of language. The general reasoning ability test measures an individual's logical ability, including evaluating the truth of a conclusion and using logic to construct the findings [7].

An evaluation is needed in working out how far the school program is running well or not, as stated by Wrightstone. et al. that evaluation in education is used to estimate the growth and development of students towards the goals and values in the curriculum [21]. Sartina et al. added that evaluation is one of several vital activities in improving the quality of education [11]. The National Examination (UN) also could be used to evaluate the concept of educational evaluation. Although the UN is a debate to be used as a national evaluation tool, the UN is no longer held again [12]. As an evaluation tool, schools can use the UTBK scores to measure the achievement of learning programs in schools. Based on the results of the 2021 UTBK distributed by LTMPT, the top 1000 schools were obtained from the number of schools from which the 2021 UTBK participants came from as many as 23,110 schools in Indonesia. With details of the test results of TPS, TPA Saintek, and TPA Soshum. The LTPMPT also describes the results of each TPS indicator from the 1000 schools. The results of the UTBK obtained can represent the quality of education in Indonesia, especially at the secondary school level. One way to describe the quality of education is to classify it into several clusters. Clustering is a method for grouping data into groups with characteristics that are as similar as possible and different from objects in other collections. The set aims to see the same profile and parts of the things that have been determined [13].

Several previous studies related to clustering analysis, namely the clustering of SMA based on the results of the National Examination (UN) and School Examination (US) to predict the quality of education in the Special Region of Yogyakarta [14]. In addition, another research using clustering is an analysis of high schools in West Java based on educational facilities to see the distribution of APBN funds in the education sector [15]. Research using clustering analysis was to group elementary and middle schools in Indonesia based on eight standards on national education standards with K-Means Fuzzy [16]. So based on this, researchers are interested in clustering the top 1000 participating schools for the 2021 UTBK based on the results of the Scholastic Potential Test to evaluate school achievement in helping students to develop the scholastic abilities needed by students at a higher level.

2 Method

A. *Data Mining*

Data Mining is a study to predict trends, correlations, and patterns in large amounts of data. According to Sjuchro, Dian W et al., data mining is a search for patterns in extensive data that were previously unknown. Usually, the data owned is researched so that the data becomes more reliable, and data mining can be used for important decisions, especially decisions related to strategy [22]. Tools used in data mining for classification, clustering, grouping, and estimation include K-Means, Improved K-Means, Partitioning around Medoids, K-Medoids, Fuzzy C-Means, etc. [22]. Data mining is developing very rapidly; many companies have spent billions of rupiah to collect large amounts of data to get conclusions related to strategies for the company's development [23].

B. *Clustering*

One of the clustering techniques in data mining is the clustering method. The clustering method in data mining is grouping several data or objects into clusters (groups) so that each data in the same set has characteristics that are as similar as possible and different from things in other collections. There are six functions in data mining, including:

i. *Function description*

When the data has been successfully processed, patterns are complex for readers to understand. Therefore researchers and analysts simply try to find ways to describe the patterns and trends contained in the data. Descriptions of these patterns and trends often provide possible explanations for a design or direction.

ii. *Estimation function*

Estimation is almost the same as classification, except that the estimation target variable is more numerical than categorical. The model is built using a complete record that provides the value of the target variable as the predicted value. Furthermore, in the following assessment, the estimated value of the target variable is made based on the value of the predictive variable. For example, we will estimate systolic blood pressure in hospitalized patients based on the patient's age, gender, weight index, and blood sodium level. The relationship between systolic blood pressure and the value of predictive variables in the learning process will produce an estimation model. The resulting estimation model can be used for other new cases.

iii. *Prediction function*

Prediction is almost the same as classification and estimation, except in predicting the value of the results in the future. Examples of predictions in business and research are:

1. Prediction of rice prices in the next three months.

2. Predict the percentage increase in traffic accidents next year if the lower speed limit is increased.

iv. *Classification function*

In the classification, there are target categorical variables. For example, income classification can be separated into three categories: high income, medium income, and low income. Then to determine the payment of an employee, a classification method is used in data mining.

