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Article

Investigating Engineering Student Learning Style Trends by Using Multivariate Statistical Analysis

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Abstract: This study aims to use group technology to classify students at the classroom level into clusters according to their learning style preferences. Group technology is used, due to the realization that many problems are similar, and that by grouping similar problems, single solutions can be found for a set of problems. The Felder and Silverman style, and the index learning style (ILS) are used to find student learning style preferences; students are grouped into clusters based on the similarities of their preferences, by using multivariate statistical analysis. Based on the developed groups, instructors can use the proper teaching style to teach their students. The formation of clusters based on the statistical analyses of two sets of data collected from students of two classes at the same level, belonging to same engineering department indicates that each class has different learning style preferences. This is an eye-opener to educators, in that different teaching styles can be used for their students, based on the students' learning styles, even though the students seem to have a common interest.

Keywords: Index learning style; similarity coefficient; Felder and Silverman; group technology

1. Introduction

During the process of preparing our engineering program, to obtain accreditation by the National Commission for Academic Accreditation and Assessment, much attention has been paid to several issues, such as the program strategic plan, curricula development processes, supporting facilities and services, staff training and development, and community services. Part of staff training includes workshops and a seminar dealing with enhancing teaching strategies that are aimed at understanding students' learning styles. Many researchers studied the factors affect the learning style of students and their influence on learning preferences, which can affect students' performance and their achievement of the intended learning outcomes. Among these factors are the students' gender, and the level and type of education [1–4]. It was found that the learning style preference of students improves their academic performance in higher education [1,3,5–8]. Also, students' learning styles are greatly affected by their cultural dimensions [9–11]. Knowing students' learning styles can help educators use proper teaching strategies that make their learning process easier, enjoyable, and more engaging. Grouping students based on their learning styles rather than randomly results in better performances of the students [12]. Faculty members can build on students' experiences and new learning opportunities can be developed after identifying students' learning styles [13]. Students' learning styles can be utilized for course evaluation purposes and for selecting the proper instructing technique and assessment [14–17]. The impact of teaching style on learning was assessed by Giles et al., who assessed different approaches in quantitative courses to establish protocols for such studies [18].

According to Eftekhar and Strong [19], there are two types of learners: Type I learners, known as form-type learners, view learning as their form. They are mainly memory-type learners, and in their minds, a good student is one who stores information and is ready to recall information from this system of storage; they are oriented toward "what" and "how many" types of questions. In contrast, type II learners, known as function-type learners, possess function-oriented minds. They are primarily relationship-type students and are believers in "why" and "how" types of questions. This type of learner sees learning as a method and procedure that determines relationships, which eventually determines parts. Their minds develop methods and procedures, if possible, on a continuous basis, and they believe that a good student is one with insight and the means to solve new problems. Dembo and Howard [20] found that linking styles to learning is a positive factor for improving student knowledge on the subject matter. It is noted in the literature that learning is a complex issue, and learning is influenced by several factors, such as the learning environment, discipline, and culture [21]. Each of the teaching strategies and learning styles offers some understanding into learning and teaching methodologies. Much attention has been paid to learning styles in engineering education [22]. Students are characterized by different learning styles, depending on how they analyze and perceive the information [23,24]. Accordingly, the development of teaching strategies that are based on students' learning styles is an important aspect for preparing future engineers. Instructions should be designed by instructors to meet the needs of engineering students. Several learning-style models have been designed [25–27].

2. Learning Styles

Several learning-style models have been subject to investigations and testing in engineering education. A famous style called the Myers–Briggs-based type indicator (MBTI) has strong learning style implications [27,28], and it was used in engineering campuses during the 1970s and 1980s [29–32]. Other models used as learning styles are Hermann [27,33], and Dunn and Dunn [34,35]. Many researchers have used learning styles developed by Kolb [36,37], and Felder and Silverman [38–41]. It is worth mentioning that the concept of a learning style is not globally accepted as an indicator, on the basis that models that are related to this approach of methodology have never been scientifically validated. Hence, the use of learning styles is considered a heuristic approach, and we believe that it is a good tool to enhance teaching approaches in engineering education. The Felder and Silverman style will be discussed in this study. A brief discussion about MBTI styles will be covered in this study in order provide a better understanding of the dimensions used to develop the learning styles used in higher education.

