Influence of Pedagogic Approaches and Learning Styles on Motivation and Educational Efficiency of Computer Science Students

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***Abstract*— The classic didactic approach that has been applied in the classroom for learning algorithms focuses on the use of lectures combined with practical exercises. In our approach, we propose a novel way for learning algorithms through interactive and collaborative experimentation. Furthermore, as far as we know, there are no existing studies that analyze the relationships that these approaches may have with the three key components in the learning process: the student's learning style, motivation during the learning process, and educational efficiency. In this paper, we present an experiment carried out in the classroom for learning greedy algorithms, which studies these components on two didactic approaches: the first one based on active teaching methodology and the second one on traditional teaching methods.**

***Index Terms*— Learning styles, Felder-Silverman model, educational efficiency, motivation.**

I. Introduction

PEOPLE perceive and acquire information differently. According to Alonso *et al.* [1], we not only perceive differently, but also we interact and respond differently in learning environments. The concept of learning styles refers to our preferences to perceive and acquire information, how our mind processes information and how it is influenced by our perceptions. Keef [2] defines learning styles as cognitive, emotional and physiological traits that serve as relatively stable indicators of how students perceive the interactions and respond to their learning environments. Kolb [3] describes them as "some learning capabilities that stand out above others as a result of hereditary apparatus of own life experiences and the demands of the current environment."

According to Alonso *et al.* [1], when the teaching style is consistent with the student's learning style, the student learns more effectively. In addition, the way in which individuals choose or tend to approach a learning situation has an impact on their performance and achievement of learning outcomes [4]. Therefore, as the implication of the learning style in the teaching process is important, it is interesting to analyze what associations or relations one's learning style has with other elements of this process. This paper presents an analysis of these learning styles in order to respond to several questions: what are the learning styles of our computer science students at the Rey Juan Carlos University, according to our selected sample? Is there any relationship between the students' learning styles and their educational efficiency and/or motivation? And finally, is there any relation with the learning methodology applied in particular? The answers to these questions can help educators to choose appropriate teaching strategies. This paper is a major contribution because it provides the learning methodology that should be applied in the classroom in order to improve students' performance and motivation.

To answer these questions, we analyzed the students' learning styles in the core subject "Design and Analysis of Algorithms" in the Software Engineering degree and Computer Engineering degree at the Rey Juan Carlos University. We performed two classroom experiences using different learning methodologies in two different groups. The experimental group, where we applied a collaborative/active teaching method based on experimentation using GreedExCol [15] (an interactive collaborative learning tool for the study of greedy algorithms that shows animations and graphics concerning their behaviour), and the control group based on a traditional teaching method (with lectures and individual work). We used various measuring instruments for learning style, motivation and educational efficiency. In this paper both the experiences and the results obtained are described.

The structure of the paper is as follows. Section II contains the Felder-Silverman model, which is the theoretical basis of the work. Section III describes the protocol, instruments and results of the evaluation of students' learning styles. In sections IV and V, the results of correlation between learning styles, educational efficiency and motivation are presented, respectively. In section VI, the results of our experiment are discussed. Finally, in section VII we include the conclusions of this paper.

II. The Felder-Silverman Model

There are several models describing different learning styles such as the Kolb model [5], [6], the Neurolinguistic Programming model, also called Visual-Auditory-Kinesthetic (VAK) [7], the Multiple Intelligences model of

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Gardner [8], the Brain Hemispheres model [9], the Brain Quadrants model [10] and the Felder-Silverman model [11].

Our work is based on the Felder-Silverman model. This model aims to capture styles of learning among engineering students and thus provides a good basis for educators to design a teaching method according to the learning needs of their students.

Our choice is based on three reasons. The first reason is the validation of this model. According to De Bello [13], to choose an appropriate model or instrument for a study or a research, this should be evaluated with regard to its reliability and validity. The Felder-Silverman model is widely validated [14], constituting thereby a consolidated tool for its reliability and validity compared to other models. The second reason is that this model is well known and recognized among engineering educators. The third and final reason for using the Felder-Silverman model is that it focuses on aspects of meaningful learning styles for the teaching of the engineering domain in which we intend to make our experience.

