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Comparison of Fairness Conditions Comparison Study with Fuzzy C-Means and K-Means Methods

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Abstract

Comparison of Fairness Conditions Comparison Study using Fuzzy C-Means and K-Means methods. The development of the character of fairness in teachers is influenced by the environmental conditions in which they grow and develop. This can be a factor that can influence the development of the fair character of teachers in the provinces of Central Java and Lampung. Therefore, this research aims to explore the fairness conditions among teachers in Central Java and Lampung provinces through a comparative study. This research involved 970 teachers spread across the islands of Java and Sumatra. The cluster sampling technique was used to take research subjects. The Comparison research method with The Fuzzy C-Means and K-Means Methods was carried out to obtain evidence regarding the fairness characteristics in teachers in Central Java and Lampung Provinces. The system testing results using the Silhouette coefficient method produced values of 0.278 (Fuzzy C-Means) and 0.287 (K-Means), respectively. This value shows that K-Means outperforms Fuzzy C-Means because its value is close to 1. Furthermore, K-Means and Fuzzy C-Means obtain scores of 0.384 and 0.224, respectively, when evaluated with DBI. It can be concluded that Fuzzy C-means is superior to K-means because the lower DBI results show a good value close to zero. These results contribute to advocates of psychological assistance for teachers, that the characteristics of fairness conditions for teachers in the provinces of Lampung and Central Java are different. This analysis provides valuable insight into understanding the factors that influence teacher fairness in the two provinces and provides a basis for developing policies that are more effective in improving conditions of fairness in the education sector.

Keywords Comparison; Fairness; Students

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1. INTRODUCTION

Unfair behavior occurs in the teacher's social system as a relationship with interrelated components. One component that influences this is the fair character possessed by the teacher. Fairness

is one of the seven virtues that a teacher must possess and develop (Wagner, 2019). Teachers will strive to create a healthy social and community life with interactions between individuals and groups that exist in harmony through this character (Sivo et al., 2017). Various problems can arise for teachers when the character of fairness is not well developed (Suparwi, 2014). In their research results, Coyne et al. (2019) stated that the character of fairness has a significant relationship to the risk of violence, intimidation, aggression, intolerance, and other unfair behavior in teachers at school. However, teachers who have this character within themselves will be able to be fair to themselves and their environment, considering themselves to be the same creatures as other people. So, it is unlikely that individuals who have this character will be involved in violent behavior.

A study by Coyne and colleagues (2019) highlighted the relationship between the character of fairness and teacher behavior at school, especially in the context of the risk of negative behavior such as violence, intimidation, aggression, intolerance, and other unfair behavior. The research found that teachers with a fair character tend to be fair towards themselves and the environment around them, including their students and colleagues. They view themselves as part of the same community as others, minimizing the possibility of engaging in violent or harmful behavior. In other words, teachers who have the character of fairness tend to respect the interests and needs of other people and act based on the principles of justice and equality. They may better handle conflict peacefully and promote an inclusive and harmonious school climate.

This research shows that building the character of fairness in teachers can be essential in preventing negative behavior, such as violence in the school environment. Therefore, fostering the character of fairness among teachers can be an effective strategy for creating a safe and supportive learning environment for all individuals at school. However, character development *fairness* in teachers is influenced by various aspects. One aspect that influences it is environmental conditions. Therefore, reducing the risk of unfair incidents in schools needs to involve various components that are the focus of intervention. These components include the teacher's environmental system, psychological aspects within the teacher, as well as factual conditions regarding policies in the educational environment. The environment is one aspect that influences the formation of character and behavior for teenage teachers (Olweus, 2016).

The developers of positive psychology have tried to study several factors that can influence the development of the character of fairness. Seligman (2019) explains that based on experience, several conditions can shape character strength, including opportunities to study and work; a supportive and consistent family, a comfortable environment and school; political stability and democracy, along with the emergence of mentors, role models, supportive peers, and family, who play a direct role both inside and outside the home.