v. *Grouping function*

Clustering is grouping records, observing or paying attention, and forming classes of objects that have similarities. A cluster is a collection of documents with similarities and dissimilarities to other groups' records.

vi. *Association function*

The association task in data mining is to find attributes that appear at once. In the business world, it is more commonly called shopping cart analysis. The association looks for a combination of goods to be sold for the next month. There are two types of clustering methods: Hierarchy and Non-Hierarchy [23]. A hierarchical Cluster is an unsupervised Learning clustering technique that involves creating clusters in a predetermined order. Sets are sorted from top to bottom. In this type of clustering, similar clusters are grouped and arranged hierarchically. It can be further divided into two types, namely agglomerative hierarchical clustering and Divisive hierarchical clustering. At the same time, Non-hierarchical Clustering involves the formation of new clusters by merging or separating sets. It does not follow a tree-like structure like hierarchical clustering. This technique groups data to maximize or minimize some evaluation criteria. K-Means Clustering is an effective way for non-hierarchical clustering. In this method, the partitions are created so that groups that do not intersect have no hierarchical relationship among themselves [24].

One of the clustering methods that have efficient and fast properties that can be used is the k-means method; this method aims to make object clusters based on attributes into k partitions [24]. K-means has a weakness caused by determining the initial center of the group. The results of the cluster formed from the K-means method depend on the initiation of the initial center value of the given collection. The development of the application of the k-means process includes the selection of distance space, how to reallocate data to clusters, and the objective function used. K-Means has also been developed to be able to model datasets that have a unique shape using kernel tricks; several problems need to be considered in using the K-Means method, including different clustering models, selecting the most appropriate model for the analyzed dataset, failure to converge, outliers detection, the shape of each cluster and overlapping problems.

vii. *Selecting K Best Number of Cluster*

In the clustering process, the most fundamental thing is cluster selection. So that the clustered data can be interpreted properly, it is necessary to select a cluster that is suitable for use [17]. With the selection of clusters that match the data, analyzing the results will make more sense. Several methods can be used in the current cluster selection, such as the silhouette score and the elbow method. Kaufman and Rouesseeuw (1990) found this method uses an index approach that compares the distance within the cluster to the distance between clusters, where the bigger the difference, the better the fit [17]. Specifically, the silhouette score $s(i)$ is defined as:

$$s(i) = \frac{b(i) - a(i)}{\max(a(i), b(i))} \tag{1}$$

where $a(i)$ represents the average distance between the $i-th$ data point and all other data points in the same cluster, while $b(i)$ represents the average minimum distance between the $i-th$ data point and all other data points in every other cluster. The silhouette score value lies in the range of -1 to 1. If the silhouette score value is around 0, , it means that the data point can still be included in other clusters (not yet stable). If the value is close to -1, , it means that the data point is in the wrong cluster (into the wrong cluster). If the value is close to 1, it means that the data points are well grouped. The level of validity in clustering is characterized by the average silhouette score of each individual. If many different K clusters are given, and the largest average silhouette score is obtained, then the K value will be chosen as the number of clusters because it can separate each data point very well [19].

In addition to using the silhouette score, in determining the best number of clusters, the elbow method can also be used. The elbow method utilizes the calculated value from Within Sum of Squares (WSS). WSS is the average distance between each data point to the nearest cluster center point or centroid. So, logically according to the definition, the smaller the WSS value, the better the cluster. Specifically, WSS is defined as:

$$WSS = \sum_{i=1}^{N_c} \sum_{x \in C_i} d\left(x, \overline{x}_{C_i}\right)^2 \tag{2}$$

where C_i is the $i-th$ cluster, N_c is the number of clusters, x_{C_i} is the centroid cluster and x is the data point [20]. So in this study, these two methods were used to select the best cluster that could be used to separate or group the data held so that the analysis process could be clearer and with the best results.

