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STUDENT SELF-REGULATION PROFILES IN ONLINE LEARNING POST-COVID-19: A CLUSTER AND DISCRIMINANT ANALYSIS APPROACH

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Abstracts
The transition to online learning has brought significant challenges and opportunities for higher education, emphasizing the importance of self-regulation as a critical skill for academic success. This study aims to profile students' self-regulation patterns in online learning environments using a combination of cluster and discriminant analyses. Data were collected from 577 undergraduate students using the Online Self-Regulated Learning Questionnaire (OSLQ), which measures six dimensions of self-regulation: goal setting, environment structuring, task strategies, time management, help-seeking, and self-evaluation. Cluster analysis, employing the K-Means method, identified three distinct student groups: (1) students with high self-regulation, excelling in goal setting, time management, and self-evaluation; (2) students with moderate self-regulation, showing adequate abilities with some limitations in task strategies and help-seeking; and (3) students with low self-regulation, struggling across all dimensions. Discriminant analysis revealed that self-evaluation, goal setting, and task strategies were the primary variables differentiating these clusters, with self-evaluation emerging as the most significant predictor. The findings underscore the critical role of self-regulation in online learning success and highlight the need for tailored interventions to support students with low self-regulation. These insights provide valuable implications for educators and institutions to design more adaptive and effective online learning strategies.
Keywords: Self-Regulated Learning, Cluster Analysis, Discriminant Analysis

INTRODUCTION

The transformation of education towards the digital era has become one of the most significant phenomena in higher education, especially over the past few decades (Karim, 2020). The development of information technology has opened opportunities for educational institutions to adopt online learning as an integral part of academic activities. This phenomenon was further accelerated by the COVID-19 pandemic, which forced a massive shift from face-to-face learning to online platforms. Lestariyanti (2020) explains that the COVID-19 pandemic compelled the entire education system to conduct all learning processes online. According to Rusdiana et al. (2020), the COVID-19 period fundamentally altered conventional education, requiring educators, lecturers, and students to adapt to online learning. This situation created both challenges and opportunities, where online learning is no longer just an alternative but a fundamental necessity to ensure the continuity of education. On the other hand, this transformation requires significant adaptation from educational institutions, lecturers, and students to effectively integrate technology into the learning process (Hasnida et al., 2024).

However, online learning also presents complex challenges, especially for students who are required to manage themselves independently (Rivers et al., 2022). Students must be able to manage their time, understand material independently, and stay motivated despite the limited social interaction characteristic of online learning. Sadikin and Hamidah (2020) argue that online learning has the advantage of fostering self-regulated learning, as it encourages students to take more responsibility for their own learning process. They also state that online learning poses specific challenges, as the separation between students and instructors means that teachers cannot directly supervise students' activities during the learning process. The reduced direct supervision from teachers and the increased distractions in the online learning environment make self-regulation a crucial skill. The inability to manage these aspects can negatively impact students' academic performance. Therefore, understanding how students regulate themselves in the context of online learning becomes highly relevant, especially to help educational institutions design more adaptive strategies to support student success (Wang et al., 2013).

Self-regulation in the context of learning can be defined as an individual's ability to plan, monitor, and evaluate their learning process independently to achieve predetermined goals (Barnard-Brak et al., 2010). This concept involves a series of skills, such as setting clear goals, organizing the learning environment, selecting effective learning strategies, managing time, and evaluating understanding of the material. These skills enable students to take ownership of their educational journey, making adjustments as needed to stay on track toward achieving their objectives. In online learning, self-regulation becomes more complex because students must adapt to a digital environment that often presents unique challenges, such as the need to manage attention amidst technological distractions. The constant presence of digital devices and the accessibility of non-academic content can divert students' focus, making it more difficult to maintain concentration on academic tasks. Atkinson (1993) in Rozali (2013) states that self-regulation involves monitoring one's own behavior by controlling environmental stimuli to modify behaviors that are not aligned with desired outcomes. The process of self-regulation not only involves motivational and metacognitive aspects, where students consciously reflect on their learning methods to achieve optimal results (Carter Jr et al., 2020). Furthermore, it requires emotional regulation to manage stress and frustration that may arise from challenges encountered during the learning process, such as technical difficulties or time pressures.

