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Profiling Learning Preferences of Undergraduate Students

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ABSTRACT—*Students learn in different ways, so it is expected that teaching methods should also vary. It is believed that identifying strong learning styles among students will help improve instruction by providing course delivery strategies tailored to different learning preferences. As a consequence, the purpose of this study was to employ cluster analysis to identify the cognitive learning dimensions on the Index of Learning Styles. The first major finding shows that the five-cluster was identified in this group of students. The second major finding shows that among 88 undergraduate students, the majority were concrete and holistic thinkers.*

Keywords— Learning preferences, cluster analysis, profile analysis

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1. INTRODUCTION

Students learn in different ways, so it is expected that teaching methods should also vary. Felder and Silverman (1988) stated that "how much a given student learns in a class is governed in part by that student's native ability and prior preparation but also by the compatibility of his or her learning style and the instructor's teaching style" (p. 674). Most importantly, instructors should recognize the variety of students' learning preferences and adapt their teaching strategies to fit this variance in order to create an optimal learning situation for most students in classes (Felder & Silverman, 1988). As Felder and Spurlin (2005) pointed out, it is possible that when learning styles and teaching styles are seriously mismatched, students' academic performance might not attain the expected outcomes.

According to the literature of learning styles, several scholars have proposed and developed learning models to explain the learning needs of students, including the Myers-Briggs Type Indicator (MBTI; Lawrence, 1994), Kolb's learning style model (Kolb, 1984), the Herrmann Brain Dominance Instrument (HBDI; Herrmann, 1990), and the Felder-Silverman leaning model (Felder & Silverman, 1988). The MBTI framework identifies four ranges of classifications: (a) extroverts or introverts, (b) sensors or intuitors, (c) thinkers or feelers, and (d) judgers or perceivers. Kolb's model classifies students as having a learning preference, of which there are four types: (a) concrete experience and reflective observation, (b) abstract conceptualization and reflective observation, (c) abstract conceptualization and active experimentation, and (d) concrete experience and active experimentation. The HBDI identifies four modes based on the function of the brain, including (a) left brain, cerebral: logical and critical; (b) left brain, limbic: sequential and organized; (c) right brain, limbic: emotional and interpersonal; and (d) right brain, cerebral: visual and holistic. The Felder-Silverman leaning model classifies different learning modes. It includes (a) sensing or intuitive learners, (b) visual or verbal learners, (c) inductive or deductive learners, (d) active or reflective learners, and (e) sequential or global learners.

The development of these models plays dual roles. As Felder and Silverman (1988) observed, "a learning-style model classifies students according to where they fit on a number of scales pertaining to the ways they receive and process information" (p. 674). On the other hand, it also implies that the development of a "teaching-style model . . . classifies instructional methods according to how well they address the proposed learning style components" (p. 674). Therefore, "most of the learning and teaching style components parallel one another" (Felder & Silverman, 1988, p. 674).

A number of educators have applied the previously mentioned four models in educational settings. Based on investigations, it is believed that educators could design better curriculums for improved teaching and learning (Du Torr, De Boer, Bothma, & Scheepers, 2012; Felder, Felder, & Dietz, 2002; Felder & Henriques, 1995; Palermo, Walker, Brown, & Zogi, 2009). Felder and Spurlin (2005) argued that the most important implication of learning styles is grounded in designing effective teaching strategies and instruction.

The objective of this study was exploratory in nature. It is believed that identifying strong learning styles among students will help improve instruction by providing course delivery strategies tailored to different learning preferences.

As a consequence, the purpose of this study was to employ cluster analysis to identify the cognitive learning dimensions on the Index of Learning Styles (ILS; Felder & Soloman, 1997), thereby profiling different groups of students to gain insights for future pedagogy development.

2. METHOD

2.1 Subjects

Because of the availability, convenience sampling was used for this study. A total of 88 subjects (51 females, 37 males) were drawn from a population of undergraduate students at a southwest private university in the United States. The mean age of students was 19.74 (*SD* = 2.48, 1 student did not answer the question) and the majority were freshman (49 students, 2 students did not answer the question). The demographic breakdown (four students did not answer the question) was as follows: 10 Asians, 4 African Americans, 23 Caucasians, 45 Hispanics, and 2 from mixed backgrounds.

