Clustering Students in The Online Learning Climate based on Internal and External Factors

by Wiyli Yustanti

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1st Wiyli Yustanti
Department of Informatics
Universitas Negeri Surabaya
Surabaya, Indonesia
wiyliyustanti@unesa.ac.id

2nd Naim Rochmawati
Department of Informatics
Universitas Negeri Surabaya
Surabaya, Indonesia
naimrochmawati@unesa.ac.id

3rd Yuni Yamasari
Department of Informatics
Universitas Negeri Surabaya
Surabaya, Indonesia
yuniyamasari@unesa.ac.id

4th Anita Qoiriah
Department of Informatics
Universitas Negeri Surabaya
Surabaya, Indonesia
anitaqoiriah@unesa.ac.id

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***Abstract*— The online learning environment is becoming a solution, growing in popularity, and accommodating variety of student lifestyles. This study wants to explain the profile of students who take online lectures based on internal and external factors that affect the learning process. Types of variables on internal and external factors have been found in previous studies. In this study, 22 variables were used with 15 indicators for internal factors, 7 indicators for external factors, and 91 data obtained from students who took the database course with the unsupervised learning approach for the clustering process. and getting the optimal number of clusters k=4.**

Keywords—unsupervised learning, k-means, online learning, internal factors, external factors

I. Introduction

The pandemic that has occurred since the beginning of 2020 has forced all educational institutions to conduct online learning. The success of a learning process involves several interrelated components, including aspects of content and designing, instruction, and learning methods, response, and providing assistance as well as evaluation for grading [1]. This concept explains the learning climate that is very influential on the quality and results of a learning process. The term climate is often associated with the weather which is defined as the meteorological conditions of an area or region. In relation to studying sciences, the learning climate refers to the social, emotional, and physical conditions in which a person acquires knowledge [2]. Wherever learning occurs, a climate of learning exists. The social, emotional, and physical impact of the learning environment greatly affects the learning experience.

Today, an online learning environment is becoming a solution, growing in popularity, and accommodating variety of student lifestyles. Many universities, high schools, and homes school associations take advantage of the online learning community, especially during this pandemic. Muilenburg and Berge [3] had reported the conclusion is about the principal factors that affect the results of the online learning climate are management structure, organizational change, technical experience, social interaction and quality, rewards and internship time, technical threats, legal issues, assessment/effectiveness, student access, and support. Lim and Morris [4] categorized a number of variables that affect course outcomes into four indicators: student characteristics, study habits, teaching variables, and course outcomes. In general, the variables that influence learning outcomes are divided into two factors, namely internal and external. Internal factors include physical, psychological, interests, and motivation as well as study habits. Meanwhile, external factors include the conditions of the home, school, community environment, facilities, and supporting access. This learning environment creates the need for strong research based on the students' characteristics in the online learning climate. This study will investigate the existence of groups in students' data based on internal and external factors that theoretically affect the results of the learning process. A clustering algorithm will be applied to reveal the hidden structured data.

II. Related Works

The previous research [5] has studied the possibility of using a data mining algorithm approach to predict student learning outcomes. The conclusion of the study states that the Neural Network (NN) ranks first for accuracy performance, the second is Decision Tree (DT). Next, Support Vector Machine (SVM) and K-Nearest Neighbor (KNN) provide the same accuracy, while the lowest prediction accuracy is shown by Naive Bayes (NB). The factors that affect the prediction accuracy are the variables used in the modeling stage. The selection of the prediction method is influenced by the type of dependent (target) variable. In general, there are two types of dependent variables, numeric and categorical. The regression model is appropriate for predicting the target variable with a numerical type, while for categorical using a classification model. Both approaches are included in supervised learning.