In line with positive psychology theory, which focuses on human strengths and virtues, as well as positive aspects of life, ecological theory also has the same understanding regarding the development of a person's character, which was introduced by Uri Bronfenbrenner, a psychologist from Cornell University in the United States (Bronfenbrenner. , & Morris., 1998). Ecological theory views that the environmental context influences human development. The reciprocal relationship between the individual and the environment will shape the individual's behavior (Bronfenbrenner, 1986). Information about a person's living environment to describe, organize and clarify the effects of varying environments. Ecological theory tries to see human interactions in systems or sub-systems.

One approach that can be taken to characterize the development of fairness character in teachers is to group them based on the factors that influence them. These factors include positive parenting, positive role models, and close relationships with family and peers (Lopez et al., 2018). These factors are interesting because, within the scope of psychosocial development and environmental psychology, individuals growing and developing into teenagers cannot be separated from the role of three other essential people: parents, peers, and teachers (Seligman, 2019). In the home environment, teenagers

often interact with their parents, while outside the environment, such as at school, teenagers interact with peers and teachers. Central Java and Lampung provinces have significant geographical, cultural, and socioeconomic differences. This study can reveal how these factors influence perceptions and conditions of fairness in the educational environment, providing valuable insights for more contextual adaptation of educational policies.

This research uses two clustering methods to compare the results, namely K-Means and Fuzzy C-Means. The K-Means method groups data based on the distance between the data and the central cluster, while the Fuzzy C-Means method is based on the degree of membership, which ranges from 0 to 1 (Zhou., & Yang, 2020). Previous research shows that both methods produce significant results with different group patterns. K-Means is very useful for classifying large amounts of data (Jamel., & Akay, 2019). Many analyses have been conducted using both clustering methods. Mingoti and Lima compared Fuzzy C-Means with several nonhierarchical clustering algorithms, such as K-Means and Self-Organization Map (SOM). The research found that Fuzzy C-Means produce better and more significant results than nonhierarchical clustering algorithms. This method is also proven to have better performance, stability, and overall robustness in data clustering. In addition, it is not affected by overlapping and outlier results, with an average recovery rate of 90% (Wiharto., & Suryani, 2020). Therefore, the grouping of environmental factors that influence the development of the character of fairness in teachers will be compared using these two methods algorithmically in this research. Thus, it is hoped that the results of this research can contribute knowledge in assisting teachers and school counselors in optimizing the development of the fair character of teachers in Central Java and Lampung Provinces. It is also hoped that this research can contribute to further research, which focuses on testing effective strategies in resolving various factors that influence the problem of unfair behavior carried out by teachers.

2. METHODS

This research was conducted using a quantitative design involving data in the form of numbers collected using a teacher burnout scale. Several stages carried out in this research include 1) data collection, 2) data preprocessing, 3) algorithm implementation, and 4) evaluation. The subjects of this research involved 970 elementary school teachers from various regions in Java (485 people) and Sumatra (485 people) using cluster sampling techniques. The teachers involved are classified into 2 categories of work period: 490 teachers have less than 10 years of service, and the remaining 480 have more than 20 years of service. Researchers use the fairness character instrument, which was previously developed by Mahfud (2023). This measuring tool has previously been developed based on the characteristics of teachers in Indonesia, so it is representative enough to be used in this research. The data collected in this research relates to aspects contained in the development of fairness character, which experts, including 1, have previously developed) utilization aspects; 2) appreciation aspect; 3) Obedience; and 4) Open attitude. The research stages were carried out through distributing instruments, data collection, analysis, and interpretation. The results of the analysis carried out in this research will describe the characteristics of the development of fairness character in teachers attending formal education institutions in Central Java and Lampung Provinces for each aspect (indicator) of fairness character.

Comparative analysis was used in this research to explore the fairness character of teachers in Central Java and Lampung provinces. The first analysis is the Fuzzy C-Means Algorithm. This analysis facilitates the creation of groups based on the degree of data membership. In this approach, determining data membership can be achieved through a degree score ranging between 0 and 1. Specifically, a data point has a membership score of 0 if it does not include members and 1 if it includes members from a fuzzy set. This analysis technique is used to explore various environmental factors that influence the development of the fairness character of teachers in Central Java Province. The second analysis for comparison uses the K-Means algorithm. This analysis uses distance to group data into several clusters

with the same characteristics. This technique is used to group factors that influence the condition of fairness among teachers in Lampung province. Evaluation is a crucial aspect that is then carried out in this research to ensure the algorithm's quality (Wiharto., & Suryani, 2020). In evaluating the performance of the Fuzzy C-Means and K-Means algorithm clustering, two standard methods are the silhouette coefficient and the Davies-Bouldin Index (DBI).