2.2 Instruments

The Index of Learning Styles (ILS) was developed by Felder and Soloman (1997) and is used for identifying different learning styles. This instrument measures learning styles on four bipolar dimensions related to the preference for the type of information perceived (sensory to intuitive), the modality by which that sensory information is most effectively perceived (visual to verbal), the manner in which it is processed (active to reflective), and the manner in which a learner progresses toward understanding (sequential to global; Felder & Silverman, 1988). More specifically, the four bipolar dimensions are the following: (a) sensing (concrete thinker) versus intuitive (abstract thinker); the S-N dimension; (b) visual (prefers visual presentations) versus verbal (prefers written and spoken explanations); the Vs-Vb dimension; (c) active (prefers working in groups) versus reflective (prefers working alone; the A-R dimension; and (d) sequential (linear thinking process) versus global (holistic thinking process; the Sq-G dimension (Felder & Spurlin, 2005, p. 103).

The ILS is a 44-question instrument designed to evaluate learning preferences based on four dimensions of the Felder-Silverman framework. Each learning style has associated with it 11 items with two options (a or b), representing one or the other category of the dimension (e.g., sensing or intuitive). The purpose of this dichotomous structure is to force participants to make a decision between the two options, thereby avoiding ambiguity and increasing the chance to detect preferences.

With regard to validity and reliability of ILS, Felder and Spurlin (2005) examined several studies using the ILS and reported adequate information for supporting the validity and reliability of this construct. Litzinger, Lee, Wise, and Felder (2007) reexamined the reliability, factor structure, and construct validity of the ILS by using random samples of 1000 students from three colleges. They concluded that the ILS "generates data with acceptable levels of internal consistency reliability, and that evidence for its construct validity from both factor analysis and student feedback is strong" (p. 316). Moreover, several advantages of using this instrument as an evaluation tool of individual learning preferences are the following: (a) it is a free web-based questionnaire, (b) it has an automatic reporting feature, and (c) it has accompanying descriptive information provided by the authors. Internal consistency reliability was checked. Cronbach's coefficient alpha revealed that the dimensions S-N, Vs-Vb, A-R, and Sq-G were 0.65, 0.56, 0.47, and 0.10 respectively. However, it is important to note that this conclusion of internal reliability is not consistent with other studies (Litzinger, Lee, Wise, & Felder, 2007).

3. RESULTS

A Pearson correlation coefficient was calculated for the relationship between participants' age and learning style dimensions. As Table 1 shows, a weak negative, but significant, correlation was found between age and both the A-R and Vs-Vb dimensions, $r = -.262$, $p < .05$, $r = -.339$, $p < .01$. Another significant weak positive correlation was found between the S-N and Sq-G dimensions, $r = .229$, $p < .05$.

Table 1: Intercorrelation among five variables

Variables	*M*	*SD*	1	2	3	4	5
1. Age	19.73	2.46	--				
2. A-R dimension	1.60	4.17	-.262*	--			
3. S-N dimension	2.83	4.73	-.054	.078	--		
4. Vs-Vb dimension	5.12	3.82	-.339**	.209	.029	--	
5. Sq-G dimension	1.90	3.25	-.185	.052	.229*	.060	--

Cluster analysis was used to develop the segmentation of students by analyzing the learning preferences of undergraduate students on the four dimensions. The clustering variables were the four learning preferences of the ILS (S-N, Vs-Vb, A-R, and Sq-G dimensions). In preparing the cluster analysis, no univariate and multivariate outliers were found. Given that the four clustering variables were metric, the squared Euclidean distance was chosen as the similarity measure. In order to remove any impact due to differing levels of dispersion, the variables were converted to *z* scores and the standardized values were used in the cluster analysis.

In applying cluster analysis to the sample of 88 undergraduate students, the researcher followed the approach of combining hierarchical and nonhierarchical methods. First, the hierarchical procedure was used to identify a preliminary set of cluster solutions as a basis for establishing the appropriate number of clusters and generating the seed points. Second, the nonhierarchical procedures were used to further improve the cluster solution. The hierarchical and nonhierarchical procedures from SPSS were used in this analysis.

3.1 Hierarchical Cluster Analysis

The average linkage method was chosen as a clustering algorithm. Figure 1 shows the dendrogram for the hierarchical cluster analysis of 88 observations. In order to identify a set of preliminary cluster solutions, the stopping rules were applied through assessing the changes in heterogeneity between cluster solutions. The focus was on large percentage changes in the agglomeration coefficient, as shown in Table 2. The largest percentage increase occurred between stages 80 and 81, followed by stages 83 and 84 and stages 81 and 82. These agglomeration coefficient changes indicate increased heterogeneity that is markedly different. As such, the stopping rule identified three cluster solutions (eight, seven, and five clusters) as candidates for the preliminary set of cluster solutions. These three cluster solutions were examined in terms of the degree and types of differences between clusters to finalize the cluster solutions.