The final Felder-Silverman model [11] consists of only four dimensions, although originally had a fifth dimension, the dimension of Organization. However, this dimension is not developed and the scales and measuring instruments do not contemplate it. Each of the other four dimensions has two categories:

Active/Reflexive: Mental processes that convert information into the knowledge perceived consist of two categories: active experimentation and reflective observation. Active experimentation involves doing something with the information in the outside world, and talking about it, while reflective observation implies examining and manipulating the information introspectively ([11, p. 678]). Students whose learning style is active do not learn much from traditional lectures or classes, but learn better by experiencing and working in groups. On the other hand, students whose style is reflexive require situations that give the opportunity to think about the information presented to them ([11, p. 679]).

Visual/Verbal: Visual learners remember better what they see: images, diagrams, flow charts, time lines, movies, demonstrations, etc. They may forget the information that is communicated verbally. However, students whose learning style is verbal remember much of what they hear and even more of what they see and hear (when the information is presented both visually and verbally). They remember and learn better from lectures, prefer verbal explanation to visual demonstration and learn effectively by explaining things to others ([11, p. 677]).

Sensory/Intuitive: The perception and intuition are two ways in which people tend to perceive the world. Perception involves observation and data collection through the senses. Intuition involves indirect perception through the unconscious: speculation, imagination and hunches. Although students use both types of faculties, most prefer to use one or the other ([11, p. 676]). Students whose style is sensory are good at memorizing facts and tend to be careful and slow in carrying out their work, while intuitive ones prefer principles, theories and innovation, dislike repetition and get bored with the details; they are good at grasping new concepts and tend to complete tasks quickly.

Global/Sequential: With a global style, students tend to learn in a fragmented way: they may feel lost for days or weeks without being able to solve simple problems or show the most basic understanding, until suddenly they "do things"; they may have difficulty working with material that only has a partial or superficial understanding. They tend to make intuitive leaps and they have difficulty explaining how to reach the solution ([11, p. 679]). However, students whose learning style is sequential feel comfortable with the material presented in a logical order of progression, following linear reasoning processes in solving problems. They can be strong in the thinking and convergent analysis and learn best when teachers present material in a steady progression of difficulty ([11, p. 679]).

For each dimension or category (e.g., Active/Reflexive), there are three levels of preference: balanced, moderate and strong. A balanced preference in a dimension means that students can learn from both categories. For example, in the case of the Active/Reflexive dimension, if a student presents a balanced preference it means that the student can learn from both an active teaching method and a reflexive one. A moderate preference in a dimension means that the student learns easier with one category than with the other one. A strong preference means that the student will have difficulty learning in an environment that does not provide that category-based environment. In short, an increase in the preference or learning style intensity decreases the capacity to adapt to the teaching environments based on the opposite teaching methods.

Definitely, understanding the results of the application of the learning styles in the Felder-Silverman model can help educators to find suitable forms or methods to present the subject to students. This approach has been advocated as an effective learning environment for teaching engineering studies [12].

III. Evaluation of Learning Styles

In this section, we present the learning styles analysis of our computer science students. First, the protocol and the instruments used are presented. Finally, the results obtained are reported.

A. Protocol

The assessments of learning styles, motivation and educational efficiency were conducted in April 2013 in the core subject "Design and Analysis of Algorithms" in the Software Engineering degree and Computer Engineering degree at the Rey Juan Carlos University.

To achieve these assessments, two groups were involved. The experimental group, formed by Computer Engineering degree students that received an active teaching methodology based on collaborative experimentation using GreedExCol tool [15] (which is a collaborative extension of GreedEx [16] that facilitates the study of behavior of greedy algorithms through animations and graphics and experimentation and comparison of different greedy algorithms); and the control group, formed by Software Engineering degree students that received a traditional teaching method (with lectures and conducting individual practical activities). The control group was formed by 44 students and the experimental group was formed by 49.

Both groups received five class sessions about greedy algorithms (between practical and theoretical content classes), of two hours each. The class sessions for both groups were the same type, differing only in two sessions. In both groups the theory sessions began with an introduction of greedy algorithms, followed by two sessions (which differ between the two groups) and ending with a series of common classes, where several classical greedy algorithms were presented (such as Dijkstra, Kruskal and Prim algorithms).

