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ANALYSIS OF FUZZY C-MEANS IN PERSONALITY CLUSTERING BASED ON THE OCEAN MODEL

Jessicha Putrianingsih Pamput[1], Salsa Dillah[2], Aindri Rizky Muthmainnah[3], Dewi Fatmarani Surianto[4,*]

[1,2,3,4]Program Studi Teknik Komputer, Fakultas Teknik, Universitas Negeri Makassar, Makassar, Indonesia
Email: [1]jesspamput@gmail.com, [2]salsadillahsldyyy@gmail.com, [3]aindririzkymuthmainnah@gmail.com, [*4]dewifatmaranis@unm.ac.id

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Abstract

Personality is the pattern of an individual's behavior in daily life, reflected in their thoughts, feelings, and actions. The Big Five Personality Traits Model, known as OCEAN, helps to understand the complexity of human personality through five main traits. The identification and classification of personality, particularly among students, impacts academic performance, personal development, anxiety levels, and risky behaviors. Collaboration between educators, mental health professionals, and career advisors is crucial to creating an educational environment that supports students' holistic development. The Fuzzy C-Means (FCM) method is used to identify students' personalities with adequate accuracy. This study adopts the OCEAN model with FCM to efficiently locate and classify students' personalities. Data were obtained from 142 respondents, resulting in 27% of respondents being classified in cluster 1, 21% in cluster 2, 18% in cluster 3, 16% in cluster 4, and 18% in cluster 5. The optimal number of clusters was determined using the Silhouette Coefficient method, which achieved a maximum value of 0.347, indicating a good level of separation and compactness among the clusters. This study has important implications for students, educators, and educational institutions to understand that an individual's personality can influence learning patterns, social interactions, and decision-making processes.

Keywords: *Clustering, FCM, OCEAN, Personality, Student, Silhouette Coefficient*

**Corresponding Author: Dewi Fatmarani Surianto*

1. INTRODUCTION

Personality is a description of how a person acts and behaves in everyday life as well as in the work environment. A person's patterns of thoughts, feelings, and behaviors reflect his or her personality, which also influences the way individual complete tasks and achieve their goals [1], [2], [3].

Quoted from [1] personality is defined as *"karakteristik yang dimiliki oleh setiap individu untuk menunjukkan atau mencerminkan kecenderungan identitas melalui pemikiran, perilaku dan emosi sebagai hasil perpaduan dari sumber genetik dan pengaruh lingkungan"*. Thus, personality represents individual characteristics influenced by genetics and the environment, which are manifested through thoughts, behaviors, and emotions.

Different types of personality can be identified with different models or approaches. A widely adopted personality model is known as the *Big Five Personality Traits Model*, which includes five broad traits known by the acronym OCEAN. This model identifies five main dimensions of personality: Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism [1]. The OCEAN model provides a structured view in understanding the complexity of human personality, and helps analyze individual behavior and responses in various life situations. Based on the student context, the model provides a comprehensive framework for understanding individual behaviors, responses, and needs in diverse educational and social environments [4], [5].

Given the differences in personality types, this provides an opportunity for the identification and categorization of personalities in various groups, ranging from school-age to working people. Personality clustering among students is an area of study that has implications for various aspects of students' lives and their academic performance. Understanding how students are grouped by personality traits can provide valuable insights into their behaviors, learning preferences, and potential challenges they may face. By identifying these groups, educators can tailor their teaching methods to better meet students' varying needs and provide appropriate support to enhance students' learning experiences. Research has shown that personality groups among students can influence academic achievement, self-advancement, anxiety levels, and even the likelihood of students engaging in risky behaviors. [6].

Moreover, the importance of personality clusters among students goes beyond academic and mental health considerations. For example, research has shown that personality clusters can influence career preferences and inclinations towards certain professions or work environments[7].

From the above issues, personality clustering among students enables collaboration between educators, mental health professionals, and career counselors to create an educational environment that supports students' holistic development and determines their future career direction. Therefore, this study aims to categorize students based on the traits or characteristics of each individual so that it can facilitate a learning environment that suits individual needs to a supportive learning experience for students.

Several previous studies have used or adopted the *Fuzzy C-Means* (FCM) method on various objects and purposes, for example for clustering health center data. [8], clustering of stunting-prone areas [9], PDAM customer complaints[10], clustering of rice yields [11], to the determination of scholarship recipients [12]. However, this research uses objects that focus on grouping student personalities.