2.1. Myers–Briggs-Based Type Indicator

The subjects under study were classified into four dimensions:

- Extraverts: They try things out; introverts: They think things through.
- Sensors: Practical; intuitors: Imaginative.
- Thinkers: They tend to make decisions based on facts; feelers: They tend to make decisions based on feelings and personal hunches.
- Judgers: They follow agendas; perceivers: They adapt to change.

2.2. The Felder–Silverman Model

The classification developed by Felder and Silverman is based on answering questions for the following four dimensions:

- What type of information the student preferentially perceives: Sensory or intuitive.
- What type of sensory information is most effectively perceived: Visual or verbal.
- How students prefer to process the information: Actively or reflectively.
- How the student characteristically progresses toward understanding: Sequentially or globally.

3. Current Practice

A literature search revealed that students' learning style preferences have been investigated through the use of descriptive statistical analyses, such as frequencies and percentages of the targeted populations. The studies reported the preferences of the targeted student populations individually. The index learning style (ILS) developed by Richard Felder and Barbra Nancy in 1991 comprises 44 questions to assess preferences on four sets of responses. The ILS is available free-of-charge from the World Wide Web to individuals who would like to assess their own preferences. A study was conducted through 36 undergraduate and 35 graduate engineering students. According to the results obtained, there was a strong preference for the visual category on the ILS. However, there was a good balance in the imagery/verbal dimension [42]. Paterson [43] showed that out of 83 undergraduate engineering students who completed the ILS in a study conducted at Michigan Technological University, 56% were classified as active (ACT) learners (44% were reflective learners, REF), 63% were sensing (SEN) learners (37% intuitive learners, INT), 74% were visual (VIS) learners (26% verbal, VRB), and 53% were sequential (SEQ) learners (47% global, GLO). Felder [27] showed that an average score of engineering students, based on several references, was as follows: 64% were classified as ACT (34% were REF), 63% were SEN (37% INT), 82% were VIS (18% VRB), and 60% were SEQ (40% GLO). Students' learning styles can be better represented by considering different characteristics within ILS dimensions. This can lead to an enhancement of the learning environment [44]. Considering students' pedagogical knowledge and learning preferences according to ILS, Serginto et al. [45] were able to propose a platform in order to automatically generate and personalize courses. The validity and reliability of using ILS on a group of engineering students was investigated by Felder and Spurlin [46] using statistical analysis.

It is obvious that the studies conducted on this subject used descriptive analyses, and they described the types of learners accordingly. Based on a student's learning style, the instructor should use proper approaches to teaching. For example, if a student belongs to sensing/active types of learning, a balanced set of materials that emphasizes practical problem-solving methods needs to be presented with material that emphasizes fundamental understanding for intuitive/reflective students [26].

4. Proposed Evaluation of Students

The current approach to learning style deals with the majority of students and the type of learners that they belong to in order to use a suitable method for teaching students and helping the outlier students whom are lagging. Darwish [47] concluded that United Arab Emirates Universities undergraduate statistics students preferred reflective over active, intuitive over sensing, verbal over visual, and global over sequential learning styles. Furthermore, it was concluded that there were no statistically significant differences along the four dimensions of learning styles, due to students' demographic and academic characteristics, except in the active–reflective and sensing–intuitive dimensions with respect to high school type. In contrast, Felder and Brent [48] indicated the importance for instructors to design a balanced teaching approach that addresses the learning needs of all students. Designing such an approach does not require the assessment of student learning style preferences; it is adequate that the instructor selects a model to address its entire category. Using the current evaluation approach will not satisfy the need for teaching students based on the majority of students that belong to certain teaching styles. For example, suppose that a group of students using ILS scored highly as active learners, while they scored low compared to their peers in the other three-scale dimensions of the ILS. The concern is that if the instructor follows the majority of students' scores as the main teaching style, he will deprive students with other learning styles. Better student' performances were obtained when students were grouped based on their learning style instead of random grouping [12]. This can help students collaborate with each other in a better way. Different teaching techniques should be planned and used to suit students' learning styles [8]. For example, the intuitive, verbal, reflective, and sequential learners typical of engineering students prefer the traditional lecture style [48].

