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AI-Based Educational Decision Analytics: K-Means Clustering of University Students' Digital Learning Readiness Using Limited and Full Attitude Schemes

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ABSTRACT

Purpose – Advancements in digital learning require students to be adequately prepared both psychologically and technologically. However, students' attitudes toward digital learning have not yet been systematically mapped using data-driven segmentation approaches. This study aims to classify university students based on similarities in their attitudes toward digital learning using the K-Means clustering algorithm and to identify the most influential dimensions distinguishing levels of digital readiness.

Methods – This study employed an exploratory quantitative design using survey data collected from 469 university students. Clustering was conducted using the K-Means algorithm implemented in the Orange Data Mining application. Two variable schemes were compared: a limited scheme comprising four constructs (Psychological Traits, Growth Mindset, Learner Motivation & Engagement, and Digital Competence) and a full scheme including six constructs with the addition of Digital Readiness & Mindfulness and Student Satisfaction. Data were normalized using Min–Max normalization, and cluster quality was evaluated using the Silhouette Coefficient.

Findings – Results indicate that both schemes consistently produced two optimal clusters representing students with high and low levels of digital learning readiness. The highest Silhouette Coefficient values were obtained at K = 2 for both schemes (0.335 for the limited scheme and 0.323 for the full scheme). Psychological Traits and Learner Motivation & Engagement emerged as the most significant differentiating dimensions between clusters, followed by Digital Competence.

Research limitations – The findings are limited to self-reported data and a single institutional context, which may constrain generalizability. Additionally, the cross-sectional design does not capture changes in student attitudes over time.

Originality – This study contributes a comparative clustering framework that integrates psychological, motivational, and technological dimensions to map digital learning readiness. The results provide a practical foundation for designing adaptive and personalized digital learning strategies based on student readiness profiles.

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INTRODUCTION

Major changes in higher education systems are occurring globally as the use of digital technology in the learning process increases (Nieto-Taborda & Luppicini, 2024). This phenomenon has become even more widespread since the COVID-19 pandemic, which has forced educational institutions to adapt to online distance learning models (Mikhaylova et al., 2021). The COVID-19 pandemic has accelerated the use of online-based education, along with the transition of schools and universities to digital platforms. In 2023, online learning methods will account for around 30% of all education delivery in Indonesia, up from only 10% in 2019. In 2024, the Ministry of Education began a program to integrate e-learning into the education system in public schools. Currently, around 75,000 schools have access to e-learning devices provided by the government, benefiting more than 20 million students (MarketResearch, 2024). However, the effectiveness of digital learning remains a challenge. Although access to online platforms has increased, active participation and student satisfaction often remain low (Akpen et al., 2024). This is influenced by various factors, including psychological traits such as self-efficacy and self-regulation abilities, which directly affect students' confidence in participating in online learning (Blayone et al., 2021).

One important factor that influences student success in online learning is self-efficacy and self-control. Students with high self-efficacy are more confident in using technology, completing tasks independently, and staying motivated (Blayone et al., 2021). A positive perception of one's abilities also increases engagement in online learning (Kallas & Pedaste, 2022). In addition, a growth mindset shapes students' learning resilience in a digital environment, as they see challenges as opportunities for growth, which influences their motivation and adaptive attitude toward new technology (Akpen et al., 2024; Kizilcec & Goldfarb, 2019; Vinther & Lauridsen, 2020).

Other factors such as learner motivation and engagement encourage active student participation in forums, assignments, and independent exploration (Joshi, 2024; Vinther & Lauridsen, 2020), as well as increasing learning satisfaction in online and blended models (Albeta et al., 2025). Digital competence includes technological skills, information literacy, and confidence in online learning (Kallas & Pedaste, 2022). Digital readiness and mindfulness reflect students' technical readiness and awareness of the digital environment. All these factors contribute to student satisfaction, which is the perception of learning quality, interaction, and technical support (Akpen et al., 2024; Albeta et al., 2025). Therefore, it is important to map students' attitudes based on a combination of these variables in order to improve the quality of digital learning (Karim Amrullah et al., 2024).

Several studies have attempted exploratory approaches. Research by Kholifah et al., (2022) shows that the majority of studies related to digital learning still use traditional statistical approaches such as SEM and regression to analyze the relationship between variables. For example, K-Means clustering algorithm to group students based on their activities in the Learning Management System (LMS). Several studies have discussed elements such as digital readiness, motivation, and student satisfaction, but they are still separate and not combined into a single comprehensive model (Sumbogo, 2022). The study by Hasim et al., (2022) focused on the development and validation of a student digital readiness instrument in Malaysia using the UTAUT and Task-Technology Fit (TTF) models. There has been no use of the Orange application as a visual analysis tool in student clustering, even though the application is easily accessible and drag-and-drop-based, which is suitable for higher education (Adzhemov et al., 2022).