The second class session differs in how to consolidate the students' knowledge of greedy algorithms. For the control group, students were presented with simple problems such as a money change problem [17] or some variants of the knapsack problem. For the experimental group, the teacher used GreedExCol for two problems: maximize the number of objects in a knapsack and maximize the added weight in a knapsack. Along with these problems, the teacher presented experimentation-related concepts and experimentation process of determining the optimal selection functions. This session ended with students experimenting the knapsack problem with the use of GreedExCol in the computer room.

In the third session (session in the computer room), both groups were asked to apply the experimental method to determine the selection function that provides an optimal solution to the activity selection problem. However, each group was provided with different resources and methodologies. On the one hand, control group students were given a file containing a Java code that implemented a generic greedy algorithm for this problem and the implementation of a particular selection function. They were asked to think and implement alternative selection functions and experiment with their optimality trying to determine the optimal one. These activities were conducted under individual work methodology. On the other hand, students in the experimental group were asked to use GreedExCol for the same optimization problem, experimenting with different functions offered by the tool to identify the optimal selection function [16]. These activities were conducted under a group methodology (four students per group). Participation in the assessments was encouraged so that students could slightly increase their practice marks in the subject.

B. Instruments

According to the objectives set previously, this work aims to answer the following questions:

1) What are the learning styles of Computer Science students at Rey Juan Carlos University, according to the selected sample?
2) Is there any relationship between learning styles and academic performance (educational efficiency) in our selected sample? If this relationship exists, is it influenced by the educational methodology or approach used (experimental or traditional)?
3) Is there any relationship between learning styles and motivation in our selected sample? If this relationship exists, does it depend on the educational methodology or approach used (experimental or traditional)?

TABLE I
LEARNING STYLES FOR ALL STUDENTS

	Control	Cont. %	Experim.	Exp. %	Total	Total %
Active	33	75%	37	76%	70	75.27%
Reflexive	11	25%	12	24%	23	24.73%
Visual	38	86%	43	88%	81	87.10%
Verbal	6	14%	6	12%	12	12.90%
Sensory	36	82%	39	80%	75	80.65%
Intuitive	8	18%	10	20%	18	19.35%
Global	12	27%	16	33%	28	30.11%
Sequential	32	73%	33	67%	65	69.89%

To answer the first question, the learning styles in the two groups were analyzed [18]. The instrument used to measure the learning styles was the Felder-Silverman questionnaire, which was responded online using the Google Drive Form tool. The questionnaire consists of 44 questions.

To answer the second question, an analysis of correlation between educational efficiency and learning styles [19] was conducted. To assess educational efficiency, an experiment was performed to measure students' knowledge in the two groups. Both groups performed a test before receiving the classes (*pretest*) and a test just after the end of the last session of this experiment (*posttest*). The knowledge test consisted of six questions about the basics of optimization and greedy algorithms, including theory and simple problems. Each test is scored on a scale from 0 (lowest grade) to 10 (highest). These tests were done on paper and returned to the teacher at the end. The analysis was carried out with the SPSS 20 program.

To give an answer to the third question, an analysis of correlation was conducted between learning styles and motivation [20]. The EMSI instrument (Motivation Scale Situational) [21] was used in the two groups to achieve the measurement of motivation, performing a first measurement of students' motivation before the experience (*pretest*) and a second measurement at the end (*posttest*). This scale is an appropriate measure for evaluating the situational motivation in the learning environment that consists of 14 items grouped into 4 dimensions: intrinsic motivation, identified regulation, external regulation and demotivation. All items respond to the same question: *"Why do you think you should perform that activity to study greedy algorithms?"*. This evaluation was performed online using a Google Drive Form tool. The analysis was carried out with the SPSS 20 program.

C. Results of Learning Styles Analysis

Table I shows the eight learning styles both for each group and jointly. In short, students in both groups are inclined to active, visual, sensory and sequential learning styles (Table I, column "Cont. %" and "Exp. %"). Therefore, the two groups prefer to learn by testing and working with others (active style), they prefer to obtain visual information

TABLE II
PREFERENCES

Preference	Control	Experimental	Total
Balanced	51.14%	45.40%	48.27%
Moderate	35.23%	41.33%	38.28%
Strong	13.63%	13.27%	13.45%

and representations (visual), they like to solve problems by following well-established procedures (sensory) and they learn in small incremental and logically related steps (sequential). According to Felder and Spurlin [12], the traditional teaching in engineering courses advantage verbal, intuitive, and sequential learners. In other words, students who learn to think about the information and prefer to work alone (reflexive), students who prefer written and spoken explanations (verbal), students who prefer principles, theories and innovation (intuitive) and students who learn in incremental steps (sequential).