Sensing and intuitive learners prefer facts, data, and observable phenomena to be presented to them as concrete formation, while they prefer abstract concepts when dealing with theories, principals, and mathematical models. On the other hand, pictures, sketches, diagrams, and flowcharts are preferred and appreciated more by visual and auditory learners [8].

This objective of this paper is to divide students of two different engineering courses into groups based on their learning style so that suitable teaching approaches and proper assessment methods can be selected accordingly to better achieve intended learning outcomes. Multivariate statistical analyses are used to group the students into clusters based on their learning styles. A brief discussion about clustering algorithms and the similarity coefficient concept is presented in the following section. A case study will illustrate this concept, and a comparison between the currently used approach and the proposed one is illustrated.

5. Clustering Algorithms Based on Similarity Coefficients

Large numbers of similarity coefficients have been proposed throughout the years.

The Jaccard similarity coefficient [49] is the most widely used general-purpose similarity coefficient: The Jaccard similarity coefficient between machine *i* and machine *j* is defined as follows:

$$S_{ij} = \frac{a}{a + b + c} \quad 0 \leq S_{ij} \leq 1, \tag{1}$$

where:

a: The number of parts that visit both machines,
b: The number of parts that visit machine *i* but not *j*,
c: The number of parts that visit machine *j* but not *i*.

The similarity coefficient is used to identify the relationship between parts regarding certain characteristics under investigation. Based on this relationship, groups of items are identified. Among the algorithms that are used to identify and to form part-families that are associated with the machine cell formation, clustering algorithms are based on the similarity coefficient method, which is used to find similarities between parts/machines, and then to group them into part-families/machine cells. Pairwise similarity coefficients between machines/parts are calculated by using specific similarity coefficient formulas. These similarities are then organized into a matrix called the similarity coefficient matrix. This matrix is used as an input for one of the clustering algorithms, such as single-linkage clustering (SLINK), complete linkage clustering, or average linkage clustering, to form part-families/machine cells, where the inputs can be the distances or similarities between pairs of objects. Single-linkage clustering forms groups by merging the nearest neighbors together according to the highest similarities between them [50]. It works as follows:

- Start with M cluster containing a M × M symmetric matrix of distance/similarities in D = $\{d_{ik}\}$.
- Find the smallest distances/similarities in D = $\{d_{ik}\}$.
- Merge the corresponding objects, *U* and *V*, to obtain the cluster, $\{UV\}$.
- The distance/similarities between $\{UV\}$ and any other cluster, *Q*, is computed by:

$$d_{\{UV\}Q} = \min\{d_{UQ}, d_{VQ}\} \tag{2}$$

The values, d_{UQ} and d_{VQ}, are the distances/similarities between the clusters, *U* and *Q*, and *V* and *Q*, respectively. The result is graphically shown in the form of a tree diagram (dendrogram). The tree diagram representing the machine cells/part-families at different levels of similarity is created by using the similarity coefficient matrix.

This concept will be used to establish clusters of students based on their learning style preferences. The ILS, developed by Richard Felder and Barbra Nancy, will be used to develop student preferences according to the four criteria used by that scale, and then a matrix containing the relationships between all students and the stated preferences will be used as the similarity matrix. Based on this matrix, a clustering algorithm described before will be used to calculate groups sharing the highest possible preferences. The following section will illustrate the application of the processes.