There are also many approaches to analyzing student learning outcomes through unsupervised learning. Unsupervised learning algorithms work by inferring models from data sets without making reference to recognized or labeled outcomes. In contrast to the supervised learning algorithms, unsupervised learning techniques cannot be applied straight to regression or classification cases because the target value is not known so that the training process cannot be carried out on this algorithm. However, unsupervised learning algorithms can be used to discover the fundamental structure of the data. The goal of unsupervised learning algorithms is to find previously unknown patterns in the data. Yamasari et al [6] has compared using the K-Mean and Fuzzy C Mean (FCM) methods to the cluster of students in academic data taken from the e-learning platform. The results of their study explained that the performance of the clustering process on student achievement can be increased through feature extraction based on the Categorical based

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Extraction Fuzzy C-Means (CBE_FCM) and Bloom's Taxonomy (BTBE_FCM) methods by looking at the aspects of the level of accuracy and execution time. Yamasari et al [7] also conducted a study to improve the validity of clustering through the silhouette index for academic data by reducing dimensions or features selection [8].

Some works related to the variables used in the analysis of students learning process can be shown by Madrid [9] which examines the relationship between internal and external factors in the teaching and learning process in foreign language courses. He mentioned that internal factors are aspects of students such as gender, social context, their self-confidence and experience, talent, age, affective state, cognitive characteristics, and personal attributes that help to comprehend the lesson. Then, external factors include the personality and characteristics of teachers and classrooms, giving a high correlation with student performance. Mirhadizadeh [10] also published her work about internal and external factors in foreign language learning. She mentioned that Internal factors are determined by individual students such as attitude, personal practice, motivation, and study behaviors. These factors are an individual part of the learner's ability to acquire a foreign language, but each aspect is interrelated. The paper also states that everyone's external factors are different, generally influenced by things outside of students' personal problems.

In the field of mathematics learning [11], the internal factor is The ability to understand language, especially the symbolic language of mathematics, often experiences difficulties and becomes one of the most significant factors in determining success or failure in solving problems. Next, the second major category of factors that affect student achievement are those that are not related to the test itself but to external factors. In this study, the external factors referred to are socioeconomic levels, family educational background, school climate, language background, and students' interest in mathematics.

Abdulrazzaq et al [12] conducted a research which investigated the factors influencing academic failure at the University of Karbala college of medicine. Their works found that time management has a large effect on students' performance. Family conditions such as parental divorce do not have a significant negative effect. Most of the students revealed that group learning outcomes were better than self-study. Ramli et al [13] also published their works in researching the association between external factors, internal factors and self-directed learning preparedness for medical students. The data analysis technique used is Structural Equation Modeling (SEM) with Partial Least Square (PLS) modeling. External factors used in this research are family and academic environment. Both variables were found to have a significant positive correlation with internal factors such as interest in learning, achievement motivation, and academic self-concept as well as the readiness for independent study of fourth-year medical students at Tadulako University. Indicators of readiness for independent learning are indirect.

Another study related to the analysis of internal and external factors that affect academic success in economics students was conducted by Maryanai et al [14]. They explained that internal factors such as intelligence, motivation, interest, attitude, and talent of students, then external factors including community, family, campus, nature and instrumental. They concluded that internal factors had a significant effect on the success of student achievement. Although both internal and external factors have a positive correlation to student learning outcomes.

A similar topic of a study presented by Navarro et al [15] is an analysis of the factors related to engineering student academic failure. The factors that are considered related to student career satisfaction are age, number of family members, working time, monthly income, daily expenses, and health. The results of statistical tests showed no significant correlation between students' satisfaction and interest. Meanwhile, students' achievement is associated with the internal factors, which are characteristics that only depend on the students themselves. On the other hand, external factors that influence students' satisfaction with their careers are family support, quality of teaching, teacher-student relationship, and quality of infrastructure; and the only correlated internal factor is the concept of self-understanding. Specifically, regarding the characteristics of students, Yu et al [16] further explored the relationship between students' personal well-being and university learning outcomes. The results show that individual well-being, measured at the start of university studies, positively predicts students' personal growth and academic performance after three years of study. The internal aspect of university participation (academic and peer learning) shows a significant mediating effect, while the external aspect (faculty experience and university environment) shows a significant mediating effect. However, the external aspect of student commitment also has a direct impact on personal growth and academic performance.