The relationship between self-regulation and academic success has been demonstrated in various studies. Students with good self-regulation skills tend to be better at overcoming the challenges of online learning compared to those with poor self-regulation (Sagitarini et al., 2023). Self-regulation enables students to identify strategies that suit their learning needs, allowing them to manage their time more effectively and stay motivated even under less supportive conditions. Ani Lestari (2021) suggests, students' interest in learning can significantly influence their self-regulation abilities, as motivated students are more likely to engage in self-regulated learning behaviors. Kuo et al. (2014) state that online learning is more student-centered, which fosters greater responsibility and autonomy in learning, allowing students to take charge of their learning process. Furthermore, self-evaluation, as one dimension of self-regulation, helps students identify gaps in their learning, enabling them to take corrective actions. In the context of online learning, self-regulation not only influences academic achievement but also contributes to retention rates and student satisfaction with the learning experience. Therefore, mapping students' self-regulation patterns is an important step in supporting their success in an increasingly dynamic online learning environment.

Although self-regulation has been recognized as an essential component in supporting academic success, most existing research focuses more on the relationship between self-regulation and learning outcomes or individual factors such as motivation and intelligence (Sirait et al., 2022). Relatively few studies attempt to explore how self-regulation varies among students or how self-regulation patterns can be categorized to understand more specific learning needs. This gap creates a significant literature deficiency, especially in the context of online learning, where the need for self-regulation is increasingly critical. Online learning environments require students to take greater responsibility for their own learning, making it essential to identify how different students manage their learning processes. Without a deep understanding of students' self-regulation profiles, efforts to design adaptive and effective learning strategies risk becoming less relevant. By identifying specific patterns of self-regulation, educators can tailor their approaches to better support students who may struggle with particular aspects of self-regulation.

The importance of mapping students' self-regulation profiles lies in the ability to identify distinct patterns that differentiate groups of students based on how they manage their learning processes. These profiles not only provide insights into students' strengths and weaknesses in managing online learning but also assist educational institutions in designing more targeted intervention programs. For example, students with low self-regulation may require specific guidance in time management or learning strategies, while those with high self-regulation may be given greater freedom to explore independent learning. By understanding these profiles, educational institutions can not only enhance students' academic success but also create more inclusive and effective online learning experiences for the entire student population.

METHODS

Measurement Instrument

The instrument used in this study is the Online Self-Regulated Learning Questionnaire (OSLQ), adapted from Barnard et al (2010). This instrument is designed to evaluate students' self-regulation abilities in online and blended learning during the COVID-19 pandemic. The questionnaire consists of 24 statements measured on a five-point Likert scale, ranging from "Strongly Disagree" to "Strongly Agree." This measurement aims to assess students' levels of self-regulation across various critical aspects that support successful learning in an online environment.

The questionnaire covers six main dimensions of self-regulation: goal setting, environment structuring, task strategies, time management, help-seeking, and self-evaluation. The goal-setting dimension focuses on understanding how well students establish learning targets and standards for their online tasks. The environment structuring dimension assesses students' ability to choose conducive learning spaces to avoid distractions during online learning. The task strategies dimension measures students' tendencies to apply specific methods, such as taking notes or completing additional tasks, to deepen their understanding of the material.

The time management dimension evaluates students' abilities to allocate their study time efficiently. Meanwhile, the help-seeking dimension examines students' initiatives to seek support from peers or instructors when facing difficulties. Lastly, the self-evaluation dimension measures students' reflection on their understanding and achievements in online learning. The overall instrument demonstrates high reliability, with a Cronbach's alpha value of 0.94, indicating strong and dependable internal consistency.