6. Data Collection

Two instructors were involved in this study; each instructor explained to his volunteer students the science and the importance of different learning styles. More emphasis was given to how the study would reflect on the teaching style and approach of the course. Students were given a link to answer the ILS questions, and they were asked to print the output of the completed questionnaire and give it to the instructor for data analysis. Consent forms were signed by all participants, including the instructors, which declared the confidentiality of the data, and that no personal information would be used, such as students' names.

After conducting the survey, each student received the results, expressed in terms of the scores for different learning-style dimensions (ACT/REF, SEN/INT, VIS/VRB, and SEQ/GLO). Scoring 1 or 3 in any dimension means that the student is fairly balanced on the two categories of the dimension, while scoring 5 or 7 means that the student has a moderate preference in one of the categories of that dimension. A student who scores 9 or 11 has a strong preference for one category of that dimension and may fail to understand the subject if taught in an environment that does not address his style preference [27]. Table 1 shows the results obtained from 32 third-level participants enrolled in the engineering economy class, while Table 2 shows the results of 14 third-level students enrolled in the reinforced concrete course.

Table 1. Engineering economy students' index learning style (ILS) results.

Student #	ACT	REF	SEN	INT	VIS	VRB	SEQ	GLO
1	5		9		3		3	
2	5			1	3			1
3	9		9		4		3	
4	7		5		1		3	
5		3	9			3		3
6		5	5		9		2	
7	3		5		5		5	
8	9			7	11			7
9		9		7		5		7
10	3			1	7		3	
11		1	1		3		5	
12		3	3		5		5	
13	7		1		3		3	
14	1			5	7			1
15	3		5		7		3	
16		1	3		5		1	
17	5		9		5		3	
18	7		5		7			3
19	1			1	3			1
20	5		9			3	3	
21	7		5		1			3
22		3	9		3			3
23		5	3		9		1	
24	1		5		7		7	
25		5		1	3		5	
26	1		3		5		1	
27		1		3		1		1
28	11		5		7		9	
29	1		5		9		5	
30	3		5			1		3
31	7			5	9			7
32	3			1	5		5	

Table 2. Reinforced concrete students' ILS results.

Student #	ACT	REF	SEN	INT	VIS	VRB	SEQ	GLO
1	1		3		3		3	
2	5			5	9		3	
3	3		1		3			1
4	1		7			1	9	
5	9			1	11			9
6	9		7		9		3	
7		9	1		3		11	
8		3	9		9		9	
9	1			5	9			7
10	7		5		7			3
11		7	1		1			3
12	7		7		7		1	
13		1		1	3		1	
14	3			1	3			3

7. Data Analysis

7.1. Data Analysis for the First Sample of Students

Minitab software [51] using complete linkage clustering was employed to develop clusters of students based on their learning styles; the results are shown in Table 3. In step 1, student number 16 joined student number 26, with their common learning style preferences having the highest similarity (93.5%). This shows that these two students have very high correlations in their level of learning style. Referring to Table 1, both of them scored 3 at SEN, 5 at VIS, and 1 at SEQ. Student number 16 scored 1 at REF and student number 26 scored 1 at ACT. This indicates that the level of similarities between their learning style is at 93.5%. They formed a new cluster called cluster 16 [29]. In step 2, student number 1 joined student number 17 to form cluster 1, with their common preferences level being 90.9%. In step 15, students belonging to the already-formed cluster 7 joined students belonging to cluster 24 to form a new cluster named cluster 7 (a new cluster 7), with a similarity level between all of them that was equal to 79.6%, and so on. By transforming the data from Table 3 to a graph for visual illustration and simple understanding, the dendrogram can be used to divide the total populations into a desired number of clusters based on the instructor's needs. Figure 1 shows a dendrogram of the developed clusters. The observations represent students' populations while the similarity indicates the level of commonality between students in their learning style preferences. Cluster 1 contains 10 students, cluster 2 contains 18 students, cluster 3 contains two students, and clusters 4 and 5 contain one student each. Cluster 1 includes the following students: 1, 17, 3, 4, 20, 18, 21, 30, 50, and 22; they shared a common similarity level for all learning style variables of about 48% (according to the dendrogram). Cluster 2 contains the following students: 2, 13, 10, 32, 11, 12, 25, 14, 16, 19, 27, 6, 23, 7, 15, 24, and 29. It is obvious that the majority of students belonged to either of the two distinct groups. Studying the variables clusters, it was shown that ACT and SEN students grouped together, and VIS and SEQ grouped together; both of these two groups also joined together. On the other hand, we had REF students and VRB students who shared common learning styles, and INT students grouped with GLO; REF, ERB, INT, and GLO formed one group.