Digital learning approaches are increasingly developing through the integration of technology and data analysis, particularly with the application of clustering techniques to understand student characteristics. The study by Sangodiah et al., (2023) shows the importance of readiness and motivation in adopting technologies such as Augmented Reality, while Brändle et al., (2023) emphasize the need for a differentiated approach due to variations in attitudes and digital competencies across disciplines Arockiam et al., (2024) used the K-Prototypes algorithm to group students' learning attitudes in e-learning, confirming the potential of segmentation for personalized learning. In the context of cluster evaluation, Chai et al., (2020) underscored the effectiveness of using the Silhouette Coefficient as a measure of cluster validity. The widespread application of the K-Means algorithm is also seen in the study by Iskandar et al., (2024) for classifying human resource readiness and by Nassir et al., (2025) in analyzing student satisfaction in project-based programs. Additionally, Borgelt & Yarikova, (2020) emphasize the role of initialization methods such as k-means++ in

improving the consistency of clustering results, while states that K-Means remains a popular method in data mining due to its simplicity, although it still requires optimization for complex data scenarios. Oti et al., (2021) expand the scope by using K-Means to group students based on their level of social support and learning motivation, showing that this approach can identify different support needs to improve academic achievement. Similarly, K-Means can be used to analyze behavior patterns such as study hours, attendance, and tutoring sessions, resulting in segmentation that can be used as a basis for specific academic interventions. These findings show that clustering techniques, particularly K-Means, are not only flexible but also relevant in improving the effectiveness of data-driven digital learning.

This study fills the gap left by previous studies by (Hasim et al., 2022) which did not use a segmentative approach such as K-Means to group students based on psychological, technical, and emotional factors, and did not utilize Orange as an intuitive visualization tool. By integrating six main variables into the K-Means clustering model, this study offers a new approach to mapping students' attitudes toward digital learning. Cluster evaluation was conducted using the Silhouette Coefficient to ensure segmentation quality in two variable schemes. The results are expected to provide empirical contributions to mapping digital student profiles and methodological contributions to more personalized and adaptive digital learning strategies.

METHOD

Research Design

This study uses an exploratory quantitative approach that aims to reveal patterns of student attitudes toward digital learning through a data-based segmentation process. The K-Means clustering algorithm was used to group students based on six main constructs, namely: Psychological Traits (PT), Growth Mindset (GM), learner motivation and engagement (LME), Digital Competence (DC), digital readiness and mindfulness (DRM), and student satisfaction (SS). To assess the quality and validity of the segmentation results, the Silhouette Coefficient evaluative metric was used. This study compared two variable schemes, namely the limited scheme (four constructs) and the full scheme (six constructs), to identify the best clustering model.

Research Process Flow

The stages of this research were designed systematically, starting from the identification of problems and objectives to conclusions and recommendations. The following is the flow of the research stages:

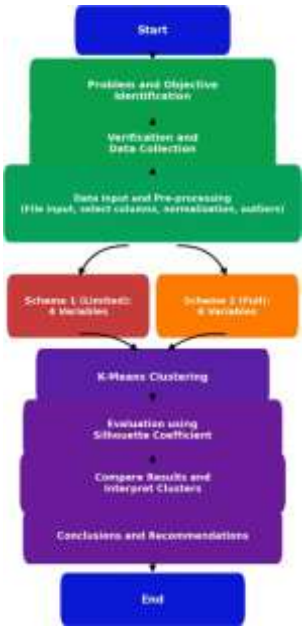

Figure 1. Research Process Flowchart

Based on Figure 1 above, which shows the research stages, the first step is to identify the problems and objectives. The main problem in digital learning lies in the imbalance of students' adaptation to

the ever-evolving online system. Many students still show negative attitudes toward digital learning, such as lack of motivation, low engagement, and inadequate digital competence. Therefore, the objective of this study is to group students based on their attitudes toward digital learning using the K-Means algorithm. This segmentation is expected to provide deeper insights into the characteristics of each group of students to support decision-making in designing more appropriate learning strategies.

After the objectives were set, data verification and collection were carried out through the distribution of online questionnaires using Google Forms. These questionnaires were developed based on validated constructs from previous literature and consisted of six main variables: Psychological Traits, Growth Mindset, learner motivation and engagement, Digital Competence, digital readiness & mindfulness, and student satisfaction. Verification was carried out by checking the completeness, content validity, and suitability of the inclusion criteria, namely active students in their second semester or above who had participated in online learning for at least one semester. A total of 467 respondents' data was successfully collected, which was then re-checked to avoid empty or duplicate data so that it could be used in the analysis.

During the data pre-processing stage, several technical adjustments were made so that the data could be analyzed using the Orange Data Mining application. The first step was column selection to ensure that only relevant variables were included in the clustering process. Next, the Likert data on a scale of 1–5 was normalized to a range of [0,1] using the Min-Max Normalization method to ensure that all variables had an equal influence. In addition, outlier values were filtered out to avoid distortion in cluster formation. This pre-processing was key to ensuring that the clustering process ran optimally and that the results could be interpreted correctly.