Aboagye et al [17] conducted a study aimed at exploring the challenges reported by college students in e-learning in the period of the coronavirus pandemic. The study revealed that accessibility factors which include internet connectivity, availability of compatible smartphones and laptops are the most important challenges faced by students in fully online learning situations. The results of further research indicate that students are not ready for a full online experience because there are social and teaching problems that must be overcome because these affect students' intention to study online.

III. Method

The framework of the method used in this study will be explained based on SEMMA approach, which was adapted from the SAS Institute as a data mining process. It has five steps (Sample, Explore, Modify, Model, and Access), resulting in the acronym SEMMA.

A. Sample

In this step, a subset of the large dataset is selected according to the model building. The purpose of this initial phase of the process is to recognize the indicators or factors (both internal and external) that affect the process. The gathered information is then selected in the categories of preparing and evaluating. For the case in this study, we use academic datasets collected from 91 students who have taken database courses by online learning platform. The survey was conducted to obtain answers related to the internal and external factors used. The indicators used for internal factors consist of 15 variables which include matters relating to the student's personality in the form of physical aspects, psychology, learning culture, motivation and interest in the subjects being followed. While external factors are more on aspects that occur outside the student's personality such as family support for online learning, for example, families provide learning facilities such as smartphones, laptops, internet access and a comfortable home learning atmosphere. The condition of the living environment is also suspected to have an effect, seen from the availability of electricity, telecommunication signals and geographical conditions.

TABLE I. FEATURES AND DATA OF STUDENTS DATA

Symbol	Feature	Type	Data Values
Internal Factors			
X_1	Gender	Categoric	0 = Male, 1=Female
X_2	Weight	Categoric	1= Underweight, 2 = Normal, 3 = Overweight, 4 = Obese
X_3	Glasses	Categoric	1 = Yes, 0 = No
X_4	Physical Health	Categoric	1 = Yes, 0 = No
X_5	Mental Health	Categoric	1 = Yes, 0 = No
X_6	Asking Activity	Categoric	1 = Yes, 0 = No
X_7	Answer Activity	Categoric	1 = Yes, 0 = No
X_8	Assigments Activity	Categoric	0 = Partly, 1 = All
X_9	Interest	Categoric	0 = Not, 1 = Rather, 2 = Yes
X_{10}	Time of Study	Categoric	1= < 5 hours, 2= $5 \leq t \leq 10$ hours, 3= > 10 hours
X_{11}	Availability of other materials	Categoric	1 = Yes, 0 = No
X_{12}	Actively seek tutorial	Categoric	1 = Yes, 0 = No
X_{13}	Repeating Study	Categoric	0 = No, 1 = Sometimes, 2 = Always
X_{14}	Doing Practice	Categoric	0 = No, 1 = Sometimes, 2 = Always
X_{15}	Discussion Activity	Categoric	0 = No, 1 = Sometimes, 2 = Always
External Factors			
X_{16}	Smartphone	Categoric	1 = Yes, 0 = No
X_{17}	Laptop	Categoric	1 = Yes, 0 = No
X_{18}	Internet	Categoric	0 = No, 1 = Sometimes, 2 = Yes
X_{19}	Home Environmenrt Support	Categoric	0 = No, 1 = Sometimes, 2 = Yes
X_{20}	Electricity	Categoric	1 = Yes, 0 = No
X_{21}	Area	Categoric	1 = Rural, 2 = Urban , 3 = Littoral
X_{22}	Ease of telecom-munication access	Categoric	1 = Worst, 2 = Middle, 3 = Best