3 Discussion

a. *Clustering Process*

The first step in analyzing the results is to cluster the data, the method used in this study is to use the K-Means clustering method. This method is used because K-Means is a clustering method by partitioning so that the data used will be grouped based on the distance between each point. Thus, it is possible that the results obtained from this method can be easily analyzed. The algorithm used in the clustering process using K-Means is as follows:

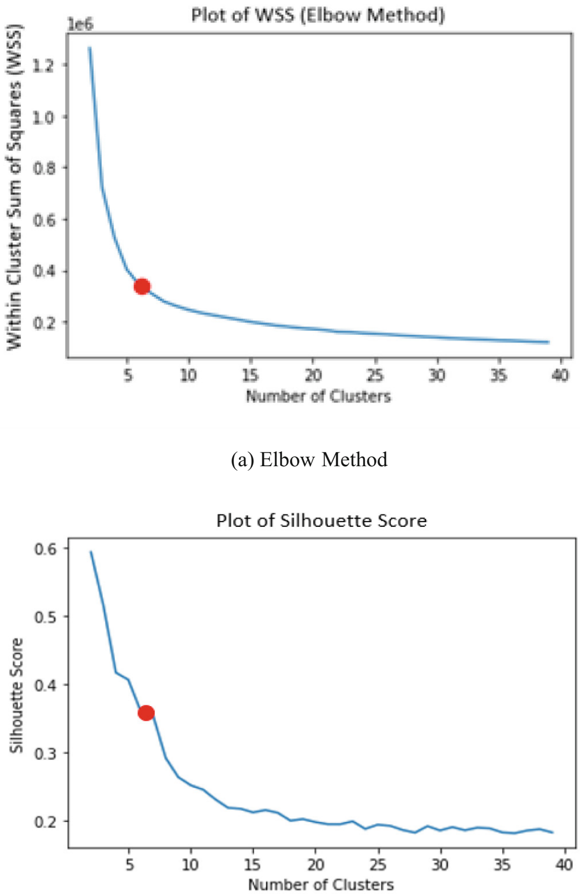
i. *K-MEANS ALGORIRTHMS*

1. Specify the number of k of clusters to assign.

2. Randomly initialize k centroid (cluster center) using random selection from the data.
3. **Repeat:**
4. **Expectation:** Assign each point to its closest centroid.
5. **Maximization:** Compute the new centroid (mean) of each cluster.
6. **Until:** the centroid positions do not change (convergence).

In the process of selecting the best k clusters, two methods are used, namely the silhouette score and the elbow method by calculating the WSS value. The results of the cluster selection analysis using the two methods are shown in Fig. 1:

In Fig. 1, the results of the WSS and Silhouette Score calculations are presented starting from $k = 2$ to $k = 40$. The results show that if you look at the WSS value when $k = 6$ the values have begun to converge or there is no significant difference after that, this value is excellent to use if only look at the WSS value. However, it turns out that



(a) Elbow Method

(b) Silhouette Method

Fig. 1. Cluster Select Method

when $k = 6$, the silhouette score is still relatively high compared to the silhouette score for other k values. Therefore, the value of $k = 6$ is very well used to group data in other words the data used in this study will see the difference and it is very good to analyze if grouping it into 6 clusters.

The results of the centroid or center of the cluster from the K-Means process with 6 clusters are shown in Table 1:

The results of the cluster which are visualized by performing dimension reduction first using principal component analysis (PCA) are presented in Fig. 2:

From Fig. 2, it is found that the cluster results are by the theory, namely, if the WSS and Silhouette Score selected are the best values, the clustering results will also be good. It can be seen that the data is very clearly separated between clusters. This shows that the results of the cluster are very well used for analysis.

b. *Descriptive Statistics*

The data in this study is secondary data for the 2021 UTBK scholastic potential test, which consists of quantitative ability test data (X_1), reading and writing comprehension

Table 1. Centroid results of each cluster with k-means

Cluster	Quantitative Ability	Reading & Writing Comprehension	General Reasoning	General Knowledge and Understanding
Advanced	654.93	622.18	627.39	631.87
High Intermediate	604.37	595.54	600.39	600.47
Intermediate	575.88	573.95	577.10	574.48
Low Intermediate	553.93	558.13	560.32	556.44
Good	534.31	542.66	542.96	539.02
Satisfactory	516.44	528.06	526.21	523.72

Fig. 2. Plot of Used Data in Each Clusters

(X_2), general reasoning (X_3), and general knowledge and understanding (X_4). This data comes from the top 1000 schools in Indonesia obtained from the LTMPT website. The following are the results of the descriptive statistics for this study's variables.

