Learning Style Identification by CHAEA Junior Questionnaire and Artificial Neural Network Method: A Case Study

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Abstract. By the lack of personalization in education, students obtain low performance in different subjects in school, particularly in mathematics. Therefore, learning style identification is a crucial tool to improve academic performance. Although traditional methods such questionnaires have been extensively used to the learning styles detection in youths and adults by its high precision, it produces boredom in children and does not allow to adjust learning automatically to student characteristics and preferences over time. In this paper, two methods for learning style recognition: CHAEA-Junior questionnaire (static method) and Artificial Neural Networks (automatic method) are explored. The data for the second technique used answers from the survey and the percentage scores from mathematical mini-games (Competitor, Dreamer, Logician, Strategist) based on Kolb's learning theory. To the validity between both methods, it was conducted a pilot study with primary level students in Ecuador. The experimental tests show that Artificial Neural Networks are a suitable alternative to accurate models for automatic learning recognition to provide personalized learning to Ecuadorian students, which achieved close detection results concerning CHAEA-Junior questionnaire results.

Keywords: Learning Style · Automatic recognition · Artificial Neural Network

1 Introduction

Several people recognize that every individual acquires and processes information based on their learning styles and abilities. The term "Learning styles" refers to the comprehension that each person learns differently based on its cognitive, affective, and psychological factors, which determines how a person perceives, interacts, and responds to the learning environment. Learning styles are described in models, which

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based on specific scales (of perception and information processing) characterized by theorists in the fields of psychology and cognitive science, classify individuals according to conventional ways that they learn [1]. In this sense, some people have found that they have a blend of learning styles, where a learning style is dominant, with far less use of the other ones. Besides, other people found that they use different styles in different circumstances.

An established problem in the primary education is the lack of customized learning to students in different areas of knowledge, where the identification and use of a mix of learning styles is a challenge yet, due to only a few educators have started to identify them to improve their learning and teaching techniques. Notably, one of the difficulties is on the study of mathematics in students worldwide, where different studies suggest that learning math is complicated, and the outcome is being a "math hater" in the subject, being Latin America (Ecuador) with one of the lowest performance worldwide. To overcome this limitation, static and automatic approaches for identifying learning styles have emerged over time.

In the past years, questionnaires have been the most common approach to identify learning styles, which are characterized by its excellent reliability and validity [2]. In any case, they have also been subjected to some criticism considering that a questionnaire is a static approach, where their results are no longer valid over time, while learning styles change continuously. As well as, in the majority of cases the filling out a questionnaire produces boredom in children. Besides, students are not aware of the importance of the survey for the future uses, which may tend to pick answers self-assertively. Even in some cases, students can be influenced by the questionnaire formulation to give answers perceived as more appropriate. To overcome its difficulties such as boredom, recent proves had established a correlation between playing styles that match with learning styles applied on entertainment games in education [3].

The learning style identification has also been investigated in technical fields like mechanical engineering, for example in [4, 5] the impact of negative knowledge is discussed and implemented as a way to prevent and improve competency in computer-aided-design modeling. In [6] practical experience is linked to theory to help the novice to improve their theoretical results, and in [7] categories of skills and knowledge are defined for defining questions and related significant scores.

Besides, in the most recent years, some automatic approaches based on Artificial Intelligence have been introduced in the learning style identification, such as Artificial Neural Networks-based (ANN) [8], and Bayesian Networks-based (BN) [9]. Since automatic approaches tend to be more accurate and less error-prone, they focus on educational systems that adjust learning to student characteristics and preferences over time.

Although numerous static and dynamic approaches for learning style identification have been introduced with high accuracy, several primary educational systems in Ecuador, mainly for learning math is still a challenge. Therefore, in this work, we explore and compare CHAEA-Junior questionnaire and an automatic method based on ANN to determine their percentage achieved in each learning style identification.

The CHAEA-Junior questionnaire has been selected due to the test reliability in identifying learning styles in children [10], which has been translated into the Spanish language by the researchers and applied in different schools in Spain. Meanwhile, the ANN method was adopted by its demonstrated speed of execution, fast learning, and its efficient predictive capabilities to categorize and learn from specific examples data [2]. ANN as a data-driven method used data gathered from the CHAEA-Junior questionnaire, and the scores in the mathematical minigames based on ADOPTA playing styles to learning styles recognition. As a case study, we evaluated both approaches in students of 11 and 12 years old of seventh-grade primary education from the school "Teodoro Gómez de la Torre" (Ibarra-Ecuador).

The rest of the paper is organized as follows. Section 2 describes the most relevant related works. The explored methods are described in Sect. 3. Experimental setup and results are presented in Sects. 4 and 5, respectively. Finally, Sect. 6 deals with the concluding remarks.