Previous research has included research on designing a student personality identification system using the *Fuzzy Tsukamoto* method, based on the personality types of melancholy, plegmatis and sanguinis which shows that the system is able to identify student personalities with an adequate level of accuracy [13]. While this research uses the OCEAN model approach using the FCM method.

In addition, another study was also conducted involving high school students as research subjects, the results of which showed the formation of two different *clusters* based on the level of procrastination and personality traits of students with the OCEAN and *Academic procrastination* model approaches. [14]. While in this study, the OCEAN model approach was carried out with the formation of five *clusters* representing each personality type.

There is also a previous study that grouped three personalities based on the OCEAN personality model by applying the *Myers-Briggs Type Indicator* (MBTI) method and dimensions to the object of research, namely employees at Campus 1 of Muhammadiyah University of Sidoarjo. The research aims to provide appropriate recommendations in recruitment, selection, and placement of employees at the university. [15]. While in this research, the OCEAN model personality clustering is carried out by applying the FCM method in personality clustering.

Based on previous studies, personality identification in students has significant importance in the context of customizing a comfortable learning style. Therefore, this study adopts the FCM method with the OCEAN model approach which aims to explore the extent of the influence of an individual's personality in the educational environment to the determination of their future career.

2. RESEARCH METHOD

The stages of this research were planned with the intention of achieving a systematic understanding and acting as a direction in completing the research. The structure of the sequence of stages is shown in Figure 1 below.

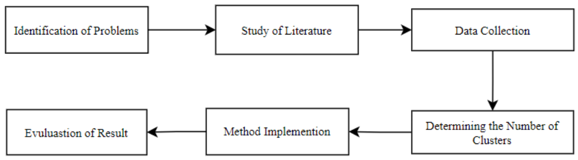

Figure 1. Research Stage

2.1 Problem Identification

At this stage, problem identification was carried out with the aim of gaining an understanding of the influence of one's personality. Observations were made on several students from different institutions in Indonesia, namely from the province of South Sulawesi and outside the province such as Kalimantan, Palangkaraya, and others. One of the issues identified was the role of a student's personality type in educational and social contexts, and its impact on learning methods, academic achievement, personal development, and even potential engagement in risky behavior. These issues have been described in detail in the introduction.

2.2 Literature Study

At this stage, a literature study was conducted through books as well as *reviews of* international journal articles and national journals relevant to the research under study. The purpose of this literature study is to gain an in-depth understanding of the research topic being investigated. The research articles reviewed need to be understood to know the previous research, identify the shortcomings of the research, and present a solid knowledge base to continue further research.

2.3 Data Collection

The data collected is the result of distributing a questionnaire consisting of 30 statement items that reflect each personality type of the OCEAN model. The use of Likert scale is used with the target respondents of students aged 15-24 years. The Likert scale has the following ratings: 1 for "Strongly Disagree", 2 for "Disagree", 3 for "Neutral", 4 for "Agree", and 5 for "Strongly Agree".

The statements used to represent each personality can be seen in Table 1 below.

Table 1. Representative Statement for each personality

No.	Statement
1	I feel that I am among those who have a high appreciation for art, culture and literature.
2	I feel that I am someone who has good organizational and planning skills.
3	I feel that I am someone who enjoys being the center of attention.
4	I feel that I am someone who makes others feel comfortable.
5	I feel that I am a person who worries easily and is easily offended.

2.4 Determining the Number of Clusters

Determining the number of clusters is done through evaluation using the Silhouette Coefficient, a method that calculates the closeness of each data point to its own cluster compared to other clusters. The Silhouette value indicates how well a data point fits in a particular cluster, where a higher value indicates that the object fits better in that cluster. The evaluation is done by comparing various cluster configurations, ranging from two to ten clusters, to find the number of clusters that gives the best results [16].

$$silhouette(O_i) = \frac{b(O_i) - a(O_i)}{max\,\{a(O_i), b(O_{i,})\}} \quad (1)$$

The Silhouette [17] calculation process involves measuring the average distance between data points and other points in the same cluster and other nearby clusters. Based on the formula used, the Silhouette value is obtained from the difference between the distance to other clusters and the distance to one's own cluster, which is then divided by the largest value between the two. The results of this evaluation help to ensure that the clusters formed are appropriate and provide optimal grouping [18].