This study applies two variable schemes for the purpose of comparing clustering performance. The first scheme is a limited scheme, which uses four main constructs: Psychological Traits, Growth Mindset, learner motivation and engagement, and Digital Competence. These four variables were selected because they represent the basic cognitive and affective aspects that most influence digital learning readiness. Meanwhile, the second scheme is a full scheme that covers all six constructs by adding digital readiness & mindfulness and student satisfaction. This addition aims to determine whether the use of a more comprehensive model can produce more meaningful segmentation compared to a minimalist model.

The K-Means algorithm is used in the clustering process because of its ability to group data without assuming a specific distribution. The process begins by determining the desired number of clusters (k), then the centroid is initialized randomly. Each data point is calculated for its distance to all centroids and grouped to the nearest centroid. After that, the position of the centroid is updated based on the average position of its cluster members. This step is repeated until there are no more significant changes to the clusters. Mathematically, the K-Means algorithm aims to minimize the following objective function:

$$J = \sum_{j=1}^{k} \sum_{i-1}^{n_j} \| x_i^{(j)} - \mu_j \|^2$$

Implementation was carried out separately for scheme 1 and scheme 2 to enable comparison of segmentation performance results.

The clustering results were evaluated using the Silhouette Coefficient metric. This metric is used to measure how well each object is within its cluster compared to other clusters. The formula for the Silhouette Coefficient is:

$$S(i) \frac{b(i) - a(i)}{\max\,(a(i), b(i)}$$

The final stage in this process is to analyze and interpret the clustering results. Each cluster is evaluated based on the average score for each construct to reveal the distinctive characteristics of each group. This analysis includes not only the number and distribution of members in each cluster, but also the mapping of the most prominent attitude patterns in each segment.

To enrich our understanding of cluster membership tendencies, we also analyzed the distribution of key variables. This distribution shows the likelihood of a student belonging to a particular cluster

based on values on constructs such as Psychological Traits and Growth Mindset. Visualizations in the form of probability curves and histograms in distribution graphs help to clearly show the transition points between clusters and confirm that some constructs have more significant separating power than others.

The comparison of effectiveness between schemes was conducted by considering the Silhouette Coefficient value and the relevance of the cluster patterns formed. The findings from this interpretation process became an important basis for designing digital learning strategies that are more personalized, adaptive, and tailored to the varying levels of readiness among students.

RESULTS AND DISCUSSION

Research Dataset

This study uses student survey data that represents their attitudes toward digital learning, which is then analysed using the K-Means clustering method. The dataset includes 469 student entries with six main attributes, namely Psychological Traits, Growth Mindset, Learner Motivation & Engagement, Digital Competence, Digital Readiness & Mindfulness, and Student Satisfaction.

All attributes were measured using a Likert scale normalized to a range of [0–1], allowing for proportional comparisons between dimensions. These attributes were selected to provide a comprehensive picture of student readiness and engagement in the context of digital learning. In addition, this data is also supplemented with demographic information such as gender, age, semester, and year of enrollment.

The data presented in Table 1 below has undergone data cleaning, which includes identifying and removing duplicates, handling missing values, and adjusting the format to align with the needs of further analysis. This process was carried out to ensure that the data used in the clustering was valid, consistent, and suitable for accurate analysis. Table 1 below presents the dataset used in this study:

Table 1. Research Dataset

No	Gender	Age	Vacation	Generation	*Psychological Traits*	*Growth Mindset*	*Learner Motivation & Engagement*	*Digital Competence*	Digital Readiness & Mindfulness	Student Satisfaction
1	Women	19	IV	2022	0.55	0.5	0.5	0.85	0.5	0.75
2	Women	19	IV	2022	0.9	0.55	0.95	0.85	0.95	0.8
3	**Men**	**19**	**IV**	**2022**	**0.85**	**0.8**	**0.85**	**0.9**	**0.6**	**0.7**
4	**Men**	**21**	**IV**	**2022**	**0.55**	**0.55**	**0.6**	**0.6**	**0.6**	**0,5**
5	**Men**	**21**	**IV**	**2022**	**0.55**	**0.5**	**0.5**	**0.6**	**0.65**	**0.5**
6	**Men**	**18**	**IV**	**2022**	**0.65**	**0.5**	**0.55**	**0.65**	**0.6**	**0.55**
7	**Women**	**19**	**IV**	**2022**	**0.5**	**0.6**	**0.8**	**0.7**	**0.75**	**0.45**
8	**Women**	**20**	**VI**	**2022**	**0.7**	**0.65**	**0.7**	**0.7**	**0.65**	**0.65**
9	**Men**	**20**	**IV**	**2022**	**0.5**	**0.7**	**0.55**	**0.6**	**0.55**	**0.5**
10	**Women**	**19**	**IV**	**2022**	**0.75**	**0.75**	**0.75**	**0.75**	**0.5**	**0.9**
11	**Women**	**19**	**IV**	**2022**	**0.7**	**0.75**	**0.7**	**0.75**	**0.75**	**0.75**
12	**Women**	**19**	**IV**	**2022**	**0.8**	**0.75**	**1**	**0.8**	**0.75**	**0.75**
13	**Women**	**20**	**IV**	**2022**	**1**	**1**	**1**	**1**	**1**	**1**
14	**Men**	**19**	**II**	**2023**	**0.75**	**0.5**	**0.5**	**0.75**	**0.75**	**0.75**
15	**Women**	**21**	**IV**	**2022**	**0.5**	**0.5**	**0.5**	**0.5**	**0.5**	**0.5**
16	**Women**	**19**	**IV**	**2022**	**0.7**	**0.95**	**0.7**	**1**	**0.95**	**0.75**
17	**Men**	**19**	**II**	**2023**	**1**	**0.95**	**1**	**0.9**	**0.85**	**0.85**
18	**Women**	**19**	**II**	**2023**	**0.5**	**0.5**	**0.5**	**0.5**	**0.5**	**0.5**
19	**Men**	**19**	**IV**	**2022**	**0.65**	**0.65**	**0.6**	**0.6**	**0.65**	**0.65**
20	**Men...**	**19**	**IV**	**2022**	**0.5**	**0.5**	**0.5**	**0.5**	**0.5**	**0.5**
...		**...**	**...**	**...**	**...**	**...**	**...**	**...**	**...**	**...**
467	**Men**	**19**	**IV**	**2022**	**0.55**	**0.5**	**0.5**	**0.45**	**0.55**	**0.55**