The only common style between our students' learning styles and those which benefit more from a traditional learning [12] is the sequential style. With that, we can presumably conclude that the two groups should learn better with a non-traditional learning methodology.

Table 2 shows the results of the students' trends. The most common preferences in descending order are balanced (51.14%), (i.e. neutral preferences), moderate and strong. For example, half of the students in the control group can learn from one dimension or another. However, 41.33% of the students in the experimental group will easily learn with a learning methodology that favors a specific dimension, e.g. active or reflexive, etc.

IV. Results of Correlation Between Learning Styles and Educational Efficiency

We present the results of correlation between learning styles (in separate groups and jointly) and educational efficiency (measured as *posttest-pretest* subtraction of the means obtained after and before receiving classes on greedy algorithms). To analyze the correlation, first we checked the normality of the samples, using Pearson correlation in the case of normal samples or Spearman correlation in the opposite case. The analysis was performed with the SPSS 20 program. We analyzed the results of students who answered the two tests. The variables analyzed in correlation were the eight learning styles (active, reflexive, visual, etc.) and the educational efficiency notes (*posttest-pretest*).

With respect to the control group, we concluded normality for visual, sensory and active styles, and educational efficiency samples (obtaining sig$>$0.05 of significance). Hence, we performed the Pearson correlation test between these styles and educational efficiency samples in which we assumed that there were no correlations (obtaining sig$>$ 0.05 of significance). Furthermore, we calculated the Spearman correlation test between the remaining styles that did not follow a normal distribution and educational efficiency that showed that there were no correlations (obtaining sig$>$ 0.05 of significance).

With respect to the experimental group, we concluded normality for active, sensory, visual and sequential styles, and educational efficiency samples (obtaining sig$>$0.05 of significance). Hence, we calculated the Pearson correlation test between these samples and educational efficiency in which we assumed that there were no correlations (obtaining sig$>$0.05 of significance). On the other hand, after interpreting the results of the Spearman correlation test for the remaining samples that did not follow a normal distribution, there was a negative correlation of **– 0.392** between educational efficiency and verbal style (obtaining sig = 0.016 of significance).

With respect to the sum of the two groups, active and visual styles and efficiency samples did follow a normal distribution (obtaining sig$>$0.05 of significance). Hence, the Pearson test was performed in which we assumed that there were no correlations (obtaining sig$>$0.05 of significance). Furthermore, we conducted the Spearman test between the remaining samples that did not follow a normal distribution and educational efficiency. According to this, there were no correlations (obtaining sig$>$0.05 of significance).

V. Results of Correlation Between Learning Styles and Motivation

We present the results of the correlation between learning styles (in separate groups and jointly) and increased motivation (*posttest-pretest* calculated from the subtraction of the means of motivation obtained before and after receiving classes on greedy algorithms). To analyze the correlation, first we checked the normality of samples. We used Pearson correlation in the case of normal samples or Spearman correlation in the opposite case. The analysis was performed with the SPSS 20 program. We analyze the results of students who answered the two tests. The variables in the correlation were the eight learning styles and the increased motivation and its four dimensions (*posttest-pretest*).

With respect to the control group, we concluded normality for active, sensory and visual styles, increased motivation (*posttest-pretest* subtraction of motivation), increased intrinsic motivation (*posttest-pretest* subtraction of intrinsic motivation dimension), increased identified regulation (*posttest-pretest* subtraction of identified regulation dimension) and increased external regulation (*posttest-pretest* subtraction of external regulation dimension) samples (obtaining sig$>$ 0.05 of significance). According to the Pearson test, there were no correlations between the analyzed samples (obtaining sig$>$0.05 of significance). Furthermore, we performed the Spearman correlation test between the remaining samples that did not follow a normal distribution in which we assumed that there were no correlations (obtaining sig$>$0.05 of significance).