2.5 Method Implementation

In this step, the data collected through the questionnaire will be processed into primary data which is then entered into the MATLAB *tool*. This research uses the *Fuzzy C-Means* method, where each data point in a cluster is determined by its membership level, which is then used for classification and determining the cluster center [12]. At this stage, the parameters are determined, including:

a. Weight: 2
b. Maximum Iterations: 100
c. Smallest Error: 0.0001
d. Initial Objective Function: 0
e. Initial Iteration: 1
f. Number of Clusters: 5 (1, 2, 3, 4, 5)

After setting the *clustering* parameters, the next step is to create the initial partition matrix and calculate the *cluster* centers. The objective function is calculated for each iteration to measure the distance of the data to the *cluster* center. The process continues by adjusting the membership degree of each data in each *cluster* through the calculation of changes in the partition matrix. A stop condition is checked to determine the end of the *clustering* process based on the difference in the objective function or reaching the maximum iteration. If it has not met the stopping criteria, the iteration continues. [19][20].

2.6 Evaluation of Results

After the implementation of the method, the results of determining and grouping the data into 5 *clusters* are obtained. The next step is to analyze the patterns that exist in each data to identify the factors that are the basis for grouping data into certain *clusters*.

3. RESULT AND DISCUSSION

At this stage, we will further discuss the data collection process and data processing carried out to obtain the results of data grouping. This process is very important to ensure that the information collected is relevant and can be processed with the right method to produce groups that suit the purpose of the research or analysis.

3. 1 Data Collection

Data collection in this study was conducted through observation of a number of students from various educational institutions in Indonesia, including South Sulawesi Province as well as areas outside the province such as Kalimantan, Palangkaraya, and others. In addition, researchers also used the method of distributing questionnaires consisting of 30 statements that reflect each aspect of the OCEAN model personality. The scoring was done using a Likert scale from 1 to 5 and lasted for 1 month. After distributing the questionnaire, 152 data were collected from students aged 15-24 years old. The data collected included information about the respondent's name, age, origin, gender, as well as responses to each statement presented in the questionnaire.

The personality assessment in this study is based on evaluations made by respondents of themselves in various aspects, ranging from social skills, behavior, to the decision-making process. The data collected from each respondent is represented in Table 2 below.

Table 2. Data Collection Results

No.	Respondent Name	Respondent's Answer				
		P1	P2	...	P29	P30
1	Elsa	3	3		3	3
2	Ziska	3	2		2	3
3	Faiz	5	3		3	3
...						
151	Ryandivanie	4	5		5	5
152	Wulandari	5	5		3	3

Description:
P1: Statement 1
P2: Statement 2
P29: Statement 29
P30: Statement 30

3. 2 Data Processing

From the 152 data obtained, a data cleaning process was carried out to eliminate consistently neutral answer patterns. In addition, from the 30 attributes initially collected, it was simplified to 5 attributes. The results of this data processing will be presented in Table 3 below, with the amount of data that has been filtered to 142 data. The data will be processed using MATLAB *tools* with the FCM method.

Table 3. Data Processing Results

No.	Respondent Name	Statement				
		P1	P2	P3	P4	P5
1	Ziska	2.666	3.166	2.833	3.166	2.833
2	Faiz	3.833	3.500	3.166	3.666	3.000
...						
141	Ryandivanie	3.500	3.333	1.333	3.500	5.000
142	Wulandari	5.000	4.000	1.833	3.500	3.666

Description:
P1: Statement 1
P2: Statement 2
P3: Statement 3
P4: Statement 4
P5: Statement 5

3. 3 Determination of the Optimal Number of Clusters

After data cleaning, the minimum number of clusters established for determining the optimal cluster count was set at 2, while the maximum was set at 10. The process of determining the number of clusters was conducted using MATLAB tools. Table 4 below presents the calculation results of the average Silhouette Coefficient values obtained from the evaluation of the tested number of clusters.

Table 4. Average Silhouette Coefficient Values Calculation Results.