B. Explore

In this phase, data exploration can be carried out with univariate or multivariate analysis by studying the relationship between data elements and identifying gaps in the data. The factors can affect the results of the analyzed studies and are highly dependent on data visualization. Prediction of the exact number of clusters will be approached with the Elbow technique. The elbow method is one of the procedures used to determine the number of clusters in dataset. This method is achieved by making a plot between the value of variation and the number of clusters. The outcomes of the plot will shape the curve and the points on the curve that make up the angle can be detected as a value as the number of clusters that can be used. The elbow method uses the results of the within cluster sum of squares (WCSS) calculation which measures the average squared distance from each point in the cluster to the cluster center.

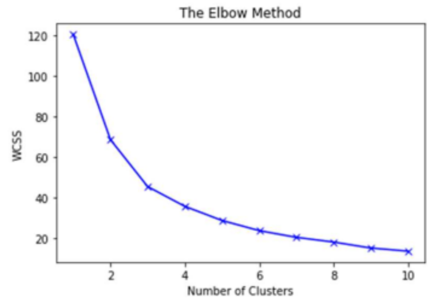

Fig. 1. Elbow method to show optimal the number of cluster (k)

The steps in the Elbow method can be done as follows:

- Perform calculations using a grouping algorithm (eg k-mean) with a value of k, for example 1 to 10.
- Calculate the total number of squares in the cluster (WCSS) for each value of k with the formulation:

$$WCSS = \sum_{C_k}^{C_n} \left(\sum_{d_i \ in \ C_i}^{d_m} distance(d_i, C_k)^2 \right) \quad (1)$$

  where ,
  C is the cluster centroids and d is the data point in each cluster.
- Plot WCSS values as the Y-axis and the number of k clusters as the X-axis.
- Analyze graph visualization and determine the optimum number of clusters based on the location of the bend (knee) on the WCSS plot to the value of k.

C. Modify

In this section, we have obtained the insights gleaned in the discovery phase from the data gathered in the sampling stage which is translated into business sense. In other terms, the data is converted and cleaned, then proceed to construct the model and re-explored if the data needs improvement and transformation.

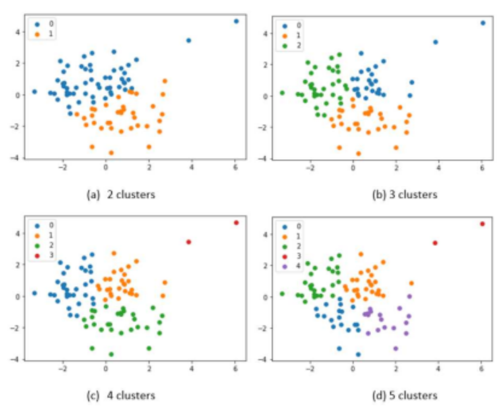

Fig. 2. Scatter plot of 2D PCA in k clusters using K-Means

The academic dataset used consists of 22 categorical variables. To make it easier to get a picture of the clusters that may be formed, then the dimension reduction is carried out using principal component analysis (PCA). The PCA process is an activity to change the main dataset into a new variable called the main component variable. So that further modeling can use the main component variables. In this case, two component variables are used with scatter plot results such as Fig.2

D. Model

The next step is modeling using a data mining or machine learning algorithm that produces a projected model that can answer the problem after data preprocessing (transforming variables and cleaning data) in the previous stage. In this study, we want to do a clustering process of student data based on student characteristics according to internal and external variables as mentioned in Table I. By looking at the results of Figure 1 and Figure 2, the clustering process will execute using the K-Means method starting from the number of clusters 2 to 5. The procedure for determining cluster labels with the K-Means algorithm can be carried out with the following procedure:

- Given an observation $(x_1, x_2, \ldots, x_n)$ where each observation is a real vector with dimension d,
- Grouping the datasets with k-means to partition n observations into k sets ($\leqslant n$), $S = \{S_1, S_2, \ldots, S_k\}$ so that to minimize the number of squares in the cluster (WCSS) or variance with the formula :

$$\arg\min_{S} \sum_{i=1}^{k} \sum_{x \in S_i} \|x-\mu_i\|^2 = \arg\min_{S} \sum_{i=1}^{k} |S_i| \, Var(S_i) \tag{2}$$

where μ_i is the mean of points in S_i

E. Access

At the final stage of the SEMMA framework, an evaluation of the model is evaluated through appropriate performance measures. The data were tested with the selected model and then tested its validity. From the results of the previous stage, it was obtained that the optimal number of clusters was in accordance with the Elbow method and plotting the K-Mean prediction results based on the reduced variables with PCA procedure located in range 2 to 5. To get the optimum k value, validation with the Silhouette coefficient was used. The Silhouette coefficient for the data set is the average of the Silhouette Coefficients from each point.

$$Silhouette\ Coefficient(i) = \frac{b(i)-a(i)}{\max\{a(i), b(i)\}} \tag{3}$$

where,

a(i) : The average distance i from all other points in the cluster.

b(i) : The smallest average distance from point i to all points in another cluster

The rule of thumb for interpreting the results of calculating the average Silhouette Coefficient is:

- If the value of *S(i)* is close to 0 it means that the point is between two clusters
- If the value of *S(i)* is closer to -1, then it is better to put in another cluster
- If *S(i)* is close to 1, then the point belongs to the right cluster

IV. Result And Discussion

In this section, we will discuss the results of clustering and student profiles obtained from this process. To simplify the explanation, it will be divided into two parts, namely the results of the optimal number of clusters and descriptive analysis of students' profiles for each cluster.

A. Optimum Cluster

Based on Figures 1 and 2 in the previous section, it can be concluded that the optimum number of clusters will be at a value of 2< k < 6. Furthermore, it is analyzed more deeply by looking at the optimal turn value and the highest Silhouette coefficient in each iteration of the k value. The results of the Elbow method on the execution time and the Silhouette value, respectively, can be seen in Figure 3,4 and 5.

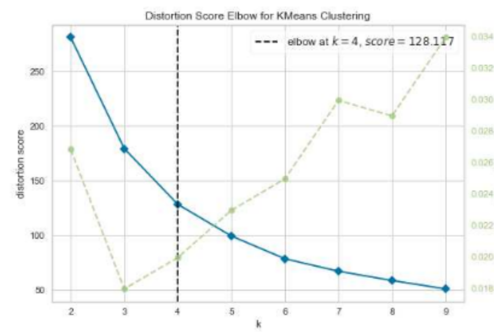

Fig. 3. Optimum k based Distortion (variance) Score for K Mean

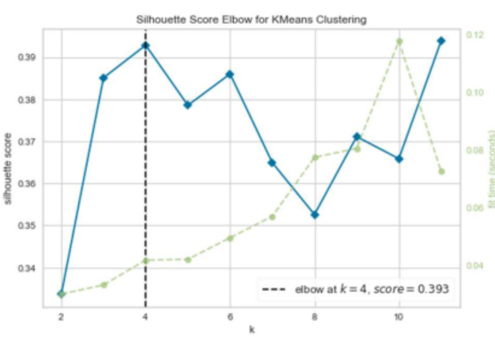

Fig. 4. Optimum k based Sillhouette Score for K Mean

It can be seen in Table II that the highest Sillhoutte coefficient value lies at $k = 4$.