With respect to the experimental group, reflexive, intuitive, verbal, sequential and global styles, and increased motivation (*posttest-pretest* subtraction of motivation) and increased intrinsic motivation samples (*posttest-pretest* subtraction of intrinsic motivation dimension) did not follow a normal distribution (obtaining sig $<$0.05 of significance). Hence, we performed the Spearman test for these samples in which we assumed that there was a negative correlation of **−0.321** between increased intrinsic motivation and intuitive style (obtaining sig = 0.036 of significance). On the other hand, after interpreting the results of the Pearson test between the remaining samples that did follow a normal distribution, there were no correlations (obtaining sig> 0.05 of significance).

With respect to the sum of the two groups, increased external regulation (*posttest-pretest* subtraction of external regulation dimension) and visual style samples did follow a normal distribution (obtaining sig>0.05 of significance). Therefore, we conducted the Pearson test in which we assumed that there was no correlation between visual style and increased external regulation. Furthermore, we performed the Spearman correlation test between the remaining samples that did not follow a normal distribution, and according to this test, there was a negative correlation **−0.253** (obtaining sig = 0.023 of significance) between global learning style and increased intrinsic motivation (*posttest-pretest* subtraction of intrinsic motivation dimension) and a negative correlation **−0.267** (obtaining sig = 0.015 of significance) between intuitive learning style and increased identified regulation (*posttest-pretest* significance of identified regulation dimension).

VI. Discussion

Most of students' learning styles are active, visual, sensory and sequential. According to Felder and Spurlin [12], the traditional teaching methodology that has been applied in engineering courses benefit more reflexive, verbal, intuitive and sequential learners. According to this interpretation, only the sequential aspect of teaching these students would be suitable for computer science students.

Regarding the results of correlation between learning styles and educational efficiency, we have found that students who had a low academic performance are those with a verbal learning style and received collaborative/active instruction. This conclusion is logical given that verbal students require written and oral explanations instead of diagrams or images (visual style), while the collaborative/active environment follows a more visual style.

We have also obtained results of correlation between learning styles and motivation. Firstly, the inverse correlation between intrinsic motivation and intuitive style detected in the experimental group suggests that students who prefer theory, principles, etc. are less motivated to perform the activity in a collaborative environment and in groups; they do not do the learning activity because it seems interesting for them or they enjoy it. Secondly, the inverse correlation between intrinsic motivation and global style detected after joining the sum of the two groups suggests that students who learn in large jumps and in piecemeal (global style) do not do the learning because they enjoy it. In addition, students who prefer principles, theories and innovation, but do not like repetition (intuitive style), do not see the benefit of the learning task, not even believe that others consider it an important task (inverse correlation between intuitive style and identified regulation).

VII. Conclusions

The results of our study have proved to be interesting. We have found that most students of the Computer Engineering and Software Engineering degrees at the Rey Juan Carlos University in the core subject "Design and Analysis of Algorithms" have an active, visual, sensory and sequential learning style; in other words, the groups analyzed can learn better with a non-traditional approach. A correlation between motivation, educational efficiency and learning styles confirmed that by applying an experimental/collaborative methodology to students whose style is intuitive, their motivation decreases, and if applying the same experimental/collaborative methodology to students whose style is verbal, their level of knowledge acquisition decreases. Overall, intuitive and verbal learners work best with a traditional approach.

In summary, if we apply visual teaching strategies to verbal learners (who require written and verbal explanations), they may not have the best academic results but not necessarily less motivation. And if we apply sensory teaching strategies to intuitive students (who prefer principles, theories and innovation), they may have less motivation but not necessarily less academic performance. However, we did not find any other correlation and, therefore, no conclusion for the rest of students.

The results of the analysis presented are interesting but are limited to a specific context (subject, academic year, grades and university), so they cannot be extrapolated to all the students of computer science in general. However, it shows the first results of a study on the matching between teaching methods and learning styles, an aspect that has received little attention in computer science.

References

[1] C. M. Alonso, D. Gallego, and P. Honey, *Los Estilos de aprendizaje: Procedimientos de Diagnóstico y Mejora*. Bilbao, Spain: Mensajero, 1994.

[2] J. W. Keefe, "Learning styles: An overview," in *NASSP's Student Learning Styles: Diagnosing and Prescribing Programs*. Reston, VA, USA: National Association of Secondary School Principals. 1979, pp. 1–17.