Clustering Results

Scheme 1 (Limited)

In the Limited Scheme, clustering is carried out by referring to four main variables, namely Psychological Traits, Growth Mindset, Learner Motivation & Engagement, and Digital Competence. Using these four variables as a basis, an evaluation is carried out to determine the most appropriate number of clusters in the application of the K-Means algorithm.

Determining the most optimal number of clusters is a crucial step in applying the K-Means algorithm. The evaluation process is carried out using the Silhouette Coefficient, a metric that assesses how accurately data is placed in its current cluster compared to if it were placed in another cluster. This coefficient ranges from -1 to 1, where a higher value indicates better quality of separation between clusters. The table below presents the average Silhouette Coefficient values for various cluster number (K) options tested in the Limited Scheme.

Table 2. Silhouette Coefficient Scheme 1 (Limited)

	Silhouette Scores
2	0.335
3	0.275
4	0.258
5	0.218
6	0.209
7	0.181
8	0.175
9	0.184
10	0.185

Based on the results in Table 2 above, the highest Silhouette Coefficient value was obtained at K = 2, which was 0.335. This indicates that the clustering model with two clusters provides the clearest separation and strongest internal cohesion compared to other configurations. After K = 2, there is a gradual decrease in the coefficient value, which indicates that adding more clusters actually reduces the quality of the separation structure between student groups.

The K-Means clustering results in the Limited Scheme produced two main clusters, namely Cluster 1 (C1) and Cluster 2 (C2), which reflect two groups of students based on their attitudes toward digital learning. The formation of each cluster was based on the similarity of scores on four main dimensions: Psychological Traits, Growth Mindset, Learner Motivation & Engagement, and Digital Competence. The following table presents some of the student data classified into each cluster, complete with scores on each attitude dimension that formed the basis of the clustering process.

Cluster 1

Table 3. Cluster 1 Grouping in the Limited Scheme

No.	**Data Ke-**	***PT***	***GM***	***LME***	***DC***	**Cluster**
1	1	0.55	0.5	0.5	0.85	C1
2	4	0.55	0.55	0.6	0.6	C1
3	5	0.55	0.5	0.5	0.6	C1
4	6	0.65	0.5	0.55	0.65	C1
5	7	0.5	0.6	0.8	0.7	C1
6	9	0.5	0.7	0.55	0.6	C1
7	14	0.75	0.5	0.5	0.75	C1
8	15	0.5	0.5	0.5	0.5	C1
9	18	0.5	0.5	0.5	0.5	C1
10	19	0.65	0.65	0.6	0.6	C1
...	....	...	....	...	....	...
207	467	0.55	0.5	0.5	0.45	C1

Based on cluster 1 table above, it shows that the majority consists of students who have low to moderate scores on the four variables analyzed. The scores for Psychological Traits, Growth Mindset, and Motivation are generally in the range of 0.50 to 0.65, indicating that their mental readiness and motivation for digital learning are still relatively limited. However, some students in Cluster 1 (C1) show slightly better mastery of Digital Competence, with scores close to 0.70.

In terms of numbers, this cluster includes around 207 (44%) students, which indicates that most respondents are in a group that still needs additional support, both in the form of attitude reinforcement and digital skills improvement. Therefore, this cluster is a strategic target for interventions such as online learning assistance programs, basic digital skills training, and growth mindset development.