Number of Clusters	Average Silhouette Coefficient
2	0.342535362723134
3	0.245833574069180
4	0.174878189234093
5	0.347477784590230
6	0.173183324168170
7	0.124411536710249
8	0.0433280555575585
9	0.0289871439327104
10	0.0808504757101267

Based on the determination of the optimal number of clusters, the highest Silhouette Coefficient value was observed at 5 clusters, with an average value of 0.347477784590230, while the lowest Silhouette Coefficient value was found at 9 clusters, with an average value of 0.0289871439327104. To clarify the visualisation of the average Silhouette Coefficient values, a graph illustrating the Silhouette Coefficient values for each cluster count is presented in Figure 2 below.

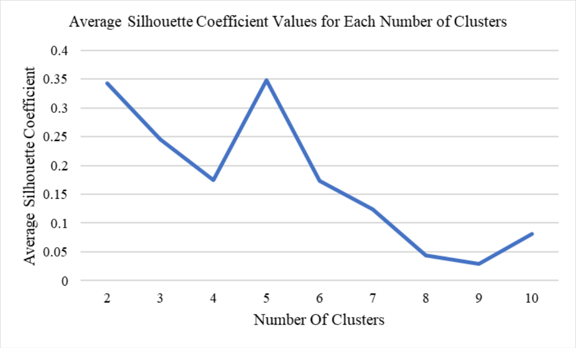

Figure 2. Graph of Average Silhouette Coefficient Values

After determining the optimal number of clusters, this cluster count will be used as the reference for further analysis in the implementation of the fuzzy c-means method, specifically for calculating the objective function values obtained at each iteration.

3. 4 Implementasi Metode Fuzzy C-Means

The data listed in Table 3 is entered into the MATLAB tool as the initial step in applying the Fuzzy C-Means (FCM) method. The parameters used for implementing FCM include a maximum number of iterations set to 100, a weighting factor of 2, a minimum error of 0.0001, an initial objective function value of 0, an initial iteration of 1, and a cluster count of 5. This cluster count is based on the evaluation of the optimal number of clusters determined in the previous stage using the Silhouette Coefficient. Attributes are converted into random numbers as elements of the initial partition matrix U, and cluster centre values are calculated for each attribute with a membership degree equal to 1 from each cluster. Based on the predefined parameters, the *cluster* center calculation results are shown in Table 5 below.

Table 5. Cluster Center Calculation Results

Cluster Center 1	3.515	3.583	3.206	3.677	3.732
Cluster 2 Center	3.405	3.650	2.903	3.736	3.153
Cluster 3 Center	2.886	2.998	2.167	3.376	4.004
Cluster 4 Center	4.087	4.295	3.772	4.193	4.099
Cluster 5 Center	3.240	3.359	2.916	3.414	3.021

Next, we will determine the objective function in each iteration which will be represented in Table 6 below.

Table 6. Objective Function Calculation Results

Iteration 1	94.49227
Iteration 2	72.04807
Iteration 3	71.97222
Iteration 4	71.87616
Iteration 5	71.72352
...	...
Iteration 82	68.9073
Iteration 83	68.90715
Iteration 84	68.90702
Iteration 85	68.90691
Iteration 86	68.90682

From the calculation results in Table 5 above, it can be observed that the iteration stops at the 86th iteration with an objective function value of 68.90682. This indicates that the iteration stopping condition has been met. Therefore, the final calculation result of this method is obtained which will be used for *cluster* formation. The results are represented in Table 7 below.

Table 7. Cluster Formation Calculation Results

No.	Respondent Name	C1	C2	C3	C4	C5
1	Ziska	0.116	0.201	0.126	0.035	0.519
2	Faiz	0.204	0.436	0.040	0.051	0.265
...						
141	Ryandivanie	0.176	0.152	0.420	0.108	0.141
142	Wulandari	0.225	0.234	0.169	0.181	0.189

Description:
The maximum value among the 5 *clusters* formed indicates that the relevant respondent data belongs to that *cluster*.

From the *cluster* formation results obtained, the pattern of personality levels owned by each *cluster* formed is identified. As shown in Figure 3, the value of each personality aspect tends to be stable except for extraversion personality which shows a significant difference. In *cluster* 1, *openness is* worth 3.57, *conscientiousness 3*.50, *agreeableness 3*.57, and *neuroticism* 3.73 while *extraversion is 3*.20. Therefore, it can be concluded that *cluster* 1 has a low *extraversion* personality level, while the *openness, conscientiousness, agreeableness*, and *neuroticism* personality levels are relatively stable, but *neuroticism is* more dominant. This shows that respondents in *cluster* 1 have personalities that tend to be anxious, easily stressed, emotionally unstable, and prone to negative feelings [1].

