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A Novel Analysis of the Index of Learning Styles of Undergraduate Engineering Students

Lauren Genith Isaza[1], PhD, Antonio Robles Gomez[2], PhD, and Rafael Pastor Vargas[3], PhD
[1]Universidad Nacional de Educación a Distancia UNED, España, lisaza3@alumno.uned.es
Universidad de los Llanos UNILLANOS, Colombia, lisaza@unillanos.edu.co
[2,3] Universidad Nacional de Educación a Distancia UNED, España, arobles@scc.uned.es, rpastor@scc.uned.es

Abstract*– This study analyzed the learning preferences of 73 undergraduate engineering students of a Mechanical Engineering class at the University of Los Llanos in Villavicencio, Colombia. The students filled out Felder-Silverman Index of Learning Styles (ILS) questionnaires during class time and their scores were tabulated into a dataset according to student number in relation to each of the four ILS learning dimensions (active/reflective, sensing/intuitive, visual/verbal, and sequential/global). This dataset was first analyzed by K-means clustering using the Elbow Method, the Silhouette Index, and the Calinski-Harabasz Index to determine the optimal number of clusters which was found to be 2. The optimal number of clusters was then applied to a hierarchical clustering analysis using Ward's Method. Each cluster was then analyzed statistically to determine the dominant learning styles in each cluster. All analyses were done using Anaconda 4.3 software. Students in Cluster 1 showed a preference for active and intuitive learning and students in Cluster 2 favored reflective and verbal learning, This analysis was a novel approach to determining dominant learning styles in a group of undergraduate engineering students. The findings highlight the potential for improved educational outcomes in engineering by aligning curriculum design with student learning preferences.

Keywords - Felder-Silverman Learning Styles Model, K-means clustering, Silhouette Score, Calinski-Harabasz Index, Hierarchical Clustering Ward´s Method.

I. Introduction

Understanding the diverse learning styles of students is necessary to improve engineering educational outcomes [1]. The Felder-Silverman Learning Styles Model (FSLSM) offers a powerful psychometric tool to assess an individual's learning preferences across the following four learning style dimensions: Active/Reflective, Sensing/Intuitive, Visual/Verbal, and Sequential/Global [2]. This approach of categorising students by their learning styles provides a mechanism by which university professors can develop their course curriculums to better meet the necessities of their students [3].

Studies have consistently shown that students achieve better understanding, retention, and application of complex concepts when taught in a manner that resonates with their learning preferences [4]. However, the challenge lies in effectively identifying and addressing the spectrum of learning styles within a classroom. Therefore, the Index of Learning Styles (ILS) created by Felder and Silverman is an excellent tool to address this challenge [5].

Hierarchical clustering has been the primary method used for developing integrated classification systems in the literature [6]. This method can be used to analyse responses to the ILS questionnaire by grouping students with similar learning preferences. This approach can reveal the diverse structure of learning styles within a group of students and can enable the development of personalised teaching strategies. By recognizing individual learning preferences, this method can greatly improve engineering education [7].

This study seeks to uncover the distribution of learning styles and examine its implications for curriculum design, instructional methods, and student study strategies. This study intends to contribute to the ongoing dialogue of the importance of adaptive teaching strategies in engineering education [8].

This research has implications beyond the world of academia, as it addresses the adaptation of engineering education and curricula to suit the diverse learning needs of students. With the onset of Industry 5.0, the study intends to provide guidance for engineering educators to innovate their teaching methods, ensuring that future engineers are not only equipped with technical skills but also possess the adaptability to succeed in their future careers [9].

This research aims to connect theoretical learning models, as in our case the Felder-Silverman model, with practical educational applications by providing a method that adapts to the unique needs of different student groups. By using both K-means and hierarchical clustering, this study examines the complex patterns of learning preferences within a class of 73 mechanical engineering students at the University of Los Llanos, Villavicencio, Colombia. The objective is to use these findings to guide customized educational strategies and curriculum adjustments that improve educational outcomes.

The novelty of this study arises from its use of advanced clustering techniques, with the combination of K-means and hierarchical clustering, to analyze learning style data based on the FSLSM. This approach represents a shift from previous methods, which often relied on simpler classification techniques. By applying these more complex statistical methods, our research provides a detailed and new perspective on the distribution of learning styles within a class of engineering students.