Based on the table, quantitative ability (X_1) has an average of 548,669 with a minimum score of 490,572 from Banten province and the maximum score from schools in DKI Jakarta province. The average score on the ability to understand reading and writing (X_2) is 552.8243, where the minimum score is 498.062 from school in the area of Bali, and the maximum score is 660.578 from school in the province of DKI Jakarta. General reasoning ability (X_3) has an average of 553.757 with a minimum score of 495.654 from Central Java province and a maximum score of 665.89 from school in DKI Jakarta province. The ability of general knowledge and understanding (X_4) has an average of 551.159 with a minimum score of 496.739 from school in the area of Lampung and a maximum score of 678.915 from school in the province of Banten. Based on the table, the maximum values for the parameters (X_1), (X_2), and (X_3) came from local schools in the DKI Jakarta province. However, it can be seen that the quantitative ability (X_1) has the highest standard deviation of 36.2824, which means that the distribution of the data is getting broader and more varied. Based on the data obtained, the schools included in the top 1000 schools come from 31 provinces in Indonesia, meaning that three sections are not included, namely the provinces of Papua, West Sulawesi, and North Sulawesi.

c. *Clustering*

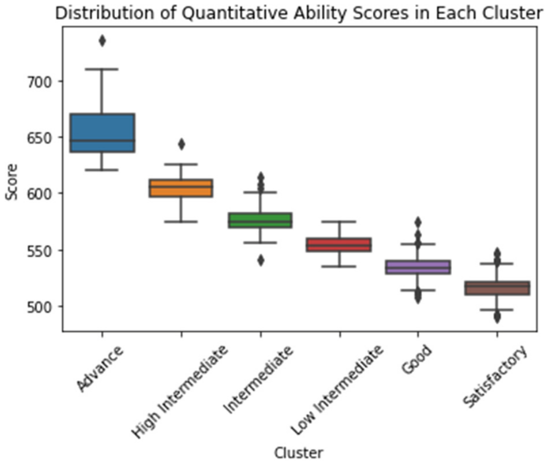
Based on the cluster analysis with K-Means conducted by the researchers, there were 6 clusters with categories: Advanced, High Intermediate, Intermediate, Low Intermediate, Good and Satisfactory (Fig. 3).

Based on the results of clustering using K-Means (see Fig. 1), it can be seen that there are certain value intervals for each cluster. Still, it is pretty challenging to determine a school with a specific score can be categorized into a group without using statistical tools, therefore in this study will then find the characteristics of each cluster with the aim of these characteristics being a clustering standard for a TPS value obtained by a school.

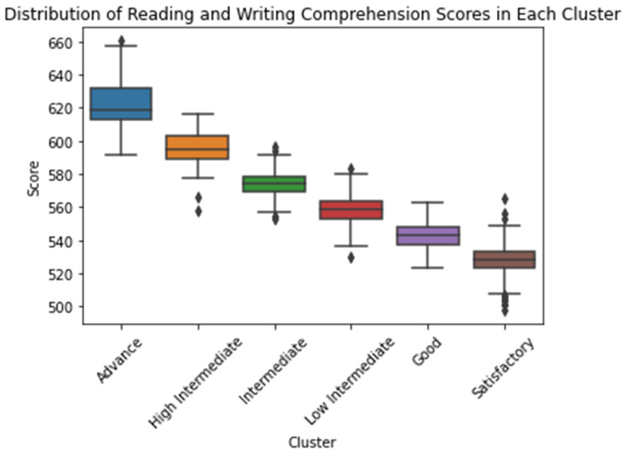
By using the formula for the number of classes of Sturgess rules, namely, $k = 1 + 3.3logN$, where N is the number of participants for the 2021 UTBK, which is 777,858 participants. Hence, $k = 1 + 3.3log777.858 = 20.4420$. Because the lowest

