A Quantitative Analysis of Student Learning Styles and Teacher Teachings Strategies in a Mexican Higher Education Institution

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ABSTRACT
Research on learning processes has shown that students tend to learn in different ways and prefer to use different teaching resources. The understanding of learning styles can be used to identify, and implement, better teaching and learning strategies, in order to allow students to acquire new knowledge in a more effective and efficient way. In this study we analyze similarities and differences in learning styles among students enrolled in computing courses, in engineering and social sciences programs at the *Instituto Tecnológico Autónomo de México* (ITAM). In addition, we also analyze similarities and differences among the teaching strategies shown by their corresponding teachers. A comparative analysis on student learning profiles and course outcomes, allow us to suggest that, despite academic program differences, there are strong similarities among the students learning styles, as well as among the teaching styles of their professors. Seemingly, a consistent pattern of how these students learn also exists: Active, Sensitive, Visual and Sequential. At the end of the paper, we discuss how these findings might have significant implications in developing effective pedagogic strategies, as well as didactic multimedia based materials for each one of these academic programs.

Keywords: Computing engineering, learning styles, teaching strategies and didactic strategies.

RESUMEN
Investigaciones sobre procesos de aprendizaje han mostrado que los estudiantes tienden a aprender en diferentes maneras y que prefieren utilizar diferentes recursos de enseñanza. El entender los estilos de aprendizaje puede servir para identificar, e implantar, mejores estrategias de enseñanza y aprendizaje, de tal forma que los estudiantes adquieran nuevo conocimiento de manera más efectiva y eficiente. Aquí, se analizan similitudes y diferencias entre estilos de aprendizaje de estudiantes inscritos en cursos de cómputo, en programas de Ingeniería y Ciencias Sociales del *Instituto Tecnológico Autónomo de México* (ITAM). Adicionalmente, se analizan similitudes y diferencias en estrategias de enseñanza de sus correspondientes profesores. Un análisis comparativo sobre perfiles de aprendizaje de los estudiantes y los resultados obtenidos en los cursos, sugiere que existen grandes similitudes entre los estilos de aprendizaje de los estudiantes, y las estrategias de enseñanza de sus profesores, a pesar de las diferencias entre sus programas académicos. También existe un patrón consistente de cómo estos estudiantes aprenden: Activo, Sensible, Visual, y Secuencial. En la última parte de este artículo se discute como estos hallazgos podrían tener una implicación significativa en el desarrollo de estrategias pedagógicas efectivas, y de materiales didácticos multimedia específicos, para cada programa educativo.

1. Introduction

Regarding learning, we find that not everyone learns the same way. Each person has a particular set of learning abilities; thus we can identify the preferences that constitute his or her learning style. Educational research tells us that "one size does not fit all" [1]. It informs us that the learning characteristics of students differ [2]. It suggests that students learn

differently, they process and represent knowledge in different ways, and they prefer to use different type of resources. Research also suggests that it is possible to diagnose a student's learning style and that some students learn more effectively when instruction is adapted to the way they learn [3]. Knowing our learning styles helps us both, teachers and students. We can elaborate better teaching-learning strategies in order to allow students to assimilate in an effective and more efficient way new information and knowledge. The understanding of learning styles can be used to identify and implement better teaching and learning strategies [4, 5].

The above statements are representative of serious mismatches between the learning styles of students and the teaching style of the instructor. In a class where such a mismatch occurs, the students tend to be bored and inattentive, do poorly on tests, get discouraged about the course, and may conclude that they are not good at the subjects of the course and give up [6]. To reduce teacher-student style conflicts, some researchers in the area of learning styles advocate teaching and learning styles be matched [7-9] and bridging the gap between teachers' and learners' perceptions plays an important role in enabling students to maximize their classroom experience.

This paper describes a comparative analysis of the learning styles of undergraduate engineering programs and economic programs in México City and the assumption underlying the approach taken here is that the way we teach should be adapted to the way learners from a particular course program.

This study addressed the following objectives in a comparative mode:

a) Identification of learning styles for undergraduate engineering programs economic and business programs and law programs;

b) Examination of the association between learning style and course performance;

c) Identification of teaching styles for the undergraduate professors of engineering programs, economic and business programs and law programs;

d) Examination of the compare learning styles with other countries;

e) Examination of the association between teaching style and course performance;

f) Examination of the association between teaching style and learning style;

g) Determination of factors including learning styles, contributing to success in introductory computer courses;

h) Determination of the effect of prior performance on course outcomes and learning styles;

The rest of the paper is organized as follows. Section II presents background material concerning students ITAM; it presents information about instruments used to identify learning styles and teaching styles theory. Section III presents the methodology used for this study. Section IV presents the study undertaken to identify and contrast the learning styles of engineering and economic students and lists the factor contributing to their success in introductory computer courses. The implication of the findings on the pedagogical design of computer courses at ITAM are presented in Section V, finally in section VI presents concluding remarks.

2. Background

2.1 Institutional and student body comparison

ITAM is a private school in México City, a nonprofit research institution with an enrollment of around 4800 undergraduate students. ITAM offers to its students, a comprehensive education that will allow them to contribute to the development of a more prosperous, just and free society. The Computer Academic Department was formed in 1983 and currently has over 550 full-time engineering students, and it offers computer courses for all the non-engineering programs, as well. In addition, engineering students take also courses from the Economics and Administrative Academic Departments. Undergraduate students at ITAM come from a diverse set of backgrounds, including from different cities of México, and are enrolled in one of 12 academic programs: Actuarial Science, Applied Mathematics, Business Administration, Business Engineering, Computer Engineering, Economics, Industrial Engineering, International Relations, Law, Political Science, Public Accounting and Financial Strategy, and Telematics Engineering. Thus, they provide a heterogeneous student population.

2.2 Learning Styles

The concept of learning style refers to the fact that each person has his/her own method or set of strategies for learning. A learning style is defined as the characteristics, strengths and preferences in the way people receive and process information [10]. The concrete strategies may vary from person to person, but have been narrowed down to certain global trends. These global trends or preferences, plus particular ways of learning, constitute the learning style [10]. The fact that not all people learn the same way can be seen in a classroom. The same lesson is given to a group of students. Some of them have better performance than others. According to Sewall (1986), there are several theories about learning styles [11]. A model of learning styles classifies students according to a scale that reflects the way they receive and process information. While there is a number of learning style assessment tools and methodologies [5], two similar assessment instruments are predominant in science and engineering education Kolb's Learning Styles Inventory (LSI) [12] and the Soloman–Felder Index of Learning Styles (ILS) [4].