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II. Background

The ILS questionnaire, developed by Richard M. Felder and Linda K. Silverman, is a diagnostic tool designed to help learner s identify their individual preferences in learning across four dimensions: Active/Reflective, Sensing/Intuitive, Visual/Verbal, and Sequential/Global. Each dimension has 11 questions, for a total of 44 questions. Students choose between two options for each question and the question answers are tabulated to give a total score between +11 and -11, reflecting their learning preference in each learning dimension, These dimensions show how learners prefer to interact with information, whether through hands-on experience or reflection, through sensing and facts or intuition and theories, by visual means or verbal explanations, and in a sequential step-by-step manner or in a global holistic approach [10].

Numerous models of learning styles are discussed in the literature, but the ILS questionnaire is the most frequently used for its comprehensive characterization of students' learning styles across different dimensions [11]. The ILS questionnaire was found to have a high level of validity and reliability by [12], who demonstrated a consistent pattern of learning style preference across different student populations and disciplines, indicating its effectiveness for developing curriculum design.

The ILS questionnaire has also been found to be reliable in a diversity of languages. For example, [13] used various statistical tests to assess the reliability and validity of the Mandarin version of the ILS by analysing 198 questionnaires given to undergraduate students. Their findings therefore support the use of this questionnaire in a diversity of geographical locations.

Studies by [14] and [15] both employed hierarchical clustering by average linkage to group students based on their learning styles. The first study grouped Information and Computer Education students at Universitas Sebelas Maret using the FSLSM [14]. The second study applied a similar approach to engineering students at Prince Sultan University [15].

However, in our study we decided to take a different approach to the clustering process by initially determining the optimal number of clusters using K-means clustering by the Elbow Method, Silhouette index, and the Calinski-Harabasz index. Taking the first step of K-means analysis ensured that we had identified the optimal number of clusters in our data, which contrasts with the previously used methods of only employing hierarchical clustering by average linkage. Subsequently, by applying hierarchical clustering by Ward´s method we were able to minimise the within-cluster variance, yielding more meaningful and cohesive student groupings. This dual-phase approach we hope will provide a more effective analysis of student learning styles.

III. METHODS

A. *Participants*

The study was conducted with 73 undergraduate students enrolled in a Mechanical Engineering course at the University Los Llanos in Villavicencio, Colombia. All participants voluntarily agreed to participate in the study and signed informed consent forms. The consent forms outlined the study's purpose, which was to identify their dominant learning styles as determined by the FSLSM and informed participants of the confidentiality of their data. They were also told that no personal information, such as student names or numbers, would be disclosed.

B. *Procedure*

Participants completed the ILS questionnaire during a regular class session. To ensure honesty and give the students enough time to do the questionnaires, the 5 percent for participation of their final grade was given for completing the questionnaire. The completed questionnaires were collected and the responses were manually tabulated. Each student's scores were calculated according to the ILS scoring guidelines, resulting in a score between -11 and 11 for each of the four dimensions of learning styles. Table 1 below shows scores for each student.