Cluster 2

Table 4. Cluster 2 Grouping in the Limited Scheme

No.	Data Ke-	*PT*	*GM*	*LME*	*DC*	Cluster
1	2	0.9	0.55	0.95	0.85	C2
2	3	0.85	0.8	0.85	0.9	C2
3	8	0.7	0.65	0.7	0.7	C2
4	10	0.75	0.75	0.75	0.75	C2
5	11	0.7	0.75	0.7	0.75	C2
6	12	0.8	0.75	1	0.8	C2
7	13	1	1	1	1	C2
8	16	0.7	0.95	0.7	1	C2
9	17	1	0.95	1	0.9	C2
10	22	0.75	0.75	0.75	0.75	C2
...	...	...	...	...	...	...
260	466	0.75	0.75	0.75	0.6	C2

Based on cluster 2 table above, it shows that the scores are moderate to high in almost all dimensions analyzed. The values for Psychological Traits, Motivation, and Digital Competence are generally above 0.70 to close to 1.00, which reflects a positive attitude towards digital learning, adequate technological readiness, and high motivation and engagement in online learning. With approximately 260 members (56%) being students, this cluster represents a group that is ready to face and respond to digital transformation in education. They have great potential to be involved as mentors, peer coaches, or digital ambassadors in academic environments.

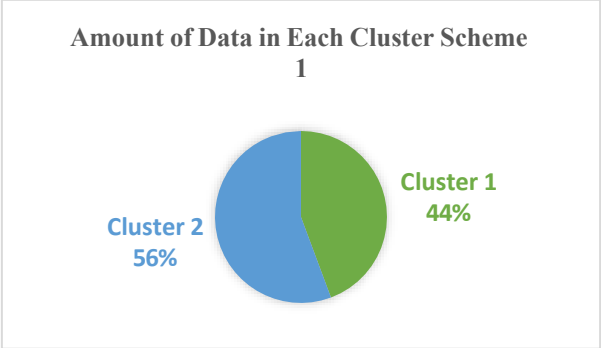

Figure 2. Percentage Statistics of Cluster Scheme 1

In general, Psychological Traits are the dimension that plays the most significant role in distinguishing student characteristics between clusters. Students with high scores in this aspect generally belong to the ready cluster (C2), while those with low to moderate scores tend to belong to the less ready cluster (C1).

In addition, Digital Competence also serves as a significant differentiating indicator, even though there are a number of students in cluster C1 who have fairly high scores in this dimension. These findings indicate that the ability to use technology is not always accompanied by strong mental readiness and motivation. Therefore, the development of digital skills should be carried out in conjunction with strengthening aspects of attitude and psychological readiness.

Scheme 2 (Full)

To determine the most optimal number of clusters in K-Means modeling on the Full Scheme, testing was conducted on variations in the number of clusters ranging from K = 2 to K = 10. Evaluation of the quality of the clustering results was carried out using the Silhouette Coefficient, which represents the level of internal consistency and clarity of separation between clusters. The following table shows the average Silhouette Coefficient values for each number of clusters tested:

Table 5. Silhouette Coefficient Scheme 2 (Full)

	Silhouette Scores
2	0.323
3	0.253
4	**0.195**
5	**0.194**
6	**0.179**
7	**0.178**
8	**0.155**
9	**0.162**
10	**0.154**

Based on the table, the highest Silhouette Coefficient value was achieved when the number of clusters (K) was 2, with a score of 0.323. This figure indicates that the clustering process was most optimal and describes the most representative segmentation of students when divided into two main groups.

Cluster 1

Table 6. Cluster 1 Grouping in the Full Scheme

No.	**Data Ke-**	***PT***	***GM***	***LME***	***DC***	***DRM***	***SS***	***Cluster***
1	1	0.55	0.5	0.5	0.85	0.5	0.75	C1
2	4	0.55	0.55	0.6	0.6	0.6	0.5	C1
3	5	0.55	0.5	0.5	0.6	0.65	0.5	C1
4	6	0.65	0.5	0.55	0.65	0.6	0.55	C1
5	7	0.5	0.6	0.8	0.7	0.75	0.45	C1
6	9	0.5	0.7	0.55	0.6	0.55	0.5	C1
7	15	0.5	0.5	0.5	0.5	0.5	0.5	C1
8	18	0.5	0.5	0.5	0.5	0.5	0.5	C1
9	19	0.65	0.65	0.6	0.6	0.65	0.65	C1
10	20	0.5	0.5	0.5	0.5	0.5	0.5	C1
…	….	…	….	…	….	….	….	…
192	467	0.55	0.5	0.5	0.45	0.55	0.55	C1

Based on cluster 1 table above, it shows that the scores are moderate in almost all dimensions, with a range of values between 0.50 and 0.65. No dimension appears to be dominant, although Digital Readiness & Mindfulness is slightly more prominent than other dimensions. This shows that students in this group are relatively open to the use of technology, but still lack motivation to learn, satisfaction, and a growth mindset.

With approximately 192 (41%) students, C1 in the Full Scheme reflects a group that is functionally technologically ready, but not yet fully mature in psychological and motivational aspects. Therefore, a more personalized and interactive learning approach is needed to encourage increased satisfaction and engagement in the learning process.