Figure 2 shows a profile analysis of three cluster solutions based on the four clustering variables. When the cluster solutions are compared, two observations can be made: (a) the five-cluster solution is clearly distinct from the other two solutions, providing a viable alternative solution, and (b) the differences are much less distinct between the eight- and seven-cluster solutions. Taken together, although the stopping rule was the starting point for identifying three cluster solutions as candidates for inclusion in the nonhierarchical cluster analysis, closer examination through profiling on the clustering variables revealed only limited differences between the eight- and seven-cluster solutions. For the purpose of parsimony, the seven-cluster solution along with the five-cluster solution, as the preliminary set of cluster solutions, were further analyzed.

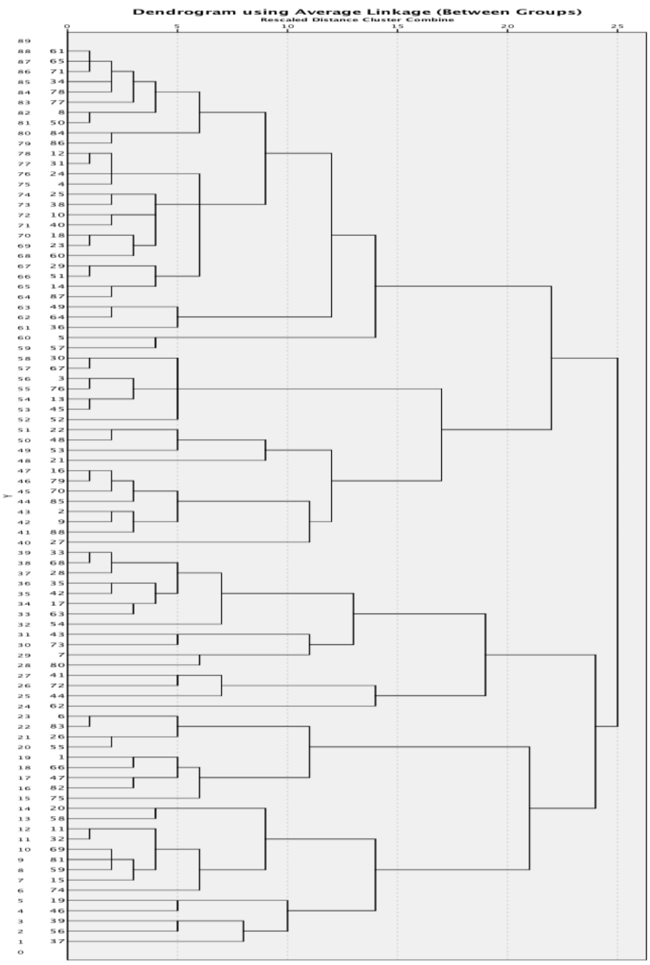

Figure 1: Dendrogram of Hierarchical Cluster Analysis

Table 2: Stopping rule for the hierarchical cluster analysis

	Hierarchical process		Stopping rule	
	Number of clusters		Agglomeration coefficient	
Stage	**Before joining**	**After joining**	**Value**	**Percentage increase to next stage**
79	10	9	5.019	4.90
80	9	8	5.265	0.27
81	8	7	5.279	19.09
82	7	6	6.287	10.85
83	6	5	6.969	14.38
84	5	4	7.971	4.44
85	4	3	8.325	7.32
86	3	2	8.934	7.75
87	2	1	9.626	--