2 Related Works

To learning styles identification, various theories typically focused on testing in teens and adults have been introduced since decades with its appropriate questionnaire, which assess and recognize with strong reliability the most aligned learning style of each learner. Kolb introduced the first theory of the Learning Style Inventory (LSI) based on experiential learning theory (ELT), which recognizes learners as Concrete experience (CE) or "feeling", Reflective observation (RO) or "observing", Abstract Conceptualization (AC) or "thinking", and Active Experimentation (AE) or "doing" [11]. Its LSI questionnaire has been used in accounting, psychology, nursing and business students [12].

Based on Kolb approach, Honey and Mumford introduced the Learning Styles Questionnaire (LSQ) [13], to remark that each individual has the sum up of all learning styles but with a main one. It describes four learning styles as follows: Activist (open-minded individual to new experiences eager to new challenges), Reflector (consider the problem in different perspectives by analysis to obtain conclusions), Theorist (logic is used to build relations and incorporate all details into an issue), and Pragmatist (applied in a practical way theories and techniques). The LSQ was modified and translated to Spanish by Alonso, Gallego, and Honey to use it in university students, which was named "Cuestionario Honey-Alonso de Estilos de Aprendizaje" (CHAEA). Additionally, considering reception and information process as two successive phases, Felder and Silverman developed a learning model with four dimensions (sensing/intuitive, visual/verbal, active/reflective, sequential/global), with its respective Index of Learning Style (ILS) questionnaire [14].

With the main objective of recognizing the learning styles in children, CHAEA-Junior [10], a reduced version of CHAEA was performed to students in elementary education level and first years of high school. This test allows verifying the learning style preference taken into consideration the psychological children characteristics between nine and fourteen years old from Spain. The results prove the reliability of the CHAEA-Junior and in a reciprocal way to the CHAEA itself.

Although static approaches as questionnaires have been the most common way to recognize learning styles with demonstrated precision, in the majority of cases produce boredom in children. For this reason, recent works have studied how the playing styles interfere in their learning styles due to nowadays children spend most of their time playing games. This correlation between playing and learning styles is known as ADOPTA (ADaptive technOlogy-enhanced Platform for eduTAinment) technique [15], which computes the results found in key performance metrics in the game (score, difficulty, and efficiency), and the answers recollected from the Honey and Mumford questionnaire. ADOPTA is based in games to education and describes the styles as: Competitors/Activists (players that like to take risk in the environment and they are fast in problem-solving), Dreamers/Reflectors (players that prefer to observe and listen to the arguments of others), Logicians/Theorists (players focused in logic analysis for task completion), and Strategist/Pragmatist (players interesting in resolving complex problems within a game in the most effective way).

Apart from the entertainment, certain affective, cognitive and psycho-social behaviors, automatic and dynamic detection of learning styles over time by gathering data about students' behavior is demanded. Therefore, in recent years, some methods to automatically predict learning styles have emerged in the Artificial Neural Networks area. Mainly, the ANN-based prediction often has been used with data from a conversational intelligent tutoring system (CITS) [8]. In this case, CITS gives the score of the learning style based in a set of rules based on Processing and Understanding dimensions from Felder-Silverman model taking into account the students' answers and behaviors in the platform. To improve the achieved accuracy, in [16] the four dimensions of the Felder-Silverman model were used, where the inputs were behavior data of a university course and the target was the learning style identified with the ILS questionnaire.

In order to find the most dominant learning style of a child, two alternative methods CHAEA-Junior questionnaire and ANN-based with ADOPTA playing styles are proposed and described in the following. It is notable that, while a child has one dominant style, the rest of the styles have itself contribution percentage to learn.

3 Methods

To identify the percentage of learning style in each individual, we apply and compare a static method: CHAEA-Junior questionnaire (CHAEA-JQ), and an automatic method: ANN. CHAEA-JQ has been selected by its demonstrated reliability by educators and academic counselors despite of being considered a boredom technique in the students [10]. For this reason, to provide entertainment in the assessment of learning style, in this work, video games to recognize the learning style based on ADOPTA playing styles have been used in conjunction with ANN. On the other hand, ANN was adopted by its attractive characteristic in the speed of execution and the updating of parameters [2, 17].

3.1 CHAEA-Junior Questionnaire (CHAEA-JQ)

CHAEA-Junior is a questionnaire focused on students of elementary education level and first years of high school. It is based on the theoretical foundations of Honey and Mumford, which is focused on experience aimed at academic improvement. The questionnaire identifies the learning styles preference of the students by a set of questions written in a way to be comprehended by the psychological children characteristics. It is characterized by its usability, speed, and ease, both in its application and in its correction by counselors and teachers.

The standard questionnaire is presented in a single folio sheet composed by 44 questions, distributed randomly, with the four groups of 11 items corresponding to the four learning styles: Active – Reflective – Theoretical – Pragmatic. The total score obtained in each Style is a maximum of 11, showing the level reached in each of the four