Data collection was conducted online via Google Forms from May to June 2023. The respondents in this study were undergraduate students from various faculties in Jakarta who voluntarily participated in the survey. The measurement results are expected to provide an in-depth understanding of students' self-regulation abilities in the context of online learning, which can ultimately serve as a reference for designing educational strategies to support the effectiveness of online learning in the future.

Procedures

The research procedure began with downloading data from the publication conducted by Irwanto (2024). The available data was imported into R software for validation and preprocessing. Irwanto's (2024) study employed a survey method with a cross-sectional approach to collect data on undergraduate students' self-regulation skills in online and blended learning environments during the COVID-19 pandemic.

The sample consisted of 577 active undergraduate students from Universitas Negeri Jakarta, recruited through purposive and snowball sampling techniques. The respondents met the inclusion criteria, which required them to be full-time undergraduate students aged 18 and above, have access to mobile devices and the internet, and be enrolled in blended learning courses.

Participants

This study involved 577 undergraduate students from Universitas Negeri Jakarta who participated in a survey on self-regulation in online and blended learning environments during the COVID-19 pandemic. The respondents consisted of 433 females (75%) and 144 males (25%), reflecting the gender distribution of the university’s student population. Participants came from eight faculties, with the Faculty of Mathematics and Natural Sciences having the highest number of participants.

The academic year distribution showed that 49% of the respondents were first-year students, followed by smaller percentages of second, third, and fourth-year students. The majority of respondents were aged between 18–20 years

(74.5%), with an average age of 20.26 years. Most participants resided in urban areas (57.9%), while the rest came from suburban or rural areas. A majority of the respondents reported spending 7–12 hours online daily (67.1%), with internet use encompassing both academic and non-academic activities.

Data Analysis

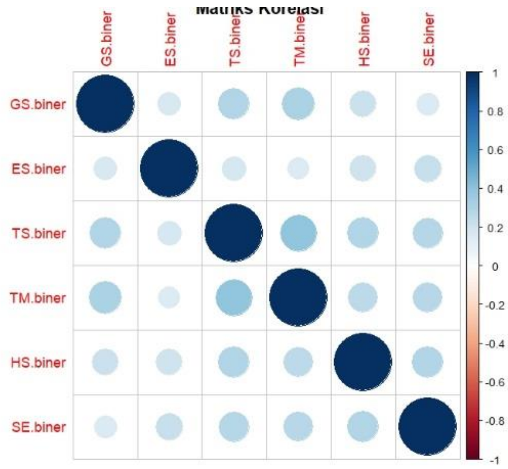
Data analysis in this study was conducted using two main approaches: cluster analysis and discriminant analysis. The initial stage involved grouping students based on their self-regulation patterns in online learning through cluster analysis. The K-Means Clustering method was employed to identify groups of students with similar characteristics. The optimal number of clusters was determined using the Elbow Method, which evaluates changes in the within-cluster sum of squares (WSS), and Silhouette Analysis, which measures within-cluster homogeneity and between-cluster heterogeneity. The clustering results produced several groups of students with distinct self-regulation patterns.

Subsequently, discriminant analysis was performed to identify variables that differentiate the clusters. This analysis utilized Linear Discriminant Analysis (LDA) to model the relationship between self-regulation dimensions as independent variables and clusters as the dependent variable. Before conducting discriminant analysis, assumptions of multivariate normality and homogeneity of variance-covariance matrices were tested. Multivariate normality was assessed to ensure that data within each cluster followed a normal distribution, while homogeneity of variance-covariance matrices was tested using Box's M Test. The discriminant analysis results not only helped identify distinguishing factors between clusters but also validated the clustering results by comparing the model's predictions with actual data.

The validation process included the use of the Silhouette Score to measure the consistency of the clustering results. Additionally, the accuracy of the discriminant model was evaluated using a confusion matrix, which indicated the alignment between model predictions and actual group assignments. All analyses were performed using the R programming language, leveraging packages such as psych, factoextra, MASS, and cluster.