Table 2. Descriptive Statistics

Parameters	Mean	St. Deviation	Minimum	Maximum
Quantitative Ability (X_1)	548.669	36.2824	490.572	735.338
Reading & Writing Comprehension (X_2)	552.8243	26.763	498.062	660.578
General Reasoning (X_3)	553.757	28.803	495.654	665.89
General Knowledge and Understanding (X_4)	551.159	30.04327	496.739	678.915



(a)



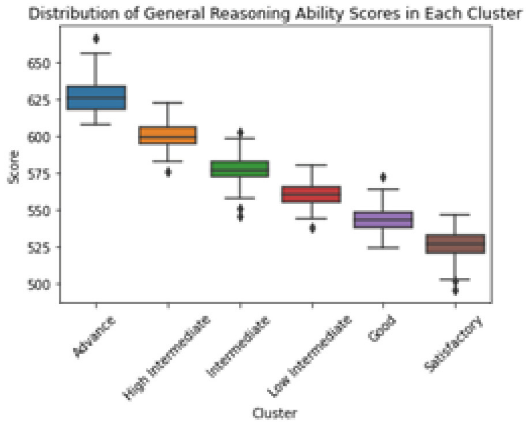
(b)

Fig. 3. Result of Clustering

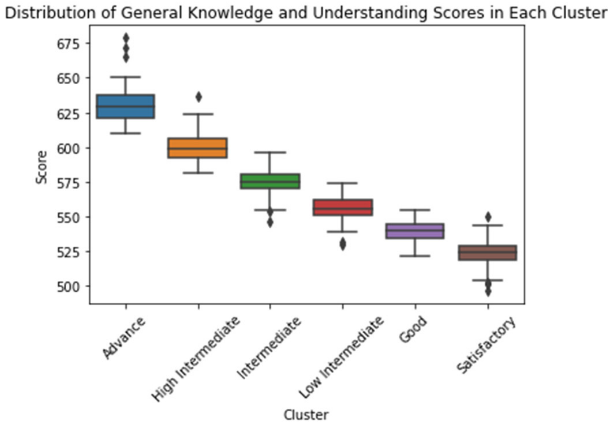
value of UTBK is 100. The highest is 1000, so the grouping of values is obtained as follows.

After grouping the scores, the researcher observed the characteristics of the scores for each school in each cluster. Each school was coded based on the group of values in the table for each variable on the TPS test, then the average value of each code was determined.

SMAN 2 Sidoarjo got a code 10 on quantitative ability because the score on that variable was 546.453. Code 10 was in the 505 to 550 interval (see table 3). In contrast,



(c)



(d)

Fig. 3. (*continued*)

reading and writing skills, general reasoning abilities, and general knowledge and understanding abilities get code 11 because the values in these variables are in the interval 550 - 595 (see table 2). Schools that are included in the Advanced Cluster have the same characteristics. Namely, they have an average code of 12 to 13.5 and have an average score in the interval of 619.2843 - 683.3403.

Meanwhile, schools in the Intermediate High Cluster have a code average in the gap from 11 to 12 and have an average score between 586.6208 - 617.8848. However, there is an overlapping of codes in the Advanced Cluster and High Intermediate Claster; namely, both clusters have code 12, so there are exceptional cases. If the TPS score shows that the school is in the code 12 category, but the average score is below 620, the school will enter the Intermediate High Cluster. Code overlapping also occurs in the Intermediate High Cluster and Intermediate Cluster, which have code averages from 10.75 to 11.25.

Table 3. Result of Grouping Schools Based on The Interval

Group Code	Interval	Group Code	Interval
1	100–145	11	550–595
2	145–190	12	595–640
3	190–235	13	640–685
4	235–280	14	685–730
5	280–325	15	730–775
6	325–370	16	775–820
7	370–415	17	820–865
8	415–460	18	865–910
9	460–505	19	910–955
10	505–550	20	955–1000

So that a particular case is needed as follows if the TPS score obtained is a school in category 11 or 11.25. Still, when the average score is above 588, the school will enter the Intermediate High Cluster, but if the TPS score is obtained, the school has an average below 588. There is at least one code of the variables in category 12; then, the school will enter the Intermediate High Cluster. The characteristics of each cluster can be seen in the following table:

Example:

To provide further explanation of the cluster characteristics in the table, the example in table 4 will be used that SMAN 2 Sidoarjo obtained an average code of 10.75, meaning that SMAN 2 Sidoarjo can enter the Low Intermediate or Good Cluster, but because the average value of SMAN 2 Sidoarjo is 554.34, which means it is above 548.6. Hence, SMAN 2 Sidoarjo is in the Low Intermediate cluster. A further example will be using the average score of all top 1000 schools to identify which group is Indonesia nationally. The following is the average data for the full 1000 schools per variable (Table 6):

From the data above, it can be concluded that Indonesia, as seen from the average of the top 1000 schools, is in the low intermediate cluster. Reviewing each group, the researchers use the Indonesian average (see table 5) as the passing grade for all schools to pass this standard. Of all schools included in the Advanced Cluster, it was found

Table 4. The Result of Sman 2 Sidoarjo.

School		Quantitative Ability	Reading & Writing Comprehension	General Reasoning	General Knowledge & Understanding	Average
SMAN 2 Sidoarjo	Score	546.453	556.228	560.335	554.345	554.34
	Code	10	11	11	11	10.75

Table 5. Characteristics Clusters

Cluster	Average Score Interval	Code	Special Case
Advance	619.284 - 683.34	More than 12	-
High Intermediate	586.621 - 617.885	11 - 12	Has the average code is 12, but the average value of TPS is below 620 Have a code average is 11 or 11.25, but the average value is above 588 Has an average below 587, and there is at least one variable getting a code of 12
Intermediate	566.323 - 587.808	10.75 - 11.25	Has the average code is 11, but the average value is below 588 Have a code average is 10.75 or 11, but the average value is above 566.3
Low Intermediate	544.792 - 571.549	10.25 - 11	Have a code average is 10.25 or 10.5 or 10.75, but the average value is above 548.6
Good	431.624 - 548.32	10 - 10.75	Has a code average of 10.25 or 10.5 or 10.75, but the average value is below 548.6 Has a code average of 10 or 10.25, but the average value is above 531.87
Satisfactory	505.73 - 532.683	9.5 -10.25	Has an average code of 10 or 10.25, but the average value is below 531.87

Table 6. Position Indonesia Based on The Average Per Variable

School		Average of Quantitative Ability	Average of Reading and Writing Comprehension	Average of General Reasoning	Average of General Knowledge and Understanding	Average of all Variables
Indonesia	Score	548.669	552.824	553.757	551.159	551.588
	Code	10	11	11	11	10.75

that no school had a Qualitative Ability score below the Indonesian average, which was 548.669. The same thing was also found in other variables, namely the Ability to Understand Reading and Writing, General Reasoning Ability, and General Knowledge and Understanding Ability there were no schools that scored below the Indonesian average. The same thing was also found in schools included in the Intermediate High Cluster; no schools scored below the Indonesian average.

In the Intermediate Cluster, 1 out of 138 schools, or around 0.725%, has a Qualitative Ability below the Indonesian average (548.669). Meanwhile, in the Ability to Understand Reading and Writing, no schools had scores below the Indonesian average (552.824). However, there are 2 out of 138 schools, or around 1,449%, that have a General Reasoning Ability score below the Indonesian average (553.757), and one school (0.725%) which has a General Understanding and Knowledge Ability score below the Indonesian average (551.159).

The number of schools in the Low Intermediate Cluster with a Qualitative Ability score below the Indonesian average (548.669) is 15 out of 153, or around 9.804%. Meanwhile, schools with the Ability to Understand Reading and Writing below the average (552.824) are 27 schools (17.65%). The number of schools that have a General Reasoning Ability score below the average (553.757) is 54 schools (35.29%), while schools that have a General Knowledge and Understanding Ability score below the average (551.159) are six schools (3.922%).

In the Good Cluster, there are 250 out of 262 schools, or around 95.42%, which have below-average Qualitative Ability scores (548.669) and 224 schools (85.50%) with below-average Reading and Writing Comprehension and General Reasoning Ability scores, and there are 251 Schools (95.80%) that have a value of General Knowledge and Understanding Ability (551.159) below the average.