TABLE 1
Indexo of Learning Styles Questionaire Scores

Student Number	1	2	3	4	5	7	8	9	10	11	12	13	14	15	
Active/Reflective	7	-3	-1	-3	-3	-3	-1	1	-5	-5	-5	-1	-1	-3	
Sensing/Intuitive	1	-7	1	-3	3	-6	-3	-1	1	-5	-7	-7	-3	-1	
Visual/Verbal	-7	-7	-1	3	-9	-5	-5	-7	-3	-7	-3	-9	-5	-1	
Sequential/Global	5	-7	-7	5	3	-6	-1	-5	1	1	-9	-3	11	1	
Student Number	16	17	18	19	20	22	23	24	25	26	27	28	29	30	
Active/Reflective	-1	1	1	5	-1	1	1	-11	9	7	1	-3	-5	-5	
Sensing/Intuitive	-3	-7	1	-3	3	1	1	-5	7	5	-1	-1	-1	-7	
Visual/Verbal	-1	-3	-9	-1	-1	-1	9	-5	3	5	-3	-5	-9	-7	
Sequential/Global	-7	-3	-5	-5	-5	-1	3	-7	9	-5	-1	-3	-9	-9	
Student Number	31	32	33	34	35	36	37	38	39	40	41	42	43	44	
Active/Reflective	1	5	-3	5	1	7	-3	1	-7	-9	-1	-5	3	-3	
Sensing/Intuitive	-7	-3	-7	3	-3	-1	-3	-5	-5	-4	-7	-1	-3	-3	
Visual/Verbal	-5	-3	-9	1	-3	-5	-9	-3	-9	-5	-9	-9	1	-9	
Sequential/Global	-5	-5	-3	5	-3	-9	-7	-1	-9	-5	-5	1	1	-3	
Student Number	45	46	47	48	49	50	51	52	53	54	55	56	57	58	
Active/Reflective	-3	-1	-5	-1	-1	-3	-3	-1	-9	-7	-5	-7	-1	-3	
Sensing/Intuitive	-5	-3	-3	-3	3	-7	-5	-1	-1	-7	-7	11	3	-9	
Visual/Verbal	-9	-9	-3	-9	-1	-5	-5	-7	-5	-3	11	-5	-5	-3	
Sequential/Global	5	-5	3	-7	-7	-5	-1	-7	-1	1	-5	-1	-1	-1	
Student Number	59	60	61	62	63	64	65	66	67	68	69	70	71	72	73
Active/Reflective	-3	1	3	-5	-3	1	-5		-5	1	1	-7	3	-7	-5
Sensing/Intuitive	-5	-5	-5	-9	-3	-3	-5	3	-7	-5	-3	-3	-7	-5	1
Visual/Verbal	-7	-1	-7	-7	-5	-7	-5	-9	-7	-7	-3	-3	3	-5	-3
Sequential/Global	-9	-7	1	-1	-1	-7	5	3	-1	-9	-5	-5	1	-5	-3

C. *K-means Clustering*

K-means clustering was chosen as its a straightforward approach mathematically and for calculating in a Python or Anaconda environment. This method is particularly useful in educational settings for grouping students with similar traits, which can help in developing more focused teaching strategies.

The accuracy of K-means clustering lies in its ability to form well-defined clusters.

D, K-means algorithm

The K-means algorithm is an iterative method for clustering. It uses distance as a measure and, given K groups in the dataset, computes the mean distance to establish the initial centroids, with each group characterized by its centroid. For a given dataset X with n multi-dimensional points and a specified number K of categories to be segmented, the algorithm employs Euclidean distance as the measure of similarity. The objective of the clustering process is to minimize the total sum of squared distances within each category:

$$\mathrm{d} = \sum_{k=1}^{k} \sum_{i=1}^{n} \|(x_i - u_k)\|^2 \tag{1}$$

In (1) k denotes the number of cluster centers, u_k signifies the center of the kth cluster, and x_i refers to the ith data point in the dataset [16].

E. Elbow Method

The elbow method involves plotting the within-cluster sum of squares (WCSS) against the number of clusters and identifying the "elbow" point where the rate of the slope's decrease sharply changes in order to determine the optimal number of clusters in the dataset [17].

By accurately determining this point, this ensures that the clusters are appropriately scaled to capture the diversity of learning styles without unnecessary complexity.

F. Silhouette Index

The Silhouette Index identifies the optimal number of clusters by calculating the difference between the mean intra-cluster distance and the minimum inter-cluster distance. This is defined in the following way:

$$\bar{S} = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{b(i) - a(i)}{max\{a(i), b(i)\}}\right) \tag{2}$$

In (2) *a(i)* denotes the mean distance from sample i to the other samples within the same cluster, while *b(i)* indicates the smallest distance from sample *i* to samples in different clusters [18,19].

In educational contexts, this index verifies that students are grouped in a way that aligns with their learning styles. The Silhouette Index's ability to validate cluster separation is necessary for confirming the accuracy of student groupings.