3. FINDINGS AND DISCUSSIONS

The dataset used is related to teachers' fairness in Central Java and Lampung provinces. Data was collected from August to October 2023. The data was then analyzed so that it could be compared. The following are the results obtained;

Fuzzy C-Means

Tabulated data obtained relates to various predictions that influence the condition of fairness among teachers in Central Java province:

Table 1. Respondent Data Matrix

X1	X2	X3	X4
60	56	64	62
58	85	57	52
49	37	52	43
58	78	78	80

Information:

X1: Utilization

X2 : Awards

X3: Obedience

X4: Open Attitude

Calculation of determining the initial value with the following conditions

Number of clusters : 3

Rank (W) : 2

Maximum Integration (Maxlter) : 1000

Error smallerst expected( ) _ : 10^{-6}

Function objectives : 0

Iteration starting : 1

The next step is to determine a random value in the form of an element matrix. Determination of three central clusters (Vkj) with equation 2. The calculation results in the first interaction are determined with equation 2 (figure 1)

$$V = \begin{bmatrix} 59.567 & 0.891 & 1.0449 & 0.976 \\ 60.257 & 0.910 & 1.0243 & 0.948 \\ 59.673 & 0.877 & 1.0603 & 0.969 \end{bmatrix}$$

Figure 1. First interaction calculation results

After carrying out the first iteration, the results obtained are P1 = 183119.163 and P0 = 0 because |P1-P0| = |183119.163 - 0| = 183119.163, which is less than the predetermined tolerance level of ξ (10^(-6)), and the current number of iterations is 1, less than the maximum limit of 1000. Therefore, the algorithm will continue to the next iteration, and the final result produces The following matrix representing the cluster center.

$$V = \begin{bmatrix} 60.448 & 52.253 & 56.113 & 54.435 \\ 72.039 & 67.682 & 69.593 & 65.791 \\ 47.693 & 41.309 & 42.399 & 41.673 \end{bmatrix}$$

Figure 2. Advanced interaction calculation results

Calculated value of objective function P33-P32 = 95866.086-95872.179 = 6.94E-07 >ξ(10-6). Therefore, it can be concluded that the objective value is smaller than the minimum error, as depicted in Figure 2.

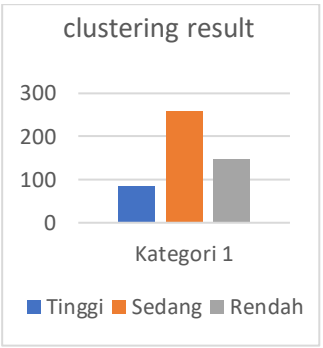


Figure 3. Clustering fairness graph (teachers in Central Java)

The graph above shows that the group that dominates fairness among teachers in Central Java province is in the middle position (Medium).

K-Means

At this stage, the data center is selected first. After that, the distance between the data and the center is calculated. Each record is placed in the group with the closest center. Furthermore, a data point closer to a certain data center will be placed into a data group. When all data points have been placed in their respective clusters, the next step is to calculate a new center using Equation 5. The iteration process continues until the data points become stable. The algorithm stops at 45 iterations in this case, and the final centroid matrix is presented below.

$$V = \begin{bmatrix} 46.274 & 41.5 & 40.559 & 39.744 \\ 72.635 & 69.627 & 70.481 & 65.788 \\ 60.318 & 50.202 & 56.100 & 54.679 \end{bmatrix}$$

Figure 4. K-Means interaction calculation

The following are the results of categorizing fairness conditions among teachers in Lampung Province.