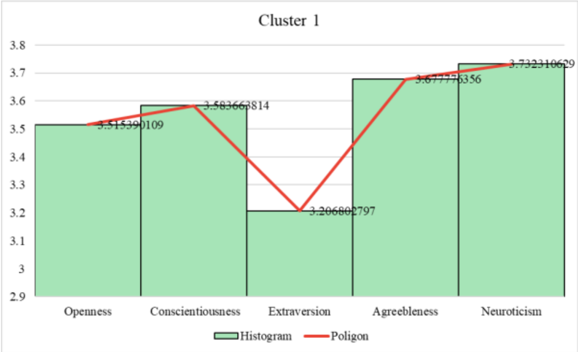

Figure 3. Personality Chart of Cluster 1

In *cluster* 2, the level of each aspect of personality tends to be stable, except for *extraversion* personality which shows significant differences. For example, *openness is* worth 3.40, *conscientiousness 3*.65, *agreeableness 3*.73, and *neuroticism* 3.15 while *extraversion is* 2.90. In *cluster* 2, *extraversion* personality tends to be low, while the levels of *openness, conscientiousness, extraversion,* and *neuroticism* are relatively stable. However, when viewed further, the highest value in *cluster* 2 is at the *agreeableness* personality level. This indicates that respondents in *cluster* 2 tend to be cooperative, trusting, kind, warm, soft-hearted, and helpful. [1], which is shown in Figure 4 below.

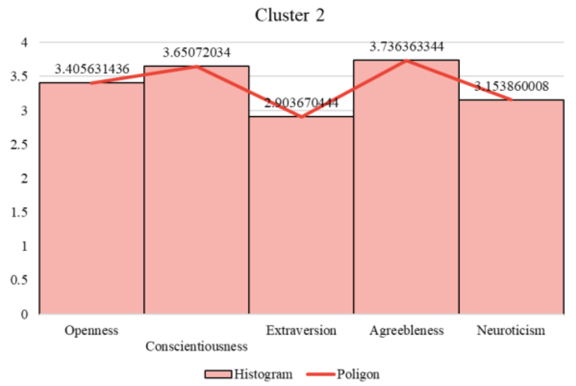

Figure 4. Personality Chart of Cluster 2

In Figure 5, the values of each personality tend to be stable, except for *extraversion* which shows a significant difference. In *cluster* 3, *openness is* 2.00, *conscientiousness* 2.99, *agreeableness* 3.37, and *neuroticism* 4.00, while *extraversion is* 2.16. From the polygon diagram below, in *cluster 3 the extraversion* personality level tends to be low, while the *openness, conscientiousness, agreeableness*, and *neuroticism* personality levels are relatively stable. However, when viewed further, the highest value in *cluster* 3 is the *neuroticism personality level*, which indicates that respondents in *cluster* 3 have personalities that tend to be anxious, easily stressed, emotionally unstable, and prone to negative feelings [1].

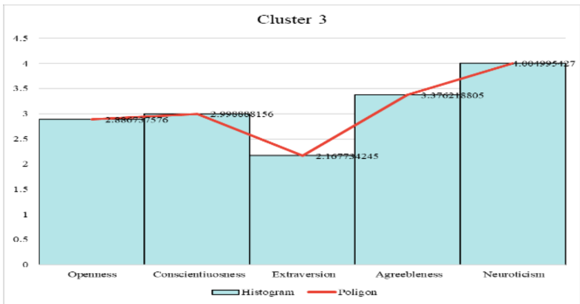

Figure 5. Personality Chart of Cluster 3

In Figure 6, the value of each personality tends to be stable, except for *extraversion* personality which shows a significant difference. In *cluster* 4, *openness is* worth 4.00, *conscientiousness 4*.29, *agreebleness 4*.19, and *neuroticism* 4.00, while *extraversion is* 3.77. It is stated that *cluster* 4 has a low *extraversion* personality value, and the personality levels of *openness*, *conscientiousness*, *agreebleness*, and *neuroticism* are relatively stable. However, the highest value in *cluster* 4 is the *conscientiousness personality* level, which indicates that respondents in *cluster* 4 have personalities that tend to be disciplined, responsible, diligent, and achievement-oriented [1].