G. Calinski-Harabasz Index

The Calinski-Harabasz Index assesses the dispersion between clusters, and it is defined as follows:

$$CH(K) = \frac{B(K)(N-K)}{W(K)(K-1)} \qquad B(K) = \left(\sum_{k=1}^{K} a_k \|\overline{x_k} - \bar{x}\|^2\right)$$

$$W(K) = \left(\sum_{k=1}^{K} \sum_{C(j)=k} \|x_j - \overline{x_k}\|^2\right) \tag{3}$$

In (3), K represents the number of clusters, B(K) denotes the inter-cluster divergence or covariance, W(K) refers to the intra-cluster divergence or covariance, and N represents the sample size. A greater B(K) indicates a higher level of dispersion between clusters, while a smaller W(K) suggests a tighter relationship within each cluster. Consequently, a higher ratio between B(K) and W(K) results in a larger value of the Calinski-Harabasz (CH) index indicating a more optimal clustering outcome [20].

In educational research, clear separation between clusters allows for targeted curriculum adjustments and more effective teaching strategies. This index helps ensure that the identified clusters are not only statistically significant but also meaningful, providing a reliable basis for educational anaylsis.

H. Hierarchical Clustering

Hierarchical clustering using Ward's method was subsequently applied to the dataset to generate a dendrogram and assign the students to the optimal number of clusters found by K-means clustering. This method was chosen for its ability to minimize the variance within each cluster [21].

Upon clustering the students, a statistical analysis was conducted to characterize each cluster. The mean and standard deviation were calculated for each of the learning style dimensions within each cluster to provide a view into the learning preferences and variabilities of the grouped students.

This method was selected because by minimizing the variance within each cluster, ensures that students within the same cluster have similar learning styles. By generating a dendrogram, as shown in Fig 2, Ward's method provides a visual tool that is highly useful for educators as it illustrates the depth and the linkage of learning style variations within any given student population.

IV. Results

A. K-Means Clustering - Elbow Method

As shown in Fig. 1, there is a noticeable change in the slope of the line after the second cluster (k=2). The line starts to flatten as it moves towards the right, which indicates that additional clusters beyond this point do not contribute as much to a decrease in the WCSS. This suggests that the "elbow" of the graph is at k=2.

B. K-means clustering - Silhouette Scores

The optimal number of clusters is the one with the highest average silhouette score. In this case, it is when n_clusters = 2, with a score of approximately 0.239 as seen in Table 2. This suggests that two is the most appropriate number of clusters for the given dataset, as it provides a better structure and separation between the clusters than the other tested numbers of clusters.

C. K-means clustering – Calinski-Harabasz Index

The optimal number of clusters based on the Calinski-Harabasz Index is the one with the highest score. In this case, it is when n_clusters = 2, with a score of approximately 24.98 as seen in Table 3. This suggests that two clusters provide the best separation and cohesion for our dataset according to the Calinski-Harabasz Index. This corroborates the findings of the Siloutte Index scores, that the optimal number of clusters is two.

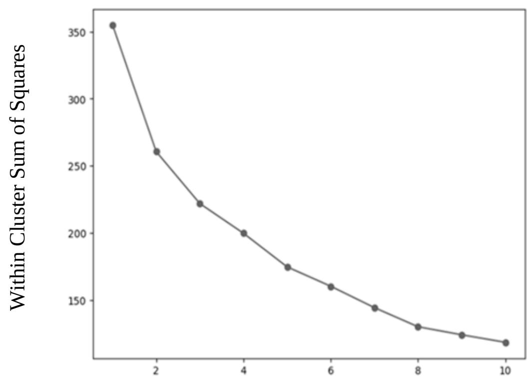

Fig. 1 Within Cluster Sum of Squares (WCSS) as a function of number of clusters (k) in the dataset

TABLE 2
Silhoutte Scores according to number of clusters

For n clusters = 2, the average silhouette score is: 0.239
For n clusters = 3, the average silhouette score is: 0,181
For n clusters = 4, the average silhouette score is: 0,160

TABLE 3
Calinski–Harabasz Index according to the number of clusters

For n clusters = 2, the Calininski- Harabasz Index is: 24.98
For n clusters = 3, the Calininski- Harabasz Index is: 20.38
For n clusters = 4, the Calininski- Harabasz Index is: 17,34

D. Hierarchical Clustering by Ward´s Method

After analyzing the ILS scores results by Hierarchical Clustering by Ward´s Method, the dendrogram in Fig 2. was created.

A dendrogram is read by analyzing the arrangement of its branches, where each branching point represents a grouping of data points, and the height of the branches indicates the dissimilarity between these groups. As seen in Fig 2. The highest branch indicates that there are two separate clusters in our dataset.