RESULTS AND DISCUSSION

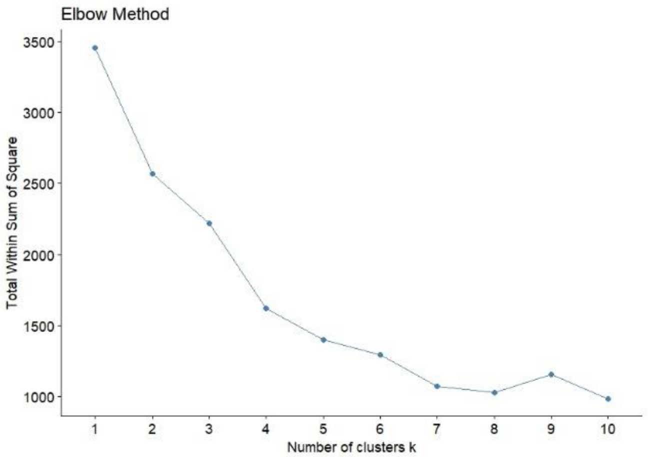
This study aimed to identify the self-regulation profiles of students in online learning through cluster analysis. The analytical steps included testing initial assumptions and determining the optimal number of clusters. The correlation matrix results among variables indicated that no variable had a high correlation coefficient (> 0.8), showing no significant multicollinearity (Figure 1). This suggests that the variables used in the analysis were independent and suitable for subsequent analysis steps.



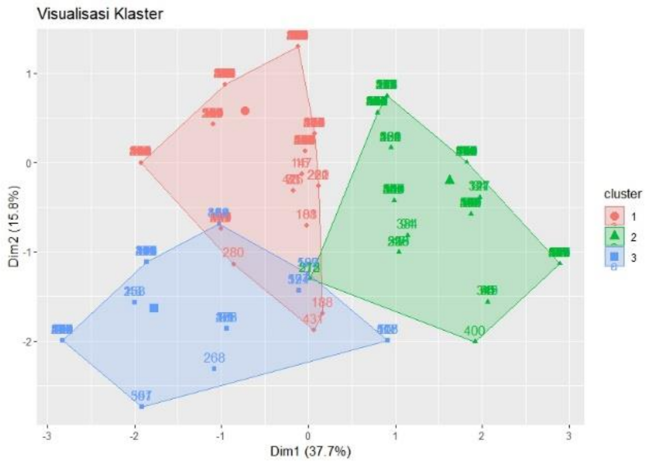
Figures 1. Correlation Matrix

The Kaiser-Meyer-Olkin (KMO) test yielded an overall value of 0.77, with each variable scoring above 0.6, confirming the adequacy of the data for further analysis. Additionally, Bartlett’s Test for Sphericity produced a chi-square value of 403.56 with a p-value < 0.001, indicating significant relationships among the variables. Both results supported the suitability of the data for cluster analysis.

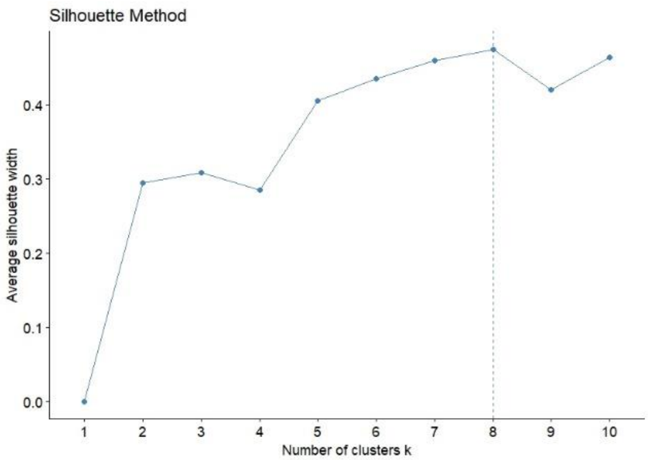
The Elbow Method was applied to determine the optimal number of clusters. The Elbow plot (Figure 2) revealed the "elbow" point at k = 3, suggesting that the optimal number of clusters was three. This finding was corroborated by the Silhouette analysis (Figure 3), which showed the highest average internal cohesion score at k = 3.