For the Satisfactory Cluster, it was found that all schools (313 schools) included in this cluster had scores of Qualitative Ability, General Reasoning Ability, and General Knowledge and Understanding Ability below the Indonesian average, while in Reading and Writing Understanding Ability, there were 310 schools (99.04%) below average. Based on the discussion above, the clustering of schools that entered the top 1000 UTBK participants, it was found that there were 36 schools in the Advance Cluster, 98 schools in the Intermediate High Cluster, 138 schools in the Intermediate Cluster, 153 schools in the Low Intermediate Cluster, and 262 schools Good Cluster, and 313 schools in the Satisfactory Cluster. This shows that many schools in Indonesia still need to improve their scholastic abilities because this review was only carried out on 1000 of the 23,110 schools participating in the 2021 UTBK.

Further discussion in the Advance Cluster shows that the TPS UTBK achievement in schools for this cluster is outstanding. It is also interesting that 88.88% of these schools are from Java Island, and 5.55% are from Sumatra Island. In the Intermedia Cluster, it was found that 76.679% of schools included in this cluster came from Java Island, followed by 11.18% from Sumatra Island and 6.07% from Kalimantan, and the rest came from other islands. Based on the clustering conducted by researchers, it was also found that in the Intermediate Cluster, 84.05% of the schools came from Java Island, the schools from Sumatra with a percentage of 11.59%, and 1.44% from Bali and Sulawesi.

This means that most schools included in the 3 clusters above come from the island of Java.

Furthermore, in the Low Intermediate Cluster, schools originating from Java have a percentage of 79.73% and 11.76% from Sumatra. In addition, schools originating from Kalimantan and Sulawesi have the same rate of 3.26% and 1.36% from Bali, and 0.65% from West Nusa Tenggara. In the Good Cluster, 79.77% of the schools came from Java, 12.59% from Sumatra, 4.19% from Kalimantan, and 3.43% from other parts of Central and Eastern Indonesia. In the Satisfactory Cluster, researchers found that 76.67% of schools in this cluster came from Java, 11.18% from Sumatra, 6.07% from Kalimantan, Bali, 3.83%, and 2.23% from Central Indonesia and East.

Based on the explanation above, most schools that enter the top 1000 UTBK 2021 participants are controlled by schools from Java, meaning Indonesia is still an important issue that must be resolved immediately. Moreover, there are 3 (three) provinces in Indonesia that have not yet entered the top 1000, namely the provinces of Papua, West Sulawesi, and North Sulawesi.

d. *Feedback For School*

From the discussion above, the researchers advise schools for each cluster, namely for schools that are included in the highest group, namely the Advanced Cluster that the education distribution that already has excellent achievements in equipping students with the skills needed for education at a higher level, to maintain and even increase this achievement. Schools in the High Intermediate and Intermediate clusters have also had outstanding achievements, so it is the same as the Advance cluster to maintain and improve. The Low Intermediate has exemplary achievements but can improve students' reading and writing skills and general reasoning abilities. As for the Good Cluster and the Satisfactory Cluster, it is necessary to improve the overall capacity in the Scholastic Potential Test, which consists of quantitative abilities, reading and writing comprehension skills, general reasoning abilities, knowledge skills, and general understanding.

Based on the analysis carried out in this study, it is also expected to be a reflection in the future, especially for schools that are not included in the top 1000, to continue to improve students' abilities in every aspect of the potential test, not only to make students pass at certain universities but to equip students in preparing themselves for the challenges ahead. It is also important that based on Merdeka Belajar, the program of Ministry of Education and Culture that in the next new student university selection (SBMPTN) there will not test many subjects but only scholastic potential test where this test measures reasoning ability [25].

Considering that scholastic talent is a vital academic ability for all students, the school needs to evaluate and determine solutions both in the learning process and in improving the supporting elements in education in schools.

4 Conclusion

After conducting the clustering process of the Computer-Based Written Examination (UTBK) 2021 participating schools that entered the top 1000, it was concluded that many schools still need to improve students' scholastic abilities to prepare themselves for global challenges. In addition, government assistance is required in order to pay attention to the distribution of education more evenly, with the aim of quality education can also be felt by students from all islands in Indonesia so that the quality of education in Indonesia will be even better.

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