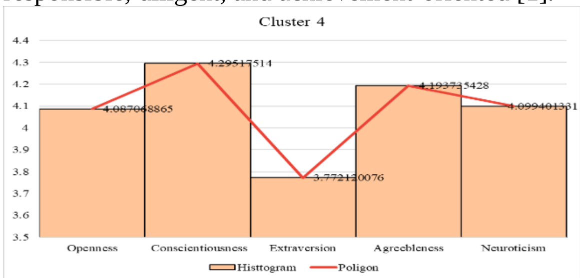

Figure 6. Personality Chart of Cluster 4

In Figure 7, the level of each personality tends to be stable, except for *extraversion* personality which shows significant differences. In *cluster* 5, *openness is* 3.24, *conscientiousness 3*.35, *agreebleness* 3.41, and *neuroticism* 3.02, while *extraversion is* 2.91. It can be stated that in *cluster* 5 the extraversion personality level tends to be low, while the *openness*, *conscientiousness*, *extraversion*, and *neuroticism* personality levels are relatively stable. However, the highest value in *cluster* 5 is the agreebleness personality value. This indicates that respondents in *cluster* 5 tend to have cooperative, trusting, kind, warm, soft-hearted, and helpful personalities [1]

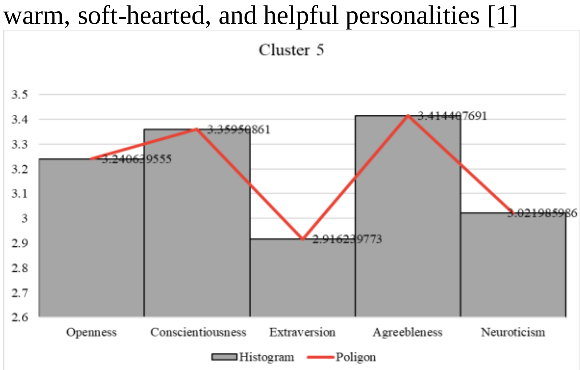

Figure 7. Personality Chart of Cluster 5

Based on the characteristic patterns of the five *clusters*, *it* can be concluded that the resulting *clusters* do not focus on one level of personality alone, but rather have diversity in all five aspects of personality with one aspect being dominant. As in *cluster* 1, *neuroticism is the dominant* personality aspect, followed by *agreebleness*, *conscientiousness*, *openness*, and *extraversion* as the lowest level of personality. *Cluster* 2 has *agreebleness* as the dominant personality level, *conscientiousness*, *openness*, *neuroticism*, and *extraversion* as the lowest personality level. In *cluster* 3, the *neuroticism personality level* is dominant, with *agreebleness*, *conscientiousness*, *openness*, and *extraversion*. *Cluster* 4 has *conscientiousness* as the dominant personality level, with *agreebleness*, *neuroticism*, *openness*, and *extraversion* as the lowest. Finally, in *cluster* 5, *agreebleness is* the dominant personality level, followed by *conscientiousness*, *openness*, *neuroticism*, and *extraversion.*

Table 8 shows the results of grouping the respondents' personalities based on the data obtained in Table 6 where 38 respondents are in cluster 1, 30 respondents are in cluster 2, 26 respondents are in cluster 3, 23 respondents are in cluster 4, and 25 respondents are in cluster 5.

Table 8. Results of personality grouping

Cluster	Respondent Name
1	Akhsan
	Nurul
	...
	Tereshia
	Taliho
2	Faiz
	Ian
	....
	Rizqi
	Wulandari
3	Hana
	Zahwa
	...
	Inggrid
	Ryandivanie
4	Syakira
	Suherni
	...
	Sandra
	Ela
5	Ziska
	Sham
	...
	Uswatun
	Juanne

4. CONCLUSION

Based on the research results, it can be concluded that the use of the fuzzy c-means algorithm successfully grouped students' personalities into 5 clusters based on the answers to the questionnaires given. Determination of the personality level was carried out by considering the more dominant aspects because each respondent had all five elements of personality but with one more prominent aspect.

Evaluation of the optimal cluster using the Silhouette Coefficient showed that 5 clusters were the optimal number with a maximum score of 0.347, which indicated good grouping. These results are essential for students, educators, and educational institutions to understand that individual personality can influence learning patterns, social interactions, and decision-making.

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