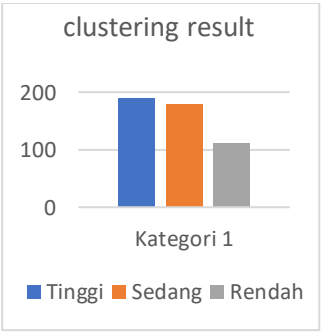


Figure 5. Clustering Fairness Graph (Teachers in Lampung Province)

Based on the graph above, the average condition of teacher fairness in Lampung Province is in the high and medium groups. If you compare Figures 3 and 5, you can see that there are differences in the characteristics of fairness conditions among teachers in Central Java and Lampung Provinces who are grouped based on where they live using the Fuzzy C-Means and K-Means algorithms.

Evaluation

In this study, the Silhouette coefficient and the DBI method were used to assess the quality of the grouping results (Sungheetha, 2020). The results are calculated by measuring each cluster's cohesion and separation of data points. On the other hand, DBI evaluates the distance between each data point and the centroid of its respective cluster. The silhouette coefficient is usually used to evaluate the homogeneity of grouping results (Jamel., & Akay, 2019).

The calculation results*Silhouette Coefficient*carried out on group data from the results of fuzzy C-Means calculations. After the results are obtained, the global value is determined using Equation 11.

Table 2. Global Silhouette Coefficient

Group	Amount of data	SI
1	145	0.284
2	221	0.299
3	129	0.252
	SI Global	0.278

Based on the calculated global silhouette coefficient value of 0.278, it can be concluded that the structure of the Fuzzy C-Means clustering algorithm is weak. Further testing of the fuzzy C-Means results was continued with the Daves Bouldin Index (DBI) with equations 12, 13, and 14. The DBI value was obtained by finding the most significant ratio value and dividing the results by the number of clusters, as in the image below.

$$DBI = \frac{1}{3}(1.254) = 0.224$$

The calculation results show that the DBI of the Fuzzy C-Means cluster is 0.224, so it is classified as being in good condition.

Next, evaluation is carried out using the same technique on the grouped data using K-Means. Through the same evaluation stages as fuzzy C-Means data, this calculation produces a Global Silhouette Coefficient value of 0.287, which indicates that the structure of the K-Means clustering algorithm is weak. This is following the evaluation of the Fuzzy C-Means algorithm using silhouette coefficients. Furthermore, the DBI values obtained in the K-Means data group are as follows:

$$DBI = \frac{1}{3}(1.152) = 0.384$$

Based on calculations, the DBI value resulting from K-Means clustering is 0.384, where the clustering results are in good condition. The DBI results show that Fuzzy C-Means clustering is better than K-Means, and the DBI value is also lower. Therefore, the results of Fuzzy C-Means clustering are close to ideal conditions where the DBI value equals zero.

Discussion

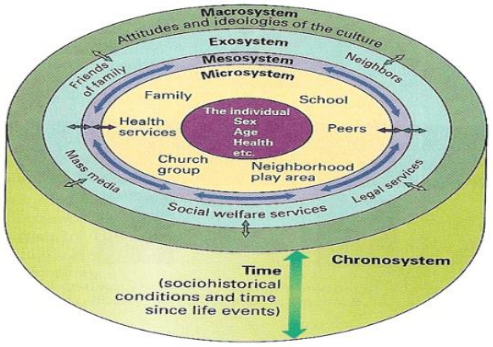
The results of comparative analysis using the fuzzy C-Means and K-Means methods have different characteristics of fairness conditions for teachers in Central Java and Lampung provinces. Therefore, it is essential to understand the various covariate factors that can influence the development of the fairness character of teachers in Central Java and Lampung. Several studies supporting the salience theory of

positive psychology have been conducted. Experiments conducted by Peguero and Bracy (2015) found that the development of the character of justice in teachers cannot take place just by relying on one factor but must involve all aspects of the teenager's closest environment. Wilbur et al. (2020) found that the most widely used strategy in developing justice character was the involvement of an approach based on the cognitive aspects of adolescents, while the least used was a multicultural approach. The results of research conducted by Biçer and Polatcan (2015) also support this research. They found that strategies involving a social justice approach can be used as a youth learning strategy in developing justice behavior in youth teachers. They explain that this is because teachers will be given an understanding of fair behavior, which is acceptable to everyone, before they change their behavior. Saydam (2018) determined the frequency of justice behavior learning strategies found in textbooks that were a source of teaching political-nationalism subjects and became references for teenagers.