Figures 2. Elbow Graphics



Figures 4. Cluster Visualization



Figures 3. Silhouette Analysis

Cluster analysis using the K-Means method identified three clusters representing the self-regulation patterns of students. The cluster visualization in the primary dimensional space (Figure 4) indicated the following: the first cluster comprised students with high self-regulation across nearly all dimensions, the second cluster exhibited moderate self-regulation characteristics, and the third cluster predominantly consisted of students with low self-regulation.

The cluster interpretations are as follows:

Cluster 1: Students in this group demonstrated strong goal-setting, time management, and self-evaluation skills, reflecting an optimal self-regulation pattern for online learning.

Cluster 2: This cluster included students with moderate self-regulation levels, indicating that they are fairly capable of managing online learning but face limitations in specific dimensions, such as seeking help or organizing their study environment.

Cluster 3: Students in this group displayed low levels of self-regulation, particularly in task strategies and self-evaluation dimensions, highlighting the need for targeted interventions to improve their online learning effectiveness.

The next analysis was a discriminant analysis aimed at identifying the key variables that differentiate student groups based on their Grade Point Average (GPA) categories. The analysis produced four discriminant functions (LD1, LD2, LD3, LD4), explaining the total variation among groups.

The results revealed that the first Linear Discriminant (LD1) accounted for 58.73% of the total variation among groups, while the second Linear Discriminant (LD2) contributed an additional 22.58%. Together, the first two functions captured 81.31% of the variation, which is sufficient to significantly distinguish the groups. Prior probabilities indicated the distribution of students across GPA categories, with the majority belonging to Group 1 (highest GPA).

The coefficients of the discriminant functions highlighted the contribution of each variable to the discriminant functions. The most influential variables for LD1, the primary discriminant function, were ES (Self-Evaluation) with a coefficient of 0.292, GS (Goal-Setting) with a coefficient of 0.187, and TS (Task Strategies) with a coefficient of 0.183. These variables emerged as the main differentiators among student groups, emphasizing that self-evaluation, goal-setting, and task strategies play a critical role in distinguishing levels of academic performance.

Table 1. Proportion of Trace

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Proportion of trace:
   LD1    LD2    LD3    LD4
0.5873 0.2258 0.1342 0.0527
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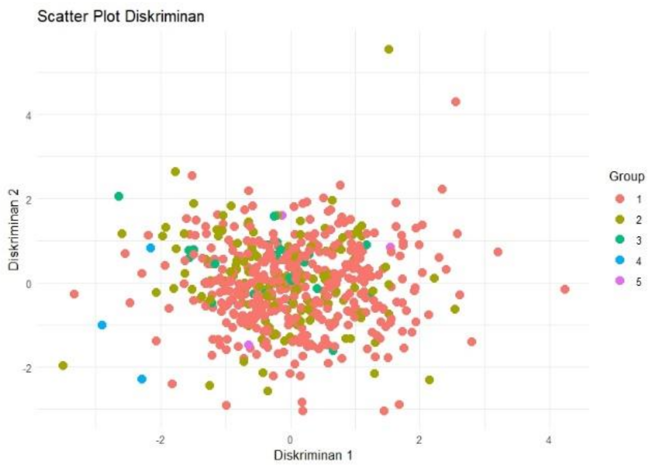
The confusion matrix reveals the accuracy of the model in predicting student groups based on GPA categories. The group with the highest GPA (Group 1) demonstrated excellent classification accuracy, with 409 out of 410 observations correctly classified. However, for other groups (Groups 2, 3, 4, and 5), misclassification occurred, indicating that the model was less effective in distinguishing groups with smaller sample sizes.