The Felder and Silverman model was selected as the base of our study [10] because it has been successfully implemented in previous work [13-15], because it has been approved by the author and other specialists [16, 17], because it is user friendly and the results are easy to interpret, and because the number of dimensions is controlled and can actually be implemented [15].

The Felder model of 1988 has 32 learning styles. A student's style can be identified by considering the following five issues in Table 1.

The natural learning style for humans is inductive. Studies have proved that most of the engineering students are inductive [18]. In 2002, Felder removed the organizational dimension from his test.

2.3 Teaching Strategies and Teaching styles

Considering that pedagogy includes teaching and learning strategies, I will provide a definition of both: Learning strategies are the strategies used to remember, learn and use information. In this case, responsibility relies on the student (comprehension and text writing, problem solving, etc.). Students go through a process where they recognize the new knowledge, review previous concepts, organize and restore that previous knowledge, match it with the new one, assimilate it and interpret everything that was seen on the subject.

Didactic teaching strategy refers to an organized and systematized sequence of activities and resources that teachers use while teaching. The main objective is to facilitate the students´ learning [19]. Teaching strategies are the elements given to the students by the teachers to facilitate a deeper understanding of the information. The emphasis relies on the design, programming, elaboration and accomplishment of the learning content. Teaching strategies must be designed in a way that students are encouraged to observe, analyze, express an opinion, create a hypothesis, look for a solution and discover knowledge by themselves. Among the different activities, we can mention the method, which is the way of developing the learning process, and among the resources, we can find the means or characteristics. On the other hand, we need to link such teaching strategies with the concept of learning styles, something that hasn't been exploited to the extent that is intended here. In this sense, some of the previous studies worth mentioning are for example those of Dunn [20], whom insists on the importance of teaching the students by using methods that adapt to their conceptual preferences. Or Cabrero et al. (2006), whom also points out how the applied teaching strategies will take effect on the teaching quality, not only from an individual point of view, but also on the collaboration of the group as a whole [21].

This study used Teaching Styles Inventory (TSI) an instrument created by the Texas Higher Education Coordinating Board from 2002 to 2007 and it was designed by Center for Occupational Research and Development (CORD) to gauge the teaching preferences and styles, the Collaborative was created to support faculty at two-year colleges

Dimension	Types	Description
What type of information does the student prefer to perceive: Sensitive / external (sights, sounds, physical sensations), or intuitive/internal (possibilities, insights, hunches)?		
Perception	Sensitive	Sensitive students prefer empirical facts, data, practical procedures and experimentation. They are patient with details, but don't like complications.
	Intuitive	Intuitive students prefer conceptual meanings, principles and theories; they get bored with details and accept complications.
Through which sensory channel is external information most effectively perceived: visual (pictures, diagrams, graphs, demonstrations), or Verbal (words, sounds)?		
Input	Visual	For the visual learners it is easy to remember the things they see: diagrams, timelines, films, demonstrations and usually prefer multimedia and simulations.
	Verbal	Verbal learners remember what they have heard, read or said. They prefer lecture or textbook learning resources.
With which organization of information is the student more comfortable: inductive (facts and observations are given, underlying principles are inferred), or deductive (principles are given, consequences and applications are deduced)?		
Organization	Inductive	Inductive learners prefer information that proceeds from particularities to generalities.
	Deductive	Deductive learners' information that proceeds from generalities to particularities.
How does the student prefer to process information: actively (through engagement in physical activity or discussion), or reflectively (through introspection)?		
Processing	Active	Active learners learn better when they work in groups and manipulate things, first-hand experimentation and social interaction.
	Reflective	Reflective learners learn better when they can think and reflect about the information that is presented to them and they work better alone, a predisposition for learning by thinking through the process and examining ideas mentally.
How does the student progress towards understanding: sequentially (in continual steps), or globally (in large jumps, holistically)?		
Understanding	Sequential	Sequential learners follow a linear reasoning process when they solve problems. They can work with a certain material once they have understood it partially or superficially. They prefer learning in a series of steps leading to broader understanding.
	Global	Global learners make intuitive leaps with the information. They can have difficulties when they try to explain how they got a solution, and they need an integral vision. They prefer o work from larger frameworks and fill in gaps; they learn by starting with broad trends and patterns and fitting individual pieces of knowledge into the structure.

Table 1. Felder dimensions.

across Texas through a collegial, cooperative approach to professional development. The TSI instrument is conveniently available on Internet [22]. The scores will provide insight into your affective learning goals for students and the teaching methods that you use to support your goals. The instrument has been constructed using a forced choice technique similar to that used in the Meyers-Briggs Type Indicator and in Kolb's Learning Style Inventory and uses four scales for measuring your preferred teaching styles:

- Learning—varies from Rote to Understanding
- Concept Representation—varies from Abstract to Applied
- Cognitive Processing—varies from Enactive to Symbolic
- Interaction—varies from Individual to Cooperative Groups

3. Methodology

3.1 Selection of courses

Introductory computer courses required of all students were chosen at the university in the second semester (August–December 2008). The study is based in three different courses. The first course is for students with economic and administrative program (Business Administration, Economics, Public Accounting and Financial Strategy, Actuarial Science and Applied Mathematics), the course name is computational tools and algorithms (CTA) , the second course is for students with law programs (International Relations, Law), the course name is computer I (CI) and the third course is for engineering programs (Computer Science, Business Engineering, Industrial Engineering, and Telematics Engineering), the course name is algorithms and programming (AP). The three courses were similar in many ways. The courses met for three hours or lecture in a laboratory. Laboratory sections were typically 30 students or less. Students at three courses were required to complete a number of homework. The three courses were for first semester.

3.2 Applied surveys

This study used the Index of Learning Styles Instrument (ILS) for the first part. The ILS is the instrument that Felder uses to evaluate a student's learning style. The ILS is conveniently available on the Internet and consists of 44 multiple-choice questions designed to separate the learning style affinities of an individual. The 44 questions have two possible answers ('a' or 'b'). The intensity of a dimension can vary from 1 to 11. This is because each dimension has 11 questions [4]. The organization dimension cannot be measured through this type of question. ILS has also been used in several computer sciences and engineering studies [23-25].

For the second part used Teaching Styles Inventory (TSI) an instrument created by the Texas Higher Education Coordinating Board from 2002 to 2007 and it was designed by Center for Occupational Research and Development (CORD) to gauge the teaching preferences and styles, the scores should provide food for thought regarding the type of students you may be best suited to teach based upon your style of teaching, or ways in which you may want to alter your style of teaching based upon the kinds of students you have in your classroom. There is no right or wrong answer; there are 12 items, each of which contains four statements about ways you might respond in your teaching, through the way you might behave, think, or feel. The answer has to be ranked at 4 (Maximum) to 1 to reflect how well they describe the way you teach [22].