Table 3. Engineering economy student cluster formations.

Step	Similarity Level %	Student Number Joined		New Cluster
1	93.5	16	26	16
2	90.9	1	17	1
3	89.8	6	23	6
4	87.1	10	32	10
5	87.1	24	29	24
6	87.1	7	15	7
7	84.2	8	31	8
8	84.2	11	12	11
9	81.7	19	27	19
10	81.7	2	13	2
11	81.2	1	3	1
12	80.6	21	30	21
13	80.6	11	25	11
14	80.6	5	22	5
15	79.6	7	24	7
16	75	4	20	4
17	73.4	2	10	2
18	70.7	1	4	1
19	70.4	14	16	14
20	65.8	14	19	14
21	62.9	18	21	18
22	61.8	6	7	6
23	59.2	2	11	2
24	57.2	2	14	2
25	55.3	1	18	1
26	47.4	1	5	1
27	45.2	2	6	2
28	35.6	1	2	1
29	31.7	8	28	8
30	12.7	1	8	1
31	0	1	9	1

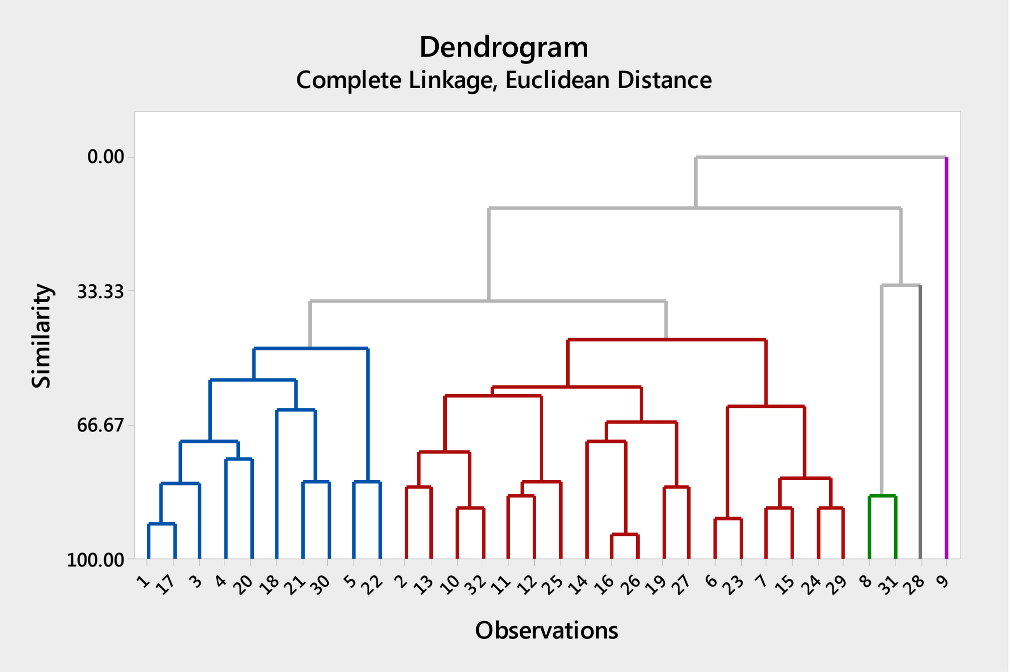

Figure 1. Engineering economy student cluster formations.