Assuming that there are two optimal clusters as determined from the K-means clustering analysis, from the dendrogram we can determine which students belong to each cluster:

Cluster 1 contains the students: 1, 3, 4, 8, 16, 17, 19, 20, 22, 23, 25, 26, 27, 31, 32, 34, 35, 36, 38, 43, 49, 51, 57, 60, 61, 63, 69, 71.

Cluster 2 contains the students: 2, 5, 7, 9, 10, 11, 12, 13, 14, 15, 18, 24, 28, 29, 30, 33, 37, 39, 40, 41, 42, 44, 45, 46, 47, 48, 50, 52, 53, 54, 55, 56, 58, 59, 62, 64, 65, 66, 67, 68, 70, 72, 73.

E. Statistical Analysis of each cluster

Using Anaconda 4.3, the mean and standard deviation were calculated for each cluster of students in terms of each learning dimension in the ILS Questionnaire to determine the dominant learning styles in each group of students.

TABLE 4
Mean and Standard Deviation for each Learning Dimension in each cluster

CLUSTER 1		
Active/Reflexive	Mean = 1.71	Standard Deviation = 3.28
Sensing/Intuitive	Mean = --1.50	Standard Deviation = 3.76
Visual/Verbal	Mean = -1.57	Standard Deviation = 3.73
Sequential/Global	Mean = -1.79	Standard Deviation = 4.43
CLUSTER 2		
Active/Reflexive	Mean = -3.84	Standard Deviation = 2.77
Sensing/Intuitive	Mean = -3.98	Standard Deviation = 3.25
Visual/Verbal	Mean = -6.49	Standard Deviation = 2.43
Sequential/Global	Mean = -3.58	Standard Deviation = 4,20

Table 4 provides detailed statistics calculating the mean and standard deviation in each learning dimension of the learning preferences within the two distinct student clusters. In Cluster 1, students show a slight preference for active learning, with a mean score of 1.71 and a standard deviation of 3.28, indicating some variability in how strongly this preference is expressed. The negative means for other dimensions like Sensing/Intuitive and Visual/Verbal suggest these students lean towards intuitive and verbal learning styles, though with considerable variability, as shown by the standard deviations.

Cluster 2, on the other hand, exhibits stronger preferences. This cluster shows a notable inclination towards verbal learning, as evidenced by a particularly low mean of -6.49 in the Visual/Verbal dimension and a smaller standard deviation of 2.43, suggesting a more uniform preference across this group. The other dimensions also show negative means, reinforcing a general trend towards reflective, intuitive, and global learning styles with less variation compared to Cluster 1.