3.3 Statistical methodology

Instead of using the X2 test [26] for ascertaining the normal distribution, a more strict statistical methodology of discordancy tests was applied [27]. In fact, before calculating the statistical parameters of central tendency and dispersion estimates, it is mandatory to test the data for possible discordant outliers [27, 28]. We used unpublished computer program DODESYS, which is based on new precise and accurate critical values recently simulated for discordancy tests [29-31]. This program ascertains the presence or otherwise of statistically contaminated observations in experimental data, and thus permits the user to calculate the mean and standard deviation values from normal samples. Then, the output data were used to estimate the mean, median, and standard deviation values. Properly rounded values were reported in Tables as suggested by [26, 28].

For evaluating possible correlations between variables, commercial package SPSS was used. The results were confirmed from ordinary least-squares linear correlations through the software OYNYL [32], which is capable of providing three types of linear correlations.

For analyze de data from more than two groups, commercial package SPSS was used. One-way ANOVA is used to test for differences among two or more independent groups. Typically, however, the one-way ANOVA is used to test for differences among at least three groups, since the two-group case can be covered by a T-test [33]. When there are only two means to compare, the T-test and the F-test are equivalent; the relation between ANOVA and t is given by F = t2. New precisely interpolated critical values for Fisher F test were used to draw statistical conclusions [34].

The precise and accurate critical values programmed in this version of DODESYS correspond to 99% confidence level (see [4, 13–15] for other application examples). This version of DODESYS relies on the precise critical values for sample sizes of nmin(1)1000 corresponding to 99% confidence level. This strict confidence level is programmed in DODESYS because it is the level recommended (e.g., [3, 4, 13–15])

4. Analysis and Results

4.1 Administration of Soloman–Felder Index of Learning Styles Instrument

During the second semester 2008, the Soloman – Felder ILS instrument was administrated to all of three courses. Response rates were above 95% with 726 total students (CTA n = 499, CI n = 87 and AP n = 140). The distribution of the students according to gender was as follows (Figure 1): Course AP 72.9% male and 27.1% female students; Course CTA 65.5% male and 34.5% female; Course CI 62.1% and 37.9% female; and all three courses 66.5% male and 33.5% female. The general proportion of male students was more than female students.

Table II shows the percentages of the three groups according to the age. The age of the students was 17 to 21 years (17 – 9%, 18 – 43%, 19 – 35.3%, 20 – 8% and 21 – 4.8%).

			Gender		
			f	m	Total
Name Course	algorithms and programming	number	38	102	140
		frequency	46.9	93.1	140
		% gender	15.60%	21.10%	19.30%
		%total	5.20%	14.00%	19.30%
	computational tools and algorithms	number	172	327	499
		frequency	167.0	332.0	499.0
		% gender	70.80%	67.70%	68.70%
		%total	23.70%	45.00%	68.70%
	computer 1	number	33	54	87
		frequency	29.1	57.9	87.0
		% gender	13.60%	11.20%	12.00%
		%total	4.50%	7.40%	12.00%
	Total	number	243	483	726
		frequency	243.0	483.0	726.0
		% gender	100%	100%	100.00%
		%total	33.50%	66.50%	100.00%

Table 2. Percentages of the three groups with the gender.

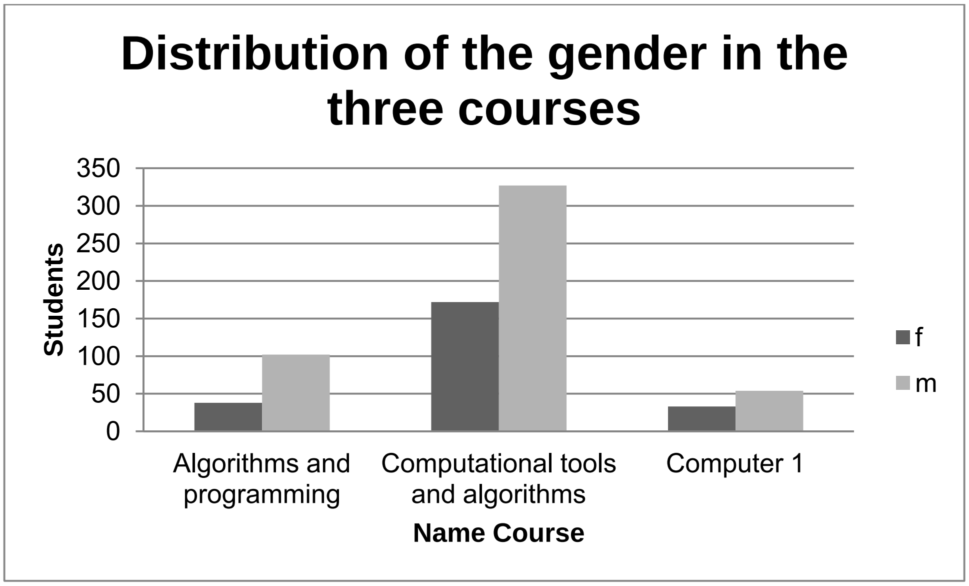

Figure 1. Distribution for course about the gender.

4.2 Learning styles comparison between AP, CTA and CI (a)

Course		Reflective-Active	Intuitive-Sensitive	Verbal-Visual	Global-Sequential
AP	Chi-Square	46.6[a]	69.9[b]	63.6[a]	100.9[b]
	Df	9	10	9	10
	Asymp. Sig.	.000	.000	.000	.000
CTA	Chi-Square	238.1[c]	218.5[c]	266.7[d]	412.7[d]
	Df	10	10	11	11
	Asymp. Sig.	.000	.000	.000	.000
CI	Chi-Square	78.4[e]	66.4[f]	35.8[f]	59.8[f]
	Df	8	10	10	10
	Asymp. Sig.	.000	.000	.000	.000

a. 0 cells (.0%) have expected frequencies less than 5. The minimum expected cell frequency is 14.0.
b. 0 cells (.0%) have expected frequencies less than 5. The minimum expected cell frequency is 12.7.
c. 0 cells (.0%) have expected frequencies less than 5. The minimum expected cell frequency is 45.4.
d. 0 cells (.0%) have expected frequencies less than 5. The minimum expected cell frequency is 41.6.
e. 0 cells (.0%) have expected frequencies less than 5. The minimum expected cell frequency is 9.7.
f. 0 cells (.0%) have expected frequencies less than 5. The minimum expected cell frequency is 7.9.