7.2. Data Analysis for the Second Sample of Students

Table 4 refers to the development of clusters related to the data from the second class of students, as extracted from the Minitab software. Student number 3 joined student number 14 to form a new cluster called #3, with 88.2% common similarity in learning preferences. At 83.3%, student number 6 joined student number 12 to form a new cluster called #6. In step 3, the already-formed cluster #3 (consisting of student 3 and student 14) joined student 1 to form a new cluster #1, and so on.

Table 4. Reinforced concrete student cluster formations.

Step	Similarity Level %	Student Number Joined		New Cluster
1	88.2	3	14	3
2	83.3	6	12	6
3	80.7	1	3	1
4	73.6	6	10	6
5	72.7	1	3	1
6	56.5	2	9	2
7	579	1	11	1
8	52.7	4	8	4
9	45.8	2	5	2
10	42.9	4	7	4
11	32.5	2	6	2
12	26.2	1	4	1
13	0	1	2	1

Referring to the dendrogram shown in Figure 2, there were four distinct groups of students formed at the 33% similarity level; three of these groups consist of three students, while the fourth consists of five students.

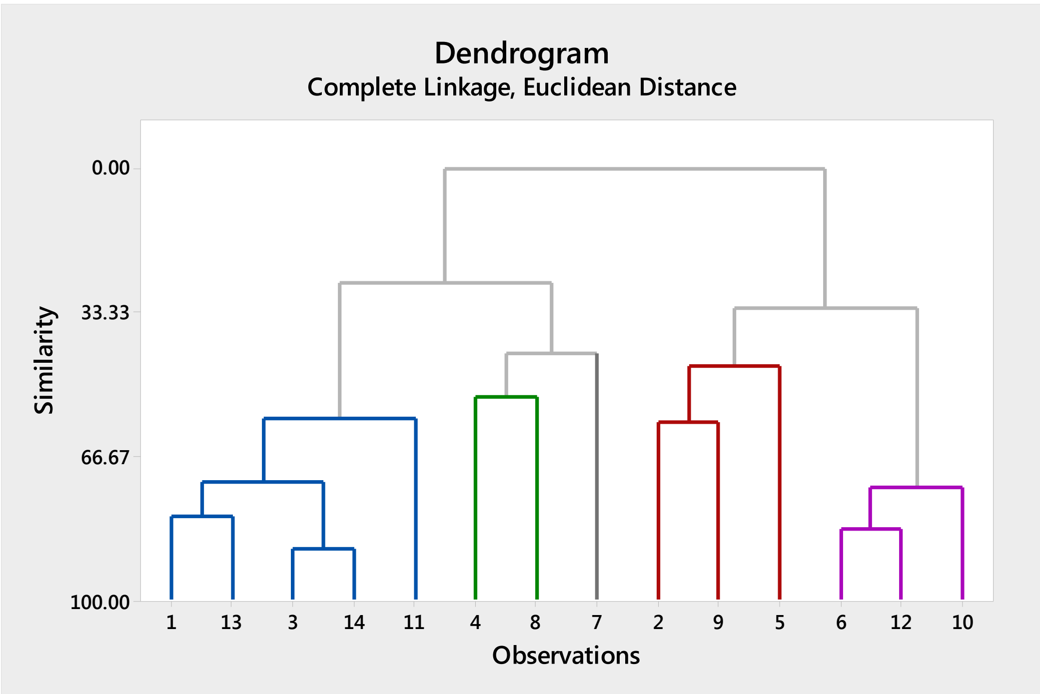

Figure 2. Reinforced concrete student cluster formations.