[3] D. A. Kolb, *Experiential Learning: Experience as the Source of Learning and Development*. Englewood Cliffs, NJ, USA: Prentice-Hall, 1984.

[4] S. Cassidy, "Learning styles: An overview of theories, models, and measures," *Edu. Psychol.*, vol. 24, no. 4, pp. 419–444, 2004.

[5] D. A. Kolb, "Learning styles and disciplinary differences," in *The Modern American College*. San Francisco, CA, USA: Jossey-Bass, 1981, pp. 233–255.

[6] P. Honey and A. Mumford, *Using Our Learning Styles*. Berkshire, U.K.: Peter Honey Publications, 1986.

[7] BECTA. (2005). *Learning Styles: An Introduction to the Research Literature*, accessed on May 20, 2014. [Online]. Available: http://dera.ioe.ac.uk/id/eprint/14118

[8] H. Gardner, *Multiple Intelligences: Gardner's Theory*. New York, NY, USA: Basic Books, 1993.

[9] R. W. Sperry, "Cerebral organization and behavior," *Science*, vol. 133, no. 3466, pp. 1749–1757, 1961.

[10] N. Herrmann, *The Creative Brain*. Lake Lure, NC, USA: Brain Books, 1988.

[11] R. M. Felder and L. K. Silverman, "Learning and teaching styles in engineering education," *Eng. Edu.*, vol. 78, no. 7, pp. 674–681, 1988.

[12] R. M. Felder and J. Spurlin, "Applications, reliability and validity of the index of learning styles," *Int. J. Eng.*, vol. 21, no. 1, pp. 103–112, 2005.

[13] T. C. De Bello, "Comparison of eleven major learning styles models: Variables, appropriate populations, validity of instrumentation, and the research behind them," *J. Reading, Writing, Learn. Disabilities Int.*, vol. 6, no. 3, pp. 203–222, 2006.

[14] M. S. Zywno, "A contribution to validation of score meaning for Felder–Soloman's index of learning styles," in *Proc. Amer. Soc. Eng. Edu. Annu. Conf. Expo.*, 2003, pp. 1–16.

[15] J. Á. Velázquez-Iturbide, M. P. Velasco, and O. Debdi, "GreedExCol: Una herramienta educativa basada en CSCL para el aprendizaje de algoritmos voraces," in *Proc. 14th Int. Symp. Inf. Technol. Commun. Edu. (SINTICE)*, 2013, pp. 96–103.
[16] J. Á. Velázquez-Iturbide, O. Debdi, N. Esteban-Sánchez, and C. Pizarro, "GreedEx: A visualization tool for experimentation and discovery learning of greedy algorithms," *IEEE Trans. Learn. Technol.*, vol. 6, no. 2, pp. 130–143, Apr./Jun. 2013.
[17] T. H. Cormen, C. E. Leiserson, R. L. Rivest, and C. Stein, *Introduction to Algorithms*. Cambridge, MA, USA: MIT Press, 2001.
[18] O. Debdi, M. P. Velasco, and J. Á. Velázquez-Iturbide, "Un análisis de estilos de aprendizaje en alumnos de Informática," Dept. Lenguajes Sistemas Informáticos I, Univ. Rey Juan Carlos, Madrid, Spain, Tech. Rep. 2014-05, 2014.
[19] O. Debdi, M. P. Velasco, and J. Á. Velázquez-Iturbide, "Análisis de correlación entre eficiencia educativa y estilos de aprendizaje," Dept. Lenguajes Sistemas Informáticos I, Univ. Rey Juan Carlos, Madrid, Spain, Tech. Rep. 2014-06, 2014.
[20] O. Debdi, M. P. Velasco, and J. Á. Velázquez-Iturbide, "Análisis de correlación entre motivación y estilos de aprendizaje," Dept. Lenguajes Sistemas Informáticos I, Univ. Rey Juan Carlos, Madrid, Spain, Tech. Rep. 2014-07, 2014.
[21] J. Martín-Albo, J. L. Núñez, and J. G. Navarro, "Validation of the Spanish version of the situational motivation scale (EMSI) in the educational context," *Spanish J. Psychol.*, vol. 12, no. 2, pp. 799–807, 2009.

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