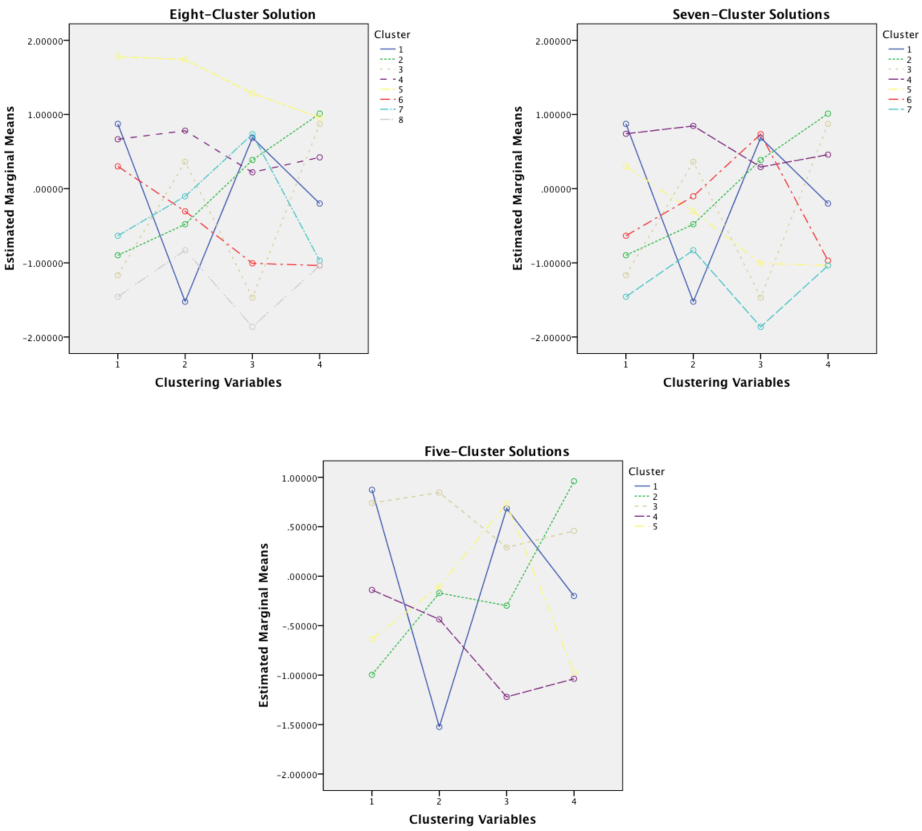

Figure 2. Profile Diagram For The Eight-, Seven-, And Five-Cluster Hierarchical Clustering Solutions.

3.2 Nonhierarchical Cluster Analysis

In the second step of the clustering process, the researcher used hierarchical methods in combination with the nonhierarchical procedures. Specifically, the researcher employed the nonhierarchical procedures to develop an optimal cluster solution for each number of clusters. The seven- and five-cluster solutions were determined to the cluster seed points. In addition, the optimizing algorithm in SPSS was used. The nonhierarchical procedure generated the seven- and five-cluster solutions shown in Figure 3. In order to validate the cluster solutions, each outcome measure was examined for differences across the clusters in the seven- and five-cluster solutions (see Table 3). For both solutions, the univariate *F* ratios show that the cluster means for all variables are significant, which indicates that both solutions maintain criterion validity. However, it is clear that the five-cluster solution is better than the seven-cluster solution (see Figure 3).

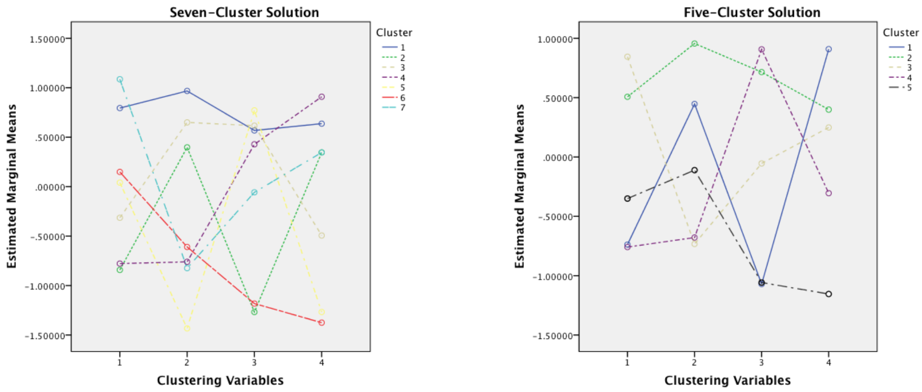

Figure 3. Profile Diagram For The Seven- And Five-Cluster Nonhierarchical Clustering Solutions.

Table 3: Assessing criterion validity for the seven- and five-cluster nonhierarchical clustering solutions

		Seven-cluster solution			
		A-R dimension	**S-N dimension**	**Vs-Vb dimension**	**Sq-G dimension**
Cluster	***n***	**Cluster centroids**			
1	19	0.794	0.968	0.568	0.638
2	15	-0.842	0.398	1.267	0.346
3	15	0.315	0.649	0.617	-0.494
4	12	-0.779	-0.760	0.428	0.909
5	8	0.041	-1.433	0.771	1.268
6	10	0.149	-0.609	-1.182	-1.375
7	9	1.086	-0.824	-0.057	-0.824
Statistical significance of criterion variables					
F value		12.718	29.460	25.493	24.266
P		<.001	<.001	<.001	<.001
		Five-cluster solution			
Cluster		**Cluster centroids**			
1	12	-0.738	0.447	-1.071	0.909
2	23	0.507	0.956	0.715	0.399
3	19	0.845	-0.733	-0.054	0.249
4	17	-0.759	-0.679	0.907	-0.305
5	17	-0.350	-0.111	-1.058	-1.154
Statistical significance of criterion variables					
F value		16.005	19.066	42.742	16.850
p		<.001	<.001	<.001	<.001