Students belonging to ACT joined students belonging to VIS to form one cluster, INT joined GLO, REF joined SEQ, and SEN joined VRB.

8. Observations and Results

Table 5 shows the centroid of the tendency of learning styles of the students in both of the groups under study. Students belonging to the reinforced concrete class had a high degree of preference for visual learning (at 5.5), followed by active learners (at 3.29), and so on. Meanwhile, students from engineering economy have the highest tendency toward visual learning, but this was less than those of the reinforced concrete class (at 4.56), followed by sensing at 3.69, and then active learners, and so on. The centroid shown in Table 5 indicates that each class has its own learning style configuration, but that they are following the same pattern of learning preferences; for example, most of the students' learning preferences in both courses are visual, then active, and so on. Using the group technology presented in this research will give the instructor a good idea about their students' learning preferences as groups, and not as individuals. Other conclusions can be inferred from this approach, such as the ability to check for outlier students, and thus dealing with them accordingly; for example, student #9 (engineering economy class) had their own learning preference, and they did not belong to any group (their similarity level with other students was 0). Also, it is evident that the engineering economy students shared a higher similarity between their learning preferences than students belonging to the reinforced concrete class.

Table 5. Students' learning style preferences.

Learning Style	Engineering Economy Class	Reinforced Concert Class
ACT	3.25	3.29
REF	1.13	1.43
SEN	3.69	2.93
INT	1.00	0.93
VIS	4.56	5.50
VRB	0.41	0.07
SEQ	2.34	2.86
GLO	1.25	1.86

Table 6 shows the formed group from the engineering economy class and their learning styles. This group of students shares a level of learning style at about 50% (refer to the dendrogram). It is clear that this group has high similarities in SEN, ACT, and VIS. Hence, the instructor can use a suitable teaching style to fit the needs of this group.

Table 6. Group 1 learning style, engineering economy students.

Student #	ACT	REF	SEN	INT	VIS	VRB	SEQ	GLO	Group ID
1	5		9		3		3		
3	9		9		4		3		
4	7		5		1		3		
5		3	9			3		3	
17	5		9		5		3		
18	7		5		7			3	1
20	5		9			3	3		
21	7		5		1			3	
22		3	9		3			3	
30	3		5			1		3	

9. Conclusions and Recommendations

In this research, group technology was used to classify students at the classroom level into clusters according to their learning style preferences. Two engineering courses with a total number of 44 students were included in the study. The Felder and Silverman index learning style was used to determine students' learning style preferences. Students were grouped into clusters based on the similarities of their preferences by using multivariate statistical analysis. Using this approach at the beginning of the semester will allow the instructor to use a suitable teaching style for the students to achieve the intended teaching outcomes. The results of this study can encourage instructors to explore the learning styles of their students to choose the proper teaching methodology/strategy and assessment method that fits each student group instead of dealing with the classroom as one unit. This helps students to better achieve the intended learning outcomes of the course. For example, the instructor of the engineering economy class may design different teaching strategies in order to serve student number 9, who has his own learning style, in order to improve his class achievements. Also, it helps the instructor conduct a more effective and fair assessment of students.

It is probable that when students in a class project work with their peers, who share a similar learning style, they will be better motivated to excel and more fruitful collaborative work is expected within such a class project. For example, in a class project, if students number 6, 10, and 12 from the reinforced concrete class work together in a project, they will do a great job because all of them share the same level of learning style (students 6, 10, and 12 scored: 9, 7, and 9; 7, 5, and 7; and 7, 7, and 7 in ACT, SEN, and VIS, respectively). By knowing each other's learning style, students will be more aware of their strengths and weaknesses and, accordingly, they will plan and conduct the needed tasks in a better and more effective way.

This study may be extended to investigate differences in learning styles between male and female students. Also, the effect of the type of program on different learning styles may be considered by comparing students of engineering and non-engineering programs.

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