TABLE II. SILLHOUTE COEFICIENT

Cluster (k)	Silhouette Score
2	0.3337
3	0.3851
4	0.3928
5	0.3851
6	0.3922

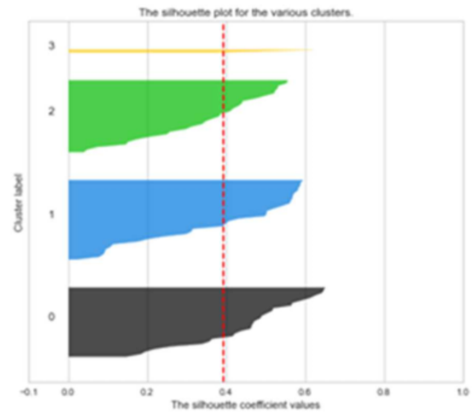

Fig. 5. Sillhoutte plot for cluster k = 4

This conclusion supports the results of the Elbow method and the original data plot based on the cluster label can be seen in Figure 6.

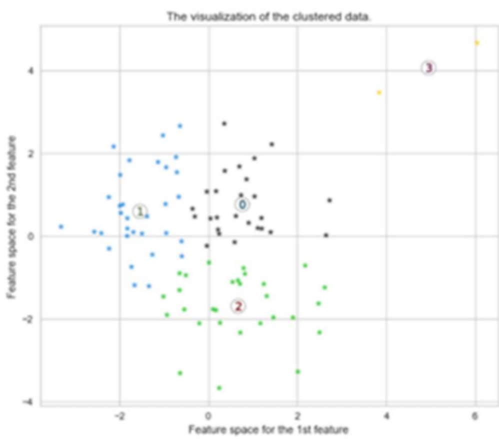

Fig. 6. Cluster original data

B. Student Profle Based Clustering

Furthermore, the profile of students in each cluster will be discussed. The number of members for each cluster can be presented in Table III.

TABLE III. CLUSTER MEMBERSHIP

Cluster (*k*)	**Number of member (*n*)**
0	29
1	32
2	28
3	2
Total	91

In the dataset used in this study, all variables are of categorical type. Therefore, the statistical descriptive analysis uses the mode measure rather than the mean value. The comparison graph of the mode values for each variable and cluster can be seen in Figure 7.

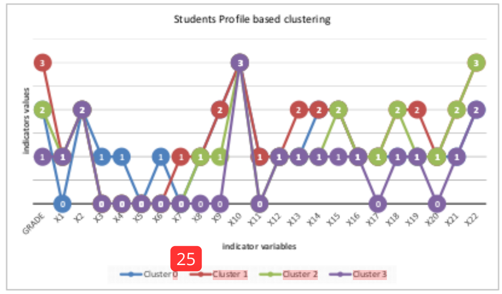

Fig. 7. Student profile based clustering

The first cluster (C0) has the characteristics of the majority being female students, wearing glasses and having been sick while attending online lectures. They are also active learners who ask questions in class and have a high interest in attending lectures. In addition, most of them have difficulty accessing the internet because they live in rural areas and most of their learning outcomes are at the level of C. Next, the group of students who are members of the second cluster (C1) are students with a minimum score of B. They are students who have good internal factor conditions and actively answer during class discussions. Most of them live in urban areas and have good internet access.

Furthermore, the third cluster (C2) has a passive student profile, where during lectures most of them never participated in discussions either to ask questions or to answer. They have low interest and motivation to learn and not trying to find other resources to increase understanding. However, they have healthy physical factors and good environmental support and have no difficulties related to internet access or supporting facilities such as smartphones or laptops. Generally, they live in urban areas and most of them are male students with C grades. The last one is the fourth cluster (C3). This group consists of male students who are lacking in all aspects, both internal and external factors. So that their learning outcomes are included in category D (fail). They live with limitations due to the difficulty of internet access and the absence of facilities such as laptops. These limitations lead to a lack of motivation, interest, and participation in online lectures. However, their mental and physical health is not a problem.

V. CONCLUSION

The conclusion of this study is that there are 4 groups of student profiles found in the dataset using the K-Means clustering algorithm. The four student profiles can be said to be (1) active learning students with limited access and facilities, (2) active learning students with good access and facilities, (3) passive learning students but with good access and facilities support, and (4) are students who are very passive and lack of access and support for online learning.

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