Cluster 2

Table 7. Cluster 1 Grouping in the Full Scheme

No.	Data Ke-	*PT*	*GM*	*LME*	*DC*	*DRM*	SS	*Cluster*
1	2	0.9	0.55	0.95	0.85	0.95	0.8	C2
2	3	0.85	0.8	0.85	0.9	0.6	0.7	C2
3	8	0.7	0.65	0.7	0.7	0.65	0.65	C2
4	10	0.75	0.75	0.75	0.75	0.5	0.9	C2
5	11	0.7	0.75	0.7	0.75	0.75	0.75	C2
6	12	0.8	0.75	1	0.8	0.75	0.75	C2
7	13	1	1	1	1	1	1	C2
8	14	0.75	0.5	0.5	0.75	0.75	0.75	C2
9	16	0.7	0.95	0.7	1	0.95	0.75	C2
10	17	1	0.95	1	0.9	0.85	0.85	C2
...	...	...	...	...	...	....	....	...
275	466	0.75	0.75	0.75	0.6	0.7	0.6	C2

Based on the cluster 2 table above, it shows characteristics with consistently high scores across all dimensions measured, with most values above 0.75. The aspects of Psychological Traits, Learner Motivation, and Student Satisfaction appear to be the most prominent. In fact, there are several individuals who achieved maximum scores (1.00) across all dimensions, reflecting a very good level of digital readiness and high satisfaction with online learning.

With a total of around 275 (59%) students, this cluster represents a group that is adaptive, independent, and highly competitive in the context of digital learning. They are highly potential to be involved in the development of advanced e-learning programs or to become strategic partners in the application of educational technology.

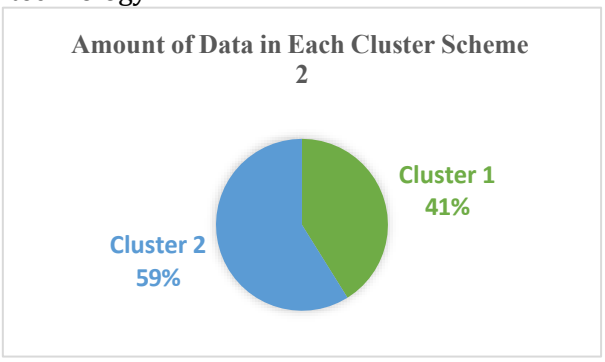

Figure 3. Percentage Statistics of Cluster Scheme 2

In general, Psychological Traits and Learner Motivation & Engagement are the two key dimensions that most distinguish student characteristics in the Full Scheme. These two variables show significant differences between the less prepared (C1) and prepared (C2) student groups, with C2 also showing higher levels of Student Satisfaction, reinforcing these differences.

Meanwhile, Digital Readiness & Mindfulness appear to be relatively evenly distributed across both clusters. Some students in cluster C1 do have fairly high scores in this aspect, but still show weaknesses in psychological and motivational aspects. These findings confirm that success in digital learning is not only determined by technological readiness alone, but also heavily depends on mental readiness and active engagement from students.

Distributions

Data distributions in each cluster provide in-depth insights into the characteristics of the variables that play the most significant role in the clustering process. Through graphical analysis of distributions, it is possible to identify the extent to which each variable distinguishes between clusters and understand the patterns of values that tend to appear in each group. This visualization facilitates the interpretation of student behavior based on variable scores, thereby providing a strong foundation for drawing conclusions and formulating strategic recommendations.

Scheme 1 (Limited)

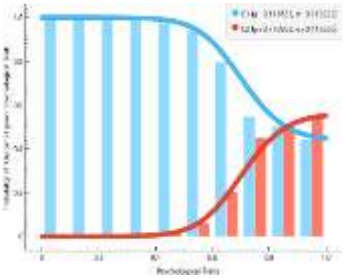

Figure 2. Distribution Graph of Scheme 1 on Psychological Traits Variables

Figure 2 shows that Psychological Traits are a very significant distinguishing variable in forming clusters. Students with low to moderate scores (0.2–0.6) were more likely to be classified in Cluster 1 (C1), with an average score of 0.5176. Meanwhile, students with high scores above 0.7 dominated Cluster 2 (C2), with an average of 0.7709. This distribution pattern indicates that psychological readiness plays a crucial role in determining students' ability to adapt to digital learning. The higher the psychological stability and resilience, the greater the chance of students being classified in the digitally ready cluster. These findings emphasize the urgency of incorporating psychological aspects into the design of more personalized and effective digital learning interventions.