Table 3. Chi Square statistic for AP, CTA and CI.

Number Course			Reflective - Active	Intuitive - Sensitive	Verbal - Visual	Global - Sequential
AP	N	Valid	140	140	140	140
		Missing	0	0	0	0
	Mean		.97	1.89	5.27	1.77
	Median		1.00	1.00	5.00	3.00
	Mode		-1	1	5	3
	Std. Deviation		4.19	4.32	4.17	3.82
	Variance		17.55	18.66	17.39	14.60
	Minimum		-9	-9	-7	-9
	Maximum		9	11	11	11
CTA	N	Valid	499	499	499	499
		Missing	0	0	0	0
	Mean		.86	2.30	3.81	1.54
	Median		1.00	3.00	5.00	1.00
	Mode		1	5	7	1
	Std. Deviation		4.17	4.33	4.54	3.75
	Variance		17.41	18.71	20.64	14.06
	Minimum		-9	-9	-11	-11
	Maximum		11	11	11	11
CI	N	Valid	87	87	87	87
		Missing	0	0	0	0
	Mean		1.55	2.70	2.40	1.53
	Median		1.00	3.00	3.00	1.00
	Mode		1	5	3	1
	Std. Deviation		3.078	3.90	4.50	4.03
	Variance		9.46	15.21	20.29	16.23
	Minimum		-7	-9	-9	-9
	Maximum		9	11	11	11

Table 4. Mean, Median, Mode and Variance for AP, CTA and CI.

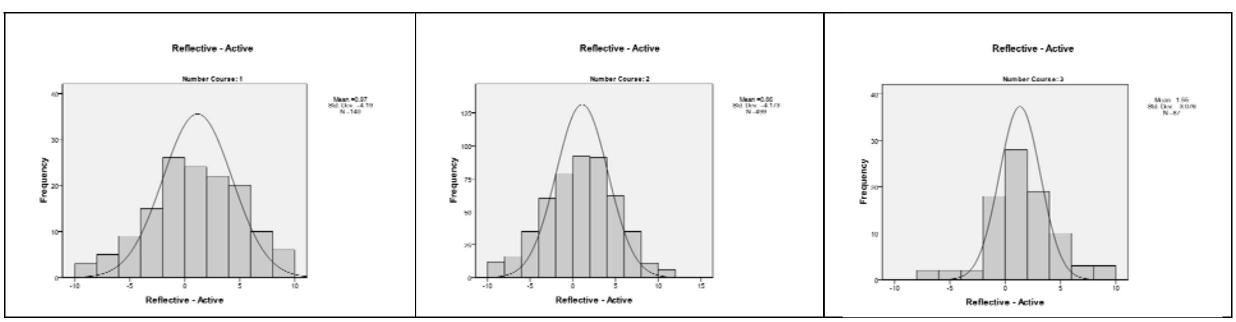

Figure 2. Results reflective – Active learning style for three groups.

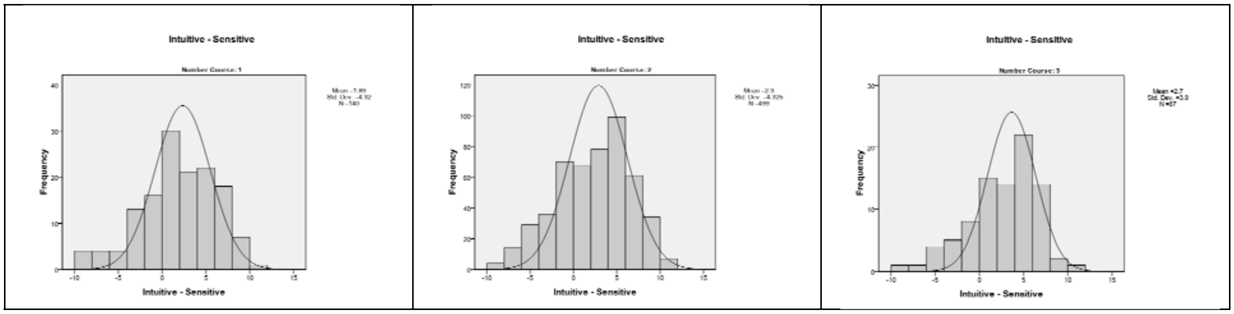

Figure 3. Results verbal - visual learning style for three groups.

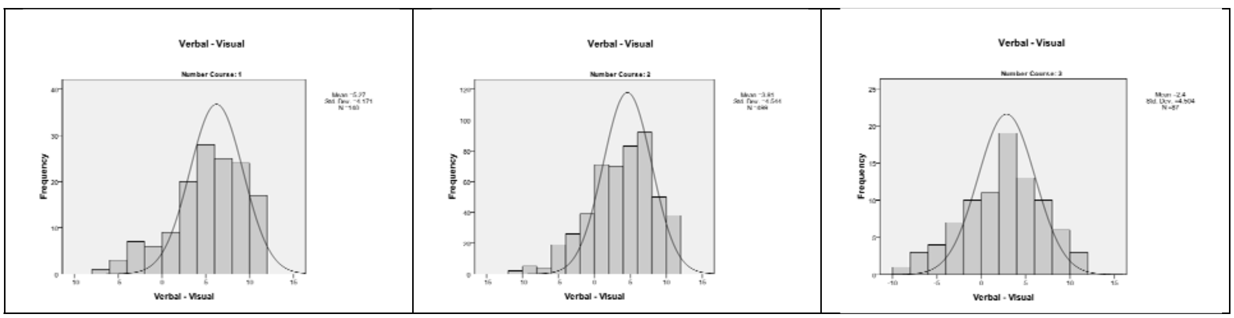

Figure 4. Results intuitive - sensitive learning style for three groups.

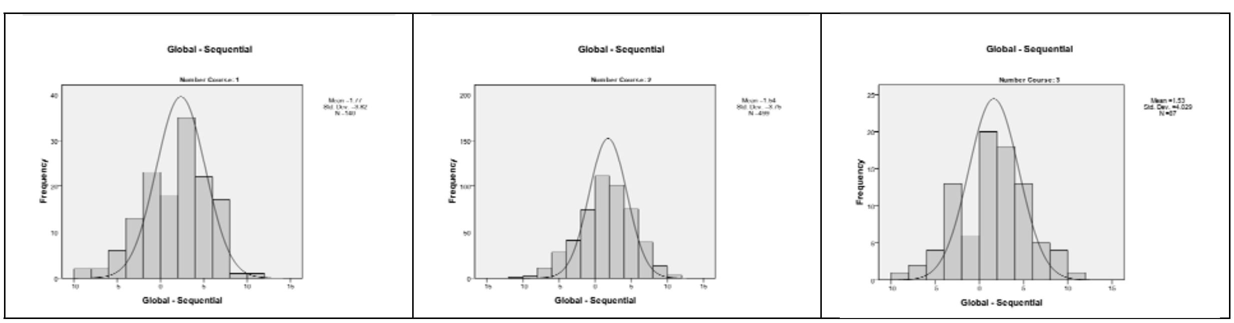

Figure 5. Results global - sequential learning style for three groups.