Table 2. Confusion Matrix of the Discriminant Model

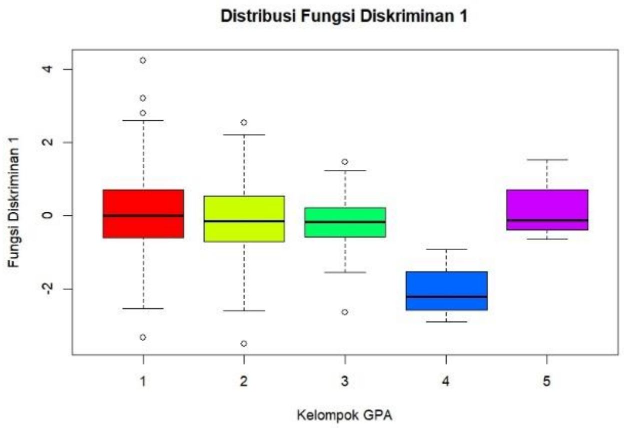
aktual	1	2	3	4	5
1	409	0	0	1	0
2	133	0	0	1	0
3	26	0	0	0	0
4	4	0	0	0	0
5	3	0	0	0	0

The scatter plot visualization shows the distribution of students based on the first two discriminant functions (LD1 and LD2). This figure illustrates that the group of students with the highest GPA (1) tends to be concentrated at positive scores on the first discriminant function (Figure 5). The scatter plot with centroids (Figure 7) displays the average position of each group. The group with the highest GPA (1) has a centroid that is significantly separated from the other groups.

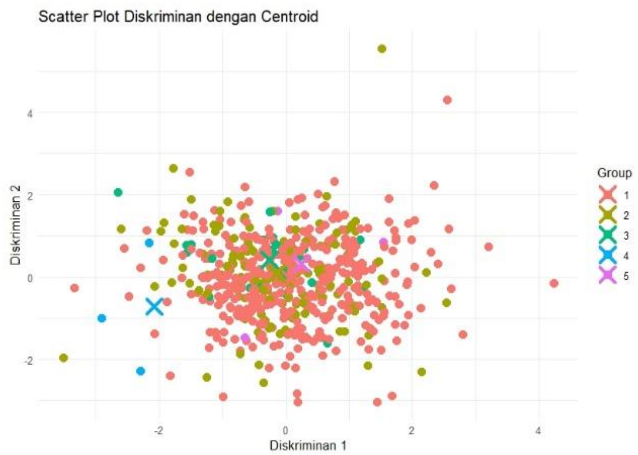
The score distribution on LD1 is also displayed through a boxplot (Figure 6), which shows that the group of students with the highest GPA has higher positive values on the first discriminant function. Conversely, the group with the lowest GPA has lower values on this function.



Figures 5. Scatter Plot



Figures 6. Boxplot



Figures 7. Scatter Plot with Centroid

CONCLUSIONS

Based on the analysis results, students' self-regulation in online learning can be categorized into three main clusters with distinct characteristics. The first cluster consists of students with high self-regulation, demonstrating optimal abilities in goal setting, self-evaluation, and time management dimensions. The second cluster includes students with moderate self-regulation, who manage online learning fairly well but still have weaknesses in task strategies and seeking help. The third cluster comprises students with low self-regulation, showing limitations in nearly all self-regulation dimensions, particularly self-evaluation and task strategies.

The key differentiating variables among the clusters, identified through discriminant analysis, are self-evaluation, goal setting, and task strategies. The self-evaluation dimension proved to be the most significant factor in distinguishing the groups, indicating that reflective and evaluative abilities play a crucial role in the success of online learning. These findings highlight the importance of enhancing self-regulation skills, particularly for students with low self-regulation, to support their academic success in online learning environments.

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