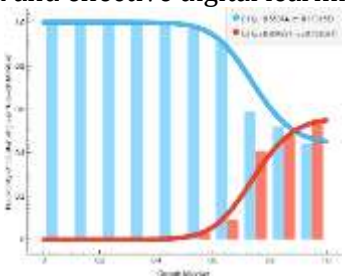

Figure 3. Distribution Graph of Scheme 1 on the Growth Mindset variable

Figure 3 shows clear differences in cluster distribution based on the Growth Mindset variable. Cluster 1 (C1), with an average score of 0.5531, is dominated by students with low to moderate Growth Mindset levels (0.2–0.6). In contrast, Cluster 2 (C2), with an average of 0.8042, is filled with students who show strong belief in their ability to develop and learn from challenges. This pattern confirms that Growth Mindset plays a strategic role in shaping students' readiness to face the dynamics of digital learning. Students with a growth mindset tend to be more resilient and adaptive to technology, making this variable important in personalized learning interventions.

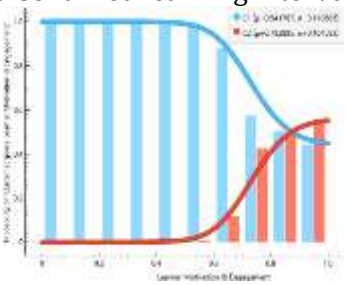

Figure 4. Distribution Graph of Scheme 1 on the variables of Learner Motivation & Engagement

Figure 4 shows the probability distribution of cluster membership based on the Learner Motivation & Engagement variable. It can be seen that students with low to moderate motivation and learning engagement scores (around 0.2–0.6) tend to be clustered in Cluster 1 (C1), with an average score of 0.5418. Meanwhile, students with high scores, especially above 0.7, are more likely to be classified in Cluster 2 (C2), with an average score of 0.7929. This distribution pattern indicates that motivation and learning engagement are significant determining factors in distinguishing students' digital readiness. Group C2 represents students who are more active, motivated, and consistently engaged in the online learning process, making them the ideal target for the implementation of learning strategies that are adaptive to learner characteristics.

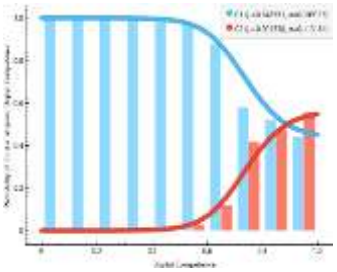

Figure 5. Distribution graph of Scheme 1 on the Digital Competence variable

Figure 5 shows the probability distribution of cluster membership based on the Digital Competence variable. It can be seen that students with low to moderate digital competence (range 0.2–0.6) are more dominant in Cluster 1 (C1), with an average score of 0.5486. Conversely, students with higher digital competence (above 0.7) tend to be clustered in Cluster 2 (C2), with an average of 0.8015. This pattern shows that digital skills mastery plays a crucial role in distinguishing students' readiness in the context of online learning. Students in Cluster 2 are reflected as a group that is not only more adaptive to technology but also ready to make the most of digital devices to support their learning process. This finding reinforces the urgency of developing digital literacy as the main foundation in technology-based learning strategies.

Scheme 2 (Full)

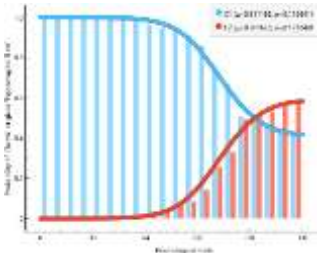

Figure 6. Distribution Graph of Scheme 2 on Psychological Traits variable

Figure 6 shows that Psychological Traits is a highly significant distinguishing variable in the formation of clusters in Scheme 2. Students with low to moderate scores (around 0.2–0.6) are more likely to be classified in Cluster 1 (C1), with an average score of 0.5111. Conversely, students with high scores above 0.7 dominate Cluster 2 (C2), with an average of 0.7616. This pattern indicates that psychological aspects remain the main indicator in distinguishing students' readiness for digital learning. The higher the stability and mental readiness of students, the greater their chances of being classified in the group that is adaptive to the online learning system.

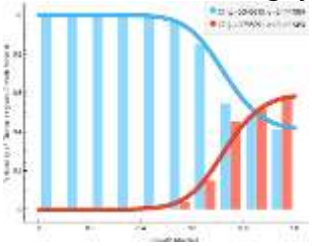

Figure 7. Distribution Graph of Scheme 2 on the Growth Mindset variable

Figure 7 shows that the Growth Mindset variable also plays an important role in distinguishing clusters in Scheme 2. Students with low to moderate scores (around 0.2–0.6) were more likely to be classified in Cluster 1 (C1), with an average score of 0.5406. Meanwhile, students with high scores above 0.7 are more dominant in Cluster 2 (C2), with an average of 0.7950. This pattern confirms that students' growth orientation and belief in their ability to develop greatly influence their readiness to face digital learning challenges. Students who have a strong Growth Mindset tend to be more motivated, adaptive, and positive in technology-based learning processes.