ANOVA

		Sum of Squares	Df	Mean Square	F	Sig.
Reflective - Active	Between Groups	35.07	2	17.54	1.06	.35
	Within Groups	11924.14	723	16.49		
	Total	11959.20	725			
Intuitive - Sensitive	Between Groups	37.38	2	18.69	1.02	.36
	Within Groups	13219.71	723	18.29		
	Total	13257.09	725			
Verbal - Visual	Between Groups	462.16	2	231.08	11.57	.00
	Within Groups	14443.52	723	19.98		
	Total	14905.680	725			
Global - Sequential	Between Groups	6.10	2	3.05	.21	.81
	Within Groups	10426.27	723	14.42		
	Total	10432.38	725			

Table 5. ANOVA for AP, CTA and CI.

Table 3 shows, the Chi square analysis of 3 groups (AP, CTA and CI) and four learning styles scales revealed no significant differences.

Figures 2-5 show comparative distributions of the various dimensions of learn learning styles for AP, CTA and CI students. Each dimension (for example, reflective- active, in Figure 1) is encoded from -11 to +11. A negative number (such as, -5 in Figure 1) indicates that the learner is predisposed towards a reflective style of learning. A positive number (such as, 5 in Figure 1) indicates that the learner is mostly active in his or her learning style. Values near zero tend to indicate that the learner does not have any marked preferences on a particular dimension.

As Table 5 shows, AP, CTA and CI students have a similar learning style distribution along the reflective – active dimension. The AP students (μ = 0.97; SD = 4.19), CTA students (μ = 0.86; SD = 4.17) and CI students (μ = 1.55; SD = 3.07) do not differ on the reflective – active dimension of learning style F(723)=1.063, at 99% confidence level [28].

As Table 5 shows, AP, CTA and CI students have a similar learning style distribution along the verbal - visual dimension. The AP students (μ = 5.27; SD = 4.17), CTA students (μ = 3.81; SD = 4.54) and CI students (μ =2.4; SD = 4.50) differ on the visual – verbal dimension of learning style F(723)=11.567, at 99% confidence level [28].

As Table 5 shows, AP, CTA and CI students have a similar learning style distribution along the intuitive - sensitive dimension. The AP students (μ = 1.89; SD = 4.32), CTA students (μ = 2.3; SD = 4.32) and CI students (μ =2.7; SD = 3.90) do not differ on the intuitive - sensitive dimension of learning style F(723)=1.022, at 99% confidence level [28].

As Table 5 shows, AP, CTA and CI students have a similar learning style distribution along the global - sequential dimension. The AP students (μ = 1.77; SD = 3.82), CTA students (μ = 1.54; SD = 3.75) and CI students (μ =1.53; SD = 4.02) do not differ on the global - sequential dimension of learning style F(723)=.212, at 99% confidence level [28].

In summary, despite the different courses backgrounds students at AP, CTA and CI have strikingly similar learning styles along all three leaning styles dimensions, only in visual and verbal differ.

4.3 Learning styles and class performance (b)

		Grade	ref-act	int-sns	vrb-vis	glob-seq
Grade	Pearson Correlation	1	-.22(**)	-.09	-.17(*)	-.10
	Sig. (bilateral)		.01	.28	.05	.22
	N	140	140	140	140	140
ref-act	Pearson Correlation	-.22(**)	1	-.08	.28(**)	-.11
	Sig. (bilateral)	.01		.32	.00	.21
	N	140	140	140	140	140
int-sns	Pearson Correlation	-.09	-.08	1	.13	.38(**)
	Sig. (bilateral)	.28	.32		.13	.00
	N	140	140	140	140	140
vrb-vis	Pearson Correlation	-.17(*)	.28(**)	.13	1	-.03
	Sig. (bilateral)	.05	.00	.13		.70
	N	140	140	140	140	140
Glob-seq	Pearson Correlation	-.10	-.11	.38(**)	-.03	1
	Sig. (bilateral)	.22	.21	.00	.70	
	N	140	140	140	140	140

** Correlation is significant at level 0.01 (bilateral).* Correlation is significant at level 0.05 (bilateral).

Table 6. Correlations AP.

		Grade	ref-act	int-sns	vrb-vis	glob-seq
Grade	Pearson Correlation	1	-.03	.04	-.00	-.00
	Sig. (bilateral)		.54	.41	.96	.94
	N	499	499	499	499	499
ref-act	Pearson Correlation	-.03	1	.12(**)	.20(**)	.09(*)
	Sig. (bilateral)	.54		.01	.00	.04
	N	499	499	499	499	499
int-sns	Pearson Correlation	.04	.12(**)	1	.14(**)	.24(**)
	Sig. (bilateral)	.41	.01		.00	.00
	N	499	499	499	499	499
vrb-vis	Pearson Correlation	-.00	.12(**)	.14(**)	1	.04
	Sig. (bilateral)	.92	.00	.02		.34
	N	499	499	499	499	499
glob-seq	Pearson Correlation	-.00	.09(*)	.24(**)	.04	1
	Sig. (bilateral)	.94	.04	.00	.39	
	N	499	499	499	499	499

** Correlation is significant at level 0.01 (bilateral).* Correlation is significant at level 0.05 (bilateral).

Table 7. Correlations CTA.

		Grade	ref-act	int-sns	vrb-vis	glob-seq
Grade	Pearson Correlation	1	.14	-.02	-.08	.08
	Sig. (bilateral)		.21	.88	.49	.44
	N	87	87	87	87	87
ref-act	Pearson Correlation	.14	1	.02	.03	.01
	Sig. (bilateral)	.21		.84	.75	.93
	N	87	87	87	87	87
int-sns	Pearson Correlation	-.02	.02	1	-.06	.15
	Sig. (bilateral)	.88	.84		.60	.16
	N	87	87	87	87	87
vrb-vis	Pearson Correlation	-.08	.03	-.06	1	.03
	Sig. (bilateral)	.49	.75	.59		.76
	N	87	87	87	87	87
glob-seq	Pearson Correlation	.08	.01	.15	.03	1
	Sig. (bilateral)	.44	.93	.16	.76	
	N	87	87	87	87	87

Table 8. Correlations CI.