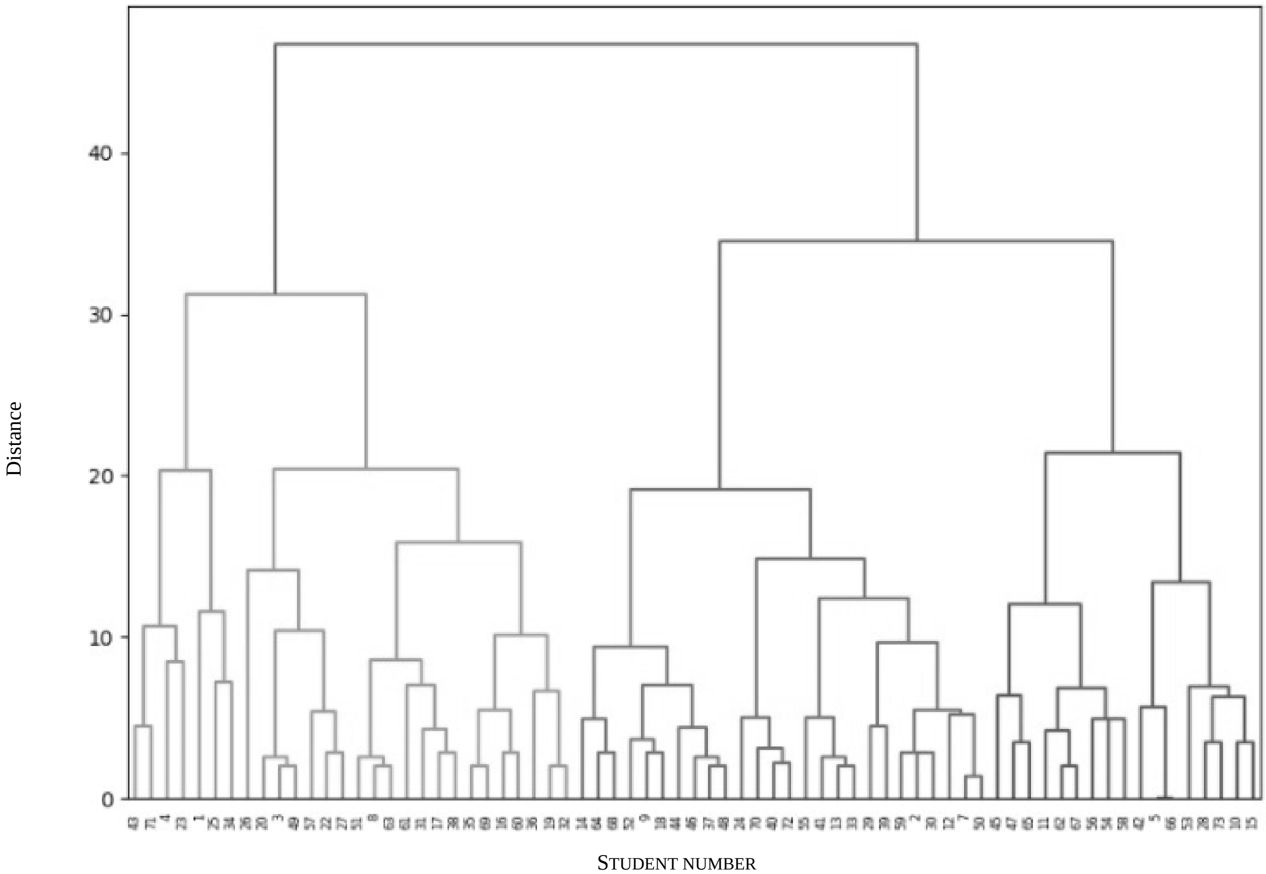

Fig. 2. Dendrogram created by Hierarchical Clustering Ward´s Method with the y-axis a measure of distance (Ward´s linkage criterion)

V. Discussion

Determining the optimal number of clusters using K-means clustering through the Elbow Method, Silhouette Score, and Calinski-Harabasz Index before applying hierarchical clustering with Ward's method provides a multi-faceted analytical approach. This pre-clustering phase ensured the chosen number of clusters was not arbitrary but was statistically validated, increasing the reliability of the hierarchical clustering accuracy.

The Elbow Method gives a visual cue on the diminishing returns of adding more clusters, the Silhouette Score quantifies how well each object lies within its cluster, and the Calinski-Harabasz Index measures the cluster's overall validity. By establishing that two clusters were optimal, we could confidently employ Ward's method for hierarchical clustering, knowing it would yield meaningful and interpretable groupings reflective of the underlying data structure.

Furthermore, we chose hierarchical clustering with Ward's method to analyse student learning styles because of all the hierarchial clustering methods, this one effectively groups students with similar learning preferences while managing the inherent variability in the data [22]. Ward's method is particularly strong against outliers, which is necessary for questionnaire data that may include extreme values [22]. The resulting clusters are both compact and easily interpretable, providing distinct profiles that are useful for developing educational interventions. These characteristics made Ward's method the most favorable choice for visualizing clear and meaningful learning style categories within our student population.

In our analysis of each cluster, we found that students in Cluster 1 have a slight preference for active and intuitive learning styles, favor verbal over visual information, and tend to a global rather than sequential understanding of course material, with their mean scores all leaning slightly towards the more active, intuitive, verbal, and global dimensions of the learning spectrum. Conversely, students in Cluster 2 exhibit a stronger inclination towards reflective and intuitive learning, with their mean scores being more negative, indicating a tendency for these attributes compared to those in Cluster 1.

This analysis that revealed two distinct clusters of learning styles provides not only a valuable strategy for improving educational methodologies but also in terms of curriculum design in engineering education. By identifying that Cluster 1 students exhibit a preference for active, intuitive, and global learning, an engineering class curriculum can include more experiential learning opportunities such as laboratories, fieldwork, and interactive simulations that align with these preferences as well as practical problem-solving, collaborative projects that contextualize engineering principles in real-world scenarios [23].