In Indonesia, research has been carried out to improve the character of justice (Suparwi, 2014). However, its application still has several limitations, including the rationalization of research subjects in developing the character of justice in themselves. This is in line with what was found by Fall, Holden, and Marquis (2017), that one of the problems, according to cognitive-oriented counseling theory, is caused by disturbances in the cognitive system in the form of cognitive distortions or disorders.

The developers of positive psychology have tried to examine several factors that can influence the development of character strengths. Seligman (2019) explains that based on experience, several conditions can shape character strength, including opportunities to study and work; a supportive and consistent family, a comfortable environment and school; political stability and democracy, along with the emergence of mentors, role models, supportive peers, and family, who play a direct role both inside and outside the home.

In line with positive psychology theory, ecological theory also has the same understanding regarding human development introduced by Uri Bronfenbrenner, a psychologist from Cornell University, United States (Bronfenbrenner., & Morris., 1998). Ecological theory views that the environmental context influences human development. The reciprocal relationship between the individual and the environment will shape the individual's behavior (Bronfenbrenner, 1986). Information about a person's living environment to describe, organize and clarify the effects of varying environments. Ecological theory tries to see human interactions in systems or sub-systems. In simple terms, this interaction can be seen in the following picture:



Picture 6. *Concept of ecological theory*

The image above explains that these important recurring factors can shape character strengths and are exciting to study. These factors include positive parenting, positive role models, and close relationships with family and peers (Lopez et al., 2018). These factors are interesting because, within the scope of psychosocial development and environmental psychology, individuals growing and developing into teenagers cannot be separated from the role of three other essential people: parents, peers, and teachers (Seligman, 2019). In the home environment, teenagers often interact with their parents, while outside the environment, such as at school, teenagers interact with peers and teachers.

The fairness of teachers in Central Java and Lampung Provinces using the Fuzzy C-Means and K-Means algorithms provides an interesting picture. Interpretation of Clustering Graphs: Clustering graphs from the two provinces show differences in the characteristics of teacher fairness conditions. In Central Java, most teachers are in the medium group, while in Lampung, most are in the high and medium groups. This could reflect differences in factors influencing fairness in the two provinces, such as educational policies, school organizational culture, and socioeconomic factors.

K-Means shows that the conditions of teacher fairness in Lampung Province are more diverse compared to Central Java. This can be inferred from the spread of groups on the clustering graph and the higher DBI values. Fuzzy C-Means, even though it has a lower DBI value, shows that Fuzzy C-Means clustering is better than K-Means. Lower DBI values indicate better cluster distribution and more apparent separation between clusters. The Silhouette coefficient is used to evaluate the homogeneity of clustering results, while DBI is used to evaluate the distance between data points, the cluster center of mass, and the separation between clusters.

The evaluation results show that although the Global Silhouette Coefficient value for both clustering algorithms tends to be weak, the DBI value for Fuzzy C-Means is better than K-Means. Although both algorithms have their respective advantages and disadvantages, in terms of cluster separation and DBI value, Fuzzy C-Means perform better in this case.

4. CONCLUSION

This research succeeded in applying the Fuzzy C-Means and K-Means methods to explore the fairness conditions among teachers in Central Java and Lampung provinces. The system testing results using the Silhouette coefficient method produced values of 0.278 (Fuzzy C-Means) and 0.287 (K-Means), respectively. This value shows that K-Means outperforms Fuzzy C-Means because its value is close to 1. Furthermore, K-Means and Fuzzy C-Means obtain scores of 0.384 and 0.224, respectively, when evaluated with DBI. It can be concluded that Fuzzy C-means is superior to K-means because the lower DBI results show a good value close to zero. These results contribute to advocates of psychological assistance for teachers that the fairness character of each teacher is different because various environmental factors influence it. Therefore, psychological assistance to prevent them from experiencing problems of injustice must involve various environmental aspects that influence the condition of fairness among teachers. This analysis provides valuable insight into understanding the factors that influence teacher fairness in the two provinces and provides a basis for developing policies that are more effective in improving conditions of fairness in the education sector.

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