To determine if learning style preferences had any relationship to the final grade in the class, a correlation between learning styles and class performance was calculate as shown in Tables 6, 7 and 8.

As Table 6 shows, a positive correlation exists between the reflective – active dimension and class performance for AP students, meaning that reflective students at AP tended to achieve higher grades in the programming class than the students with an active learning orientation. This result is consistent with prior research [23, 24, 35], which found that students with a predominant reflective learning style achieved higher grades. No such correlation was present for CTA and CI. These results suggest that our current teaching approach is biased towards verbal learning style, which is consistent with the findings of Chamillard and Karolick (1999) report that reflective and verbal learners performed better than other [24].

The only other significant correlation in Table 6 is between the verbal – visual dimension and class performance for AP students; students who were more visual in their learning also tended to do better in the programming class. No such correlation appears for CTA and CI.

As Table 6 and Table 7 shows, a positive correlation exists between the reflective – active dimension and verbal – visual dimension for AP and CTA students, and another positive correlation exists between the intuitive – sensing and global – sequential dimension for AP and CTA students. These results suggest that reflective learners are correlated with the verbal learners while intuitive learners are correlated with global learners. These findings are also consistent with prior research [36, 37].

Table 9 shows the dominant learning style percentages of AP from ITAM learners as compared with similar learners from other countries as reported in [17,38]. For example, the first column shows that 61% of the respondents at ITAM were primarily active learners as similar to 57% in the University of Sao Paulo, Brazil. In general, Table III shows that the learning styles of ITAM in AP students are in ranges similar to those ranges or students from comparable universities in the United States and Latin America, the dominant learning style for these universities are Sensitive, visual and sequential learning styles, only in U. of Minnesota and University of Puerto Rico are under 50% in active learning style.

5.1 Dominant Learning Styles compared with others countries (c)

Institution/Country	Active	Sensitive	Visual	Sequential
AUS, United Arab Emirates	51%	64%	79%	71%
U. of Minnesota Duluth, USA	46%	65%	90%	70%
Ryerson University, USA	53%	66%	86%	72%
U. Belo Horizonte, Brazil	65%	81%	79%	67%
University of Puerto Rico, USA	47%	61%	82%	67%
U. of Sao Paulo, Brazil	57%	68%	80%	51%
University of Kingston	51%	64%	79%	71%
ITAM, México	61%	70%	81%	68%

Table 9. AP students from ITAM dominant learning style percentages in comparison with institutions from other countries [17] [28]

5.2 Identification teaching styles (d)

The Teaching styles survey was designed by Center for Occupational Research and Development (CORD) to gauge the teaching preferences and styles. It has twelve items, rank the statement that best describes the response with a “4”. The next most descriptive statement should receive a “3,” the next a “2,” and finally, rank the least descriptive statement with a “1”.

During the second semester 2008, the teaching styles instrument was administrated to instructors’ of three courses. Response rates were above 74% with 17 instructors with 512 total students (CTA n = 316, CI n = 56 and AP n = 140), the gender was 65.9% male and 34.1% female students. The Table 10 and Table 11 shows the percentage of the three groups with the gender, Figure 6 show the distribution for course about the three groups.

		Frequency	Percentage	Valid Percentage	Accumulated Percentage
Valids	AP	140	27.3	27.3	27.3
	CTA	316	61.7	61.7	89.1
	CI	56	10.9	10.9	100.0
	Total	512	100.0	100.0	

Table 10. Frequency Learning styles & teaching styles.

		Sex		Total
		f	m	f
IdCourse	1	38	102	140
	2	117	199	316
	3	20	36	56
Total		175	337	512

Table 11. Learning styles & teaching styles.

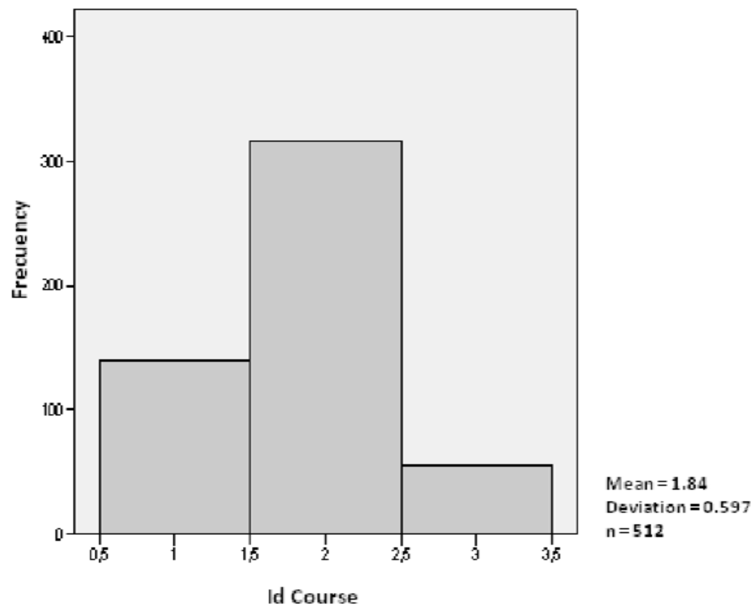

Figure 6. Distribution for three groups.

Quadrant A = Instructor prefers rote learning to analysis (Example: Students memorize abstract facts, such as multiplication Tables and atomic weights, through repetition.)

Quadrant B = Instructor prefers rote learning and focuses on practical applications (Example: Students learn practical facts about the real world, such as the available numerical apertures on fiber optics and the tensile strength of different sizes of nails.)

Quadrant C = Instructor prefers analysis to rote learning but does not focus on practical applications (Example: Students learn abstract processes, such as how to plot vectors representing forces on an unidentified object in an undefined space.)

Quadrant D = Instructor prefers analysis to rote learning and focuses on familiar applications (Example: Students are presented with real-world problems in which they use formulas and processes such as plotting designs for car parts using AutoCAD [22].

Figure 7 shows the dominant teaching style percentages of AP from ITAM learners as compared with similar learners from other countries as reported in [17] [38]. For example, the first column shows that 61% of the respondents at ITAM were primarily active learners as similar to 57% in the University of Sao Paulo, Brazil. In general,

Quadrant A= Instructor prefers to have student's process information via symbols and language and work as individuals (Example: Students listen to a lecture.)