For Cluster 2, with their pronounced reflective, intuitive, and verbal learning preferences, curriculum design can incorporate structured reflective components, such as case studies that require in-depth analysis, and assignments that encourage exploration of the theoretical basis of engineering concepts. Courses could be designed to include more lectures that provide comprehensive overviews of topics before delving into details, coupled with discussions that facilitate deeper analysis of the material [24].

In regards to the practical implications of our study, using our clustering strategy in engineering education could enable the development of courses adapted to a diverse range of learning preferences, not only the ones identified in our group of students. By analyzing the specific clusters that exist in a class, curriculum developers could design more personalized teaching methods that cater to the varying learning styles identified in their classes This approach would ensure that the curriculum remains flexible and responsive to the learning profiles of various and differing groups of students.

These clustering methods are also a valuable tool for refining faculty development programs. Educators could be equipped with the ILS and our clustering method to improve their teaching methodology. Training programs could emphasize adaptive teaching methods and the use of our clustering methods to support different learning needs. This focus on adaptive education, not the traditional one-size-fits-all all approach, would not only enhance the quality of instruction but also create a more inclusive and engaging learning environment,

Our approach to analyzing student learning styles aligns with adaptive e-learning strategies, such as the study done by [25], which emphasized the importance of creating adaptive environments based on learning styles. Our clustering technique can significantly contribute to designing e-learning platforms, ensuring they are more engaging and effective for students.

Our clustering method could also significantly enhance the analysis of student behaviors in Massive Open Online Course (MOOC) platforms. By initially determining the optimal number of clusters with K-means clustering and then further analysis through Ward's method of hierarchical clustering, a more accurate segmentation of student learning styles can be achieved. This approach would help with the identification of patterns and learning preferences in large, diverse student populations. MOOC platforms can therefore develop more personalized and effective learning experiences by creating individualized content and pedagogical strategies [26].

The findings of [27] demonstrated that AI is starting to become more widely adopted and integrated into educational institutions. The use of integrated computer systems, along with other technologies, AI can be expanded to include the use of humanoid robots and web-based chatbots to independently or collaboratively perform teachers´ responsibilities [27].

Our study remains relevant despite AI advancements in education because it offers a focused, data-driven approach to understanding student learning styles through clustering analysis, which is complementary to AI's wide applications. While AI has evolved to include intelligent systems and even humanoid robots for teaching, our method provides a foundational analysis that can inform and enhance these AI technologies. By understanding student groupings and learning preferences, AI applications can be more effectively developed and applied in educational contexts, ensuring they address the specific needs and behaviors of different groups of students.

Our study does have several limitations that future research could address to strengthen our findings. One limitation is the variability in cluster compositions that might occur across different student groups. Our reliance on self-reported data from the ILS questionnaire could introduce bias or inaccuracies in assessing learning preferences. Future studies could supplement this with observational or performance-based data to confirm the validity of the use of the ILS. Further research might also explore the presence of more than two clusters, particularly in larger or more diverse datasets. While our study identified two main clusters, additional analyses could uncover more subtypes of learning preferences. Such studies would not only confirm our methods but also refine the strategies used to align educational practices with student needs.

Future research building on our study could also look into how our clustering-based insights improve engineering curriculum design, particularly in MOOCs and other e-learning environments. By customizing these platforms to align with engineering students' learning styles, future studies can measure improvements in engagement, comprehension, and retention. New research could also explore the integration of our approach into AI-driven educational tools. We believe that such studies would not only validate our approach but also refine the teaching strategies for content delivery and direct curriculum design of undergraduate engineering education.

VI. Conclusion

We believe that our cluster analysis method greatly aids in the development of engineering student curricula. This method can also be integrated into MOOCs and e-learning platforms, making them more responsive to engineering students' diverse learning styles. By creating educational content and developing teaching strategies based on learning styles, we can improve student engagement, comprehension, and retention in diverse student groups. Additionally, these approaches can inform AI-driven educational tools, ensuring they are better aligned with the needs of engineering students, thus creating a more effective and inclusive learning environment. Therefore, our approach can improve both traditional and digital educational platforms better preparing engineering students for their future careers.

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