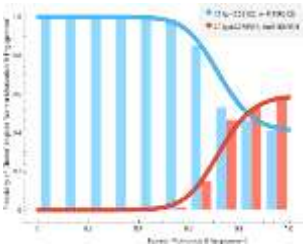

Figure 8. Distribution Graph of Scheme 2 on the variables of Learner Motivation & Engagement

Figure 8 shows that the Learner Motivation & Engagement variable clearly distinguishes cluster membership in Scheme 2. Students with low to moderate motivation and engagement scores (around 0.2–0.6) tend to belong to Cluster 1 (C1), with an average score of 0.5312. Conversely, students with high scores (above 0.7) are more dominant in Cluster 2 (C2), which has an average of 0.7865. This pattern indicates that motivation and active engagement in digital learning are crucial indicators of learning readiness. Students who are more motivated and engaged tend to belong to groups that are more adaptive and responsive to digital-based learning.

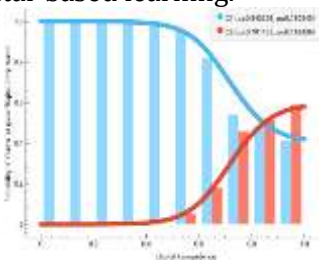

Figure 9. Distribution graph of Scheme 2 on the Digital Competence variable

Figure 9 shows that the Digital Competence variable contributes significantly to cluster separation in Scheme 2. Students with low to medium digital competence scores (around 0.2–0.6) are more likely to be classified in Cluster 1 (C1), with an average score of 0.5432. Conversely, students with high digital competence scores (above 0.7) were more dominant in Cluster 2 (C2), with an average of 0.7916. These findings confirm that the level of mastery of digital technology is one of the main indicators in identifying students' readiness for digital learning, where group C2 reflects individuals who are more confident and competent in utilizing learning technology.

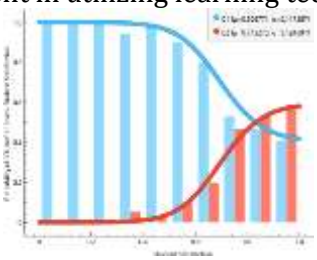

Figure 10. Distribution Graph of Scheme 2 on the Student Satisfaction variable

Figure 10 shows that the Student Satisfaction variable is also a factor that clearly distinguishes clusters in Scheme 2. Students with low to moderate satisfaction levels (around 0.2–0.6) are mostly classified in Cluster 1 (C1), with an average score of 0.5068. Conversely, students with high satisfaction levels (above 0.7) tend to be in Cluster 2 (C2), with an average of 0.7753. This pattern indicates that satisfaction with the digital learning experience is strongly correlated with students' readiness and acceptance of the online learning model, making this variable an important indicator in cluster mapping.

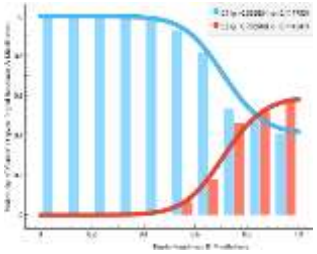

Figure 11. Distribution Graph of Scheme 2 on the variables of Digital Readiness & Mindfulness

Figure 11 shows that the Digital Readiness & Mindfulness variable plays an important role in distinguishing student clusters in Scheme 2. Students with low to moderate digital readiness and awareness (around 0.3–0.6) are mostly classified in Cluster 1 (C1), with an average score of 0.5589. Meanwhile, those with high digital readiness and mindfulness (above 0.7) are more dominant in Cluster 2 (C2), with an average score of 0.7869. These findings emphasize that technological readiness accompanied by digital self-reflection is a crucial element in segmenting students who are adaptive to a dynamic digital learning environment.

CONCLUSION

This study successfully grouped students based on their attitudes toward digital learning by applying the K-Means algorithm to two variable schemes, namely the limited scheme and the full scheme. The clustering results in both schemes consistently produced two main clusters: students with high readiness (C2) and students with low readiness (C1). Based on the evaluation using the Silhouette Coefficient, the most optimal number of clusters was two, with the highest values of 0.335 for the limited scheme and 0.323 for the full scheme. Psychological Traits and Learner Motivation & Engagement emerged as the most significant differentiating factors between clusters, followed by Digital Competence. Although some students in the cluster were not quite ready to demonstrate adequate digital skills, this was not always accompanied by adequate mental readiness and motivation. These findings indicate that the development of digital skills should be accompanied by support for psychological aspects and increased learning motivation. Therefore, the results of this study provide an important foundation for the design of more personalized and responsive digital learning strategies, tailored to the characteristics and readiness of each group of students.

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AUTHOR CONTRIBUTION STATEMENT

AR and SA Conceptualization, research design, instrument development, data collection, data preprocessing, K-Means modeling and analysis, interpretation of results, manuscript drafting, and final revision. EN, and FGP Instrument review, data verification, methodological validation, visualization support, discussion development, proofreading, and manuscript editing. All authors have read and agreed to the published version of the manuscript.

AI DISCLOSURE STATEMENT

The authors used ChatGPT (OpenAI) during the preparation of this work for English language refinement, clarity improvement, and structural editing of several manuscript sections. After using the tool, the authors thoroughly reviewed, validated, and edited the content as needed and take full responsibility for the accuracy, originality, and integrity of the final manuscript.

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