Quadrant B= Instructor prefers to have student's process information via symbols and language and work in groups (Example: Students discuss problems in groups.)

Quadrant C=Instructor prefers to have students learn through manipulative used individually. (Example: Working individually at computers, students explore physics principles by manipulating variables in interactive web-based applets.)Quadrant D=Instructor prefers to have students learn through hands-on activities completed collaboratively (Example: team lab projects) [22].

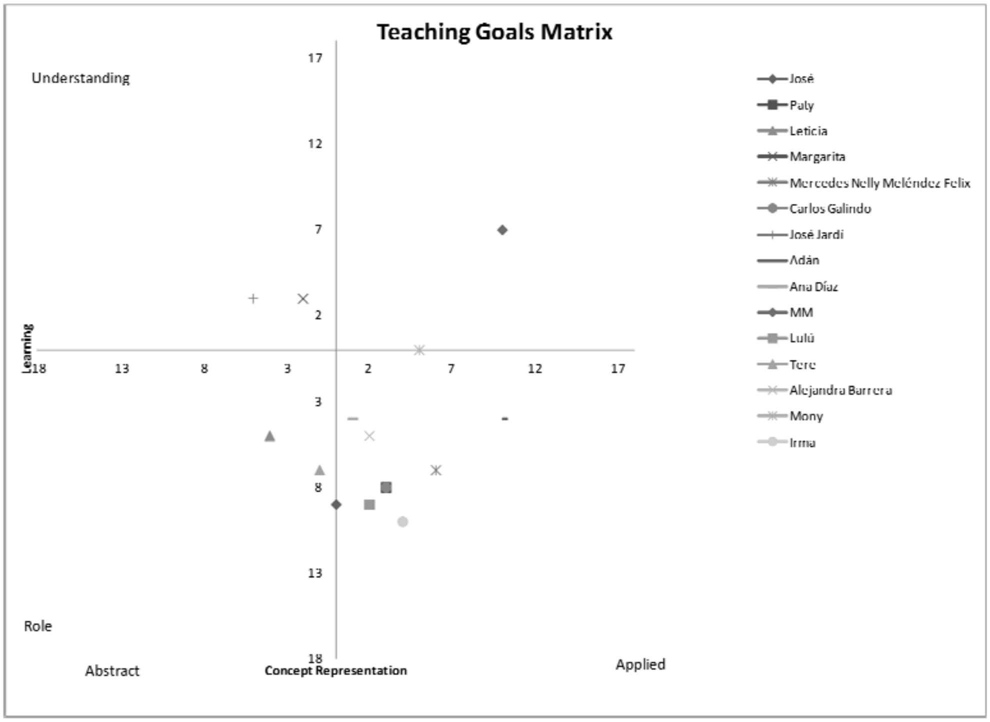

Figure 7. Teaching Goals Matrix Interpretation.

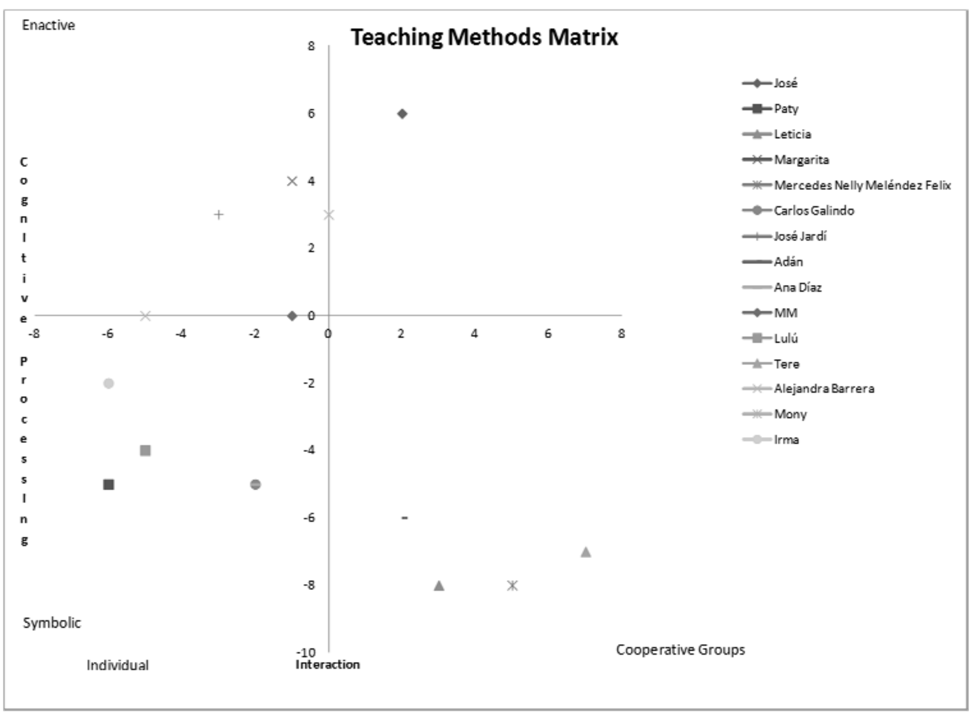

Figure 8. Teaching Methods Matrix Interpretation.

5.3 Teaching styles and course grades (e)

These results suggest that the students' work alone have better performance that in cooperative group, as shows in Table 12.

		Grade	AbstractAply	UnderstRote	IndCoop	Enactive-Simbolic
Grade	Pearson Correlation	1	-.08	.02	.23(**)	.02
	Sig. (bilateral)		.07	.58	.00	.67
	N	512	512	512	512	512
AbstractAply	Pearson Correlation	-.08	1	-.07	.04	-.30(**)
	Sig. (bilateral)	.07		.11	.35	.00
	N	512	512	512	512	512
UnderstRote	Pearson Correlation	.02	-.07	1	.01	.41(**)
	Sig. (bilateral)	.58	.11		.80	.00
	N	512	512	512	512	512
IndCoop	Pearson Correlation	.23(**)	.04	.01	1	-.23(**)
	Sig. (bilateral)	.00	.35	.80		.00
	N	512	512	512	512	512
Enactive-Symbolic	Pearson Correlation	.02	-.23(**)	.41(**)	-.23(**)	1
	Sig. (bilateral)	.67	.00	.00	.00	
	N	512	512	512	512	512

** Correlation is significant at level 0.01 (bilateral).

Table 12. Correlation teaching styles & course performance.