4. DISCUSSION

Before providing the conclusion, several limitations of this study should be noted. First, the nature of this study is exploratory and based on only 88 students from one institution. Therefore, the results of this study cannot be generalized for populations of all ages. Second, the internal reliability of the Vs-Vb, the A-R, and the Sq-G dimension were quite low. Further studies of using ILS should address this issue. Finally, it is unclear that how students' perception of teaching styles match their learning styles in classrooms and to what extent this interaction impacts their learning satisfaction. By including the evaluation of teaching style as additional examining factor and using qualitative interview might untangle this relationship.

The primary purpose of this study was to use cluster analysis to explore the learning preferences of the sample of 88 undergraduate students. After profiling the final cluster solution, the first major finding shows that the five-cluster was identified in this group of students. Based on the results from this study, the following conclusions can be drawn from each cluster. Twelve students were in the first cluster. They were active and visual learners, preferring visual presentations, and they were intuitive and holistic thinkers. The second cluster had the largest number of students (n = 23). They were verbal learners, preferring written and spoken explanations, and they were reflective, intuitive, and holistic thinkers. Students in the third cluster preferred to work alone; they were visual learners and global and concrete thinkers. The fourth cluster demonstrated that students tended to have active, sensing, verbal, and sequential learning styles. The last cluster showed that students in this group were concrete thinkers. They also preferred to work in groups, preferred visual presentations, and used more of a linear thinking process.

The second major finding shows that among 88 undergraduate students, the majority were concrete and holistic thinkers. This observation has an important implication of pedagogy practice. In order to deliver better content, an instructor could consider using case studies or other concrete examples to explain important theories or concepts. Additionally, mind mapping or other useful approaches to assist students to identify relationships might be useful in providing a holistic picture of the content.

The emphasis of learning styles has been well documented in the literature (Sims & Sims, 2006). The major interest in learning styles centers on “the issues of diversity, approaches in the classroom, technology and achievement” (Hickcox, 2006, p. 13). As the current study showed, in this sample the diversity of learning preferences was confirmed (5 clusters were found). These findings provide an important implication for the instructor in that “one size does not fit all.” Namely, the instructor should utilize different kinds of approaches to stimulate/match students’ learning styles, thereby enhancing the quality of formal learning opportunities (Bedford, 2006). A good example to be considered to improve teaching approaches and meet different needs of students is to use Kolb learning model (Kolb 1984). Sharp (2006) in her article provided several examples to use this model in the higher education.

As Jorgensen (2006) argued, “it is not simply about what students learn; it is about how they learn…. Differentiated instruction is a response to differentiated learning and differentiated learning is the product of each person’s unique combination of learning patterns” (p. 212). She warmed that if we do not acknowledge the individuality of each learner, “we are doomed to fail in creating classroom environments where all students have an equal chance to succeed at learning” (p. 221). In terms of pedagogy, Burke and Doolan (2006) contended that lecture is not appropriate method for a majority of students to process information. Rather, “many students’ learning styles dictate a need for exploration and further investigation through simulations, manipulations, models, role-playing, and computers” (p. 166). Most importantly, as Sharp (2006) pointed out, “using teaching strategies based on an awareness of learning styles can enhance the learning experience for students and, therefore, help instructors meet the accountability demands in education today” (p. 93).

This study is unique in that it attempted to use cluster analysis to demonstrate the heterogeneity of students’ learning preferences in the classroom. It is recommended that recognizing this difference is the first step to achieve a better learning of students and then based on this result, the instructor should reflect how to assist his students by employing alternative methods to enhance learning. It is suggested that using a balanced approach to accommodate, for example, visual and verbal learners or sequential and global learners. Although it might be a challenging task, there is no excuse to educate students for the better purpose.

A vital process for better teaching practices in a classroom is to create profiles of students based on their learning preferences. In so doing, it not only maximizes students’ learning outcomes through the appropriate use of pedagogy, but it also assists teachers to deliver and design a better curriculum which tailors to students’ learning preferences. In short, one of responsibilities teachers hold is to identify their students’ learning styles and in turn make use of this insight to nurture expected and accountable learning fruits.

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