5.4 Teaching styles and learning styles (f)

The comparison of teaching styles and learning styles also resulted in some interesting relationships. Sensitive learners tend to gain better understanding when they are practical, don´t like courses without an immediate link to the real world [39], hence the concept representation - abstract and Cognitive Processing— symbolic were a good correlation to get a better understanding of the course contents. Visual-verbal hence the concept Representation—varies from abstract than applied. We will discuss more on these results in section V.

6. Implication on Pedagogical Design

The study presented here should allow the teacher to determine the most appropriate teaching strategy and course material. Different approaches can be used. A recommendable approach consists in clustering students with similar learning styles and using the appropriate teaching strategy and material for each of the groups. Usually, the teacher is not able to implement such an approach, due for example to course time constraints, unavailability of the appropriate resources, etc. Should this be the case, another plausible

		act-ref	sns-int	vis-vrb	seq-glob	Abstract Aply	Underst Rote	IndCoop	Enactive Symbolic
act-ref	Pearson Correlation	1	.05	.19 (**)	.02	-.04	.07	-.05	.07
	Sig. (bilateral)		.30	.00	.67	.35	.14	.24	.11
	N	512	512	512	512	512	512	512	512
sns-int	Pearson Correlation	.05	1	.12 (**)	.26 (**)	-.12 (**)	.07	.02	.13(**)
	Sig. (bilateral)	.30		.01	.00	.01	.13	.61	.00
	N	512	512	512	512	512	512	512	512
vis-vrb	Pearson Correlation	.19 (**)	.12 (**)	1	-.01	-.019 (*)	.02	.00	.03
	Sig. (bilateral)	.000	.007		.894	.024	.651	.985	.510
	N	512	512	512	512	512	512	512	512
Seq-glob	Pearson Correlation	.02	.27 (**)	-.01	1	-.06	.03	.07	.05
	Sig. (bilateral)	.67	.00	.89		.19	.57	.13	.319
	N	512	512	512	512	512	512	512	512
AbstractAply	Pearson Correlation	-.04	-.12 (**)	-.10 (*)	-.06	1	-.07	.04	-.30(**)
	Sig. (bilateral)	.35	.01	.02	.19		.11	.35	.00
	N	512	512	512	512	512	512	512	512
UnderstRote	Pearson Correlation	.07	.07	.02	.03	-.07	1	.01	.41(**)
	Sig. (bilateral)	.14	.13	.651	.574	.109		.802	.000
	N	512	512	512	512	512	512	512	512
IndCoop	Pearson Correlation	-.05	.02	.00	.07	.04	.01	1	-.23(**)
	Sig. (bilateral)	.24	.61	.99	.13	.35	.80		.00
	N	512	512	512	512	512	512	512	512
Enactive Symbolic	Pearson Correlation	.07	.13 (**)	.039	.055	-.30 (**)	.41 (**)	-.23 (**)	1
	Sig. (bilateral)	.11	.00	.51	.31	.00	.00	.00	
	N	512	512	512	512	512	512	512	512

** Correlation is significant at level 0.01 (bilateral).

- Correlation is significant at level 0.05 (bilateral).

Table 13. Correlations between teaching styles & learning styles.

approach consists of the identification of the "group average style" and the selection of the material accordingly. A third alternate approach (and perhaps the most recommendable one, should the resources allow it) consists of the use of different types of materials (thus targeting different styles) for a set of two or three learning units at a time. The selected material would be used on a rotational basis. This can be done with the integration of teams or groups of students having different learning styles. The adoption of this third approach allows the creation of team group skills for the students. In this situation the teacher might want to focus only on the teaching strategy that is representative of each category of learning style. This is illustrated in the following; overall recommendations are presented to select teaching strategy.

Sensitive learning style: The content must be practical, courses must have an immediate connection with the real world, using concrete methods that are oriented towards facts and procedures that follow previously established techniques. The requested homework must be detailed, not global, including problem solving, laboratory exercises and concept memorization.
Intuitive learning style: The content must be innovative, oriented to theory and meanings, with abstractions and mathematical formulae, avoiding repetitive methods. The requested homework must include the discovery of relations and actions. The introduction of new concepts can be used but not as memorizing facts but as abstractions.

Visual learning style: The content must be a heavy on visual components. The requested homework must include actions to visualize, the information gathering must use visual representations, images must be used in order to make it easier for the students to remember the contents, and the teacher can request diagrams that summarize the homework.

Verbal learning style: The content must have a lot of oral and textual components. The requested homework must include written essays or oral presentations, the information gathering must use textual representations, texts must be used in order to make it easier for the students to remember the contents, and the teacher can request abstracts that summarize the homework.

Active Learning Style: Students tend to comprehend and assimilate new information when they practice using it (discussion, implementation, group presentations) and rather learn working with others. The content must be applicable. The requested homework must include work in groups.
Reflexive learning style: Students observe and ponder experiences. Data are collected and analyzed thoroughly about before any conclusion is made. The content must be related with experiences. The requested homework must include personal work.

Sequential Learning Style: The content must be written orderly, step-by-step. The requested homework must consist of small orderly steps that are logically associated to the problems being solved. This allows content to be shown in steps (chapters).

Global learning style: The content must be written in big leaps, suddenly and almost randomly. Students can solve complex problems quickly and put things together in an innovative way but may have difficulties to explain how they did it. This allows seeing everything as a whole [10, 15, 40].
All of these features are key learning elements for educational settings. We believe that above outcomes can serve as guideline for the lectures in choosing the right content for the right audience in their courses. Existing studies show that matching learning styles with teaching styles is advantageous to academic achievements [41].

7. Conclusion

In this study three broad determinations have been made: a) first, a great similarity in learning styles is present between American and Middle Eastern students; the same similarity in learning styles AP students and CTA students suggests the possibility of constructing pedagogical designs for courses, but not for CI students; b) second, we have been successful in establishing several significant relationships in learning styles, our results suggest that reflective learners are correlated with global learners, these findings are also consistent with those reported by Alfonseca et. al. [36], and may be used to form appropriate groups in programming assignments or projects; c) third, the study outcomes clearly suggest that today's students are flexible in stretching their learning styles to accommodate varying teaching methods, they further suggest that learning styles of today's learners facilitate them to experience emerging and varying technologies while their learning preferences are not limited to a particular tool.

This work is part of our ongoing research on incorporating emerging e-learning tools in educational settings. Therefore, to further strengthen our study results, we plan to conduct follow up studies in the use of specific e-learning tools for different learning styles and teaching strategies. The aim would be to help people in getting a better performance whilst learning. We hypothesize this could enhance the teaching-learning process, that is, when introducing innovative elements, students might acquire new knowledge in a more flexible and adaptable way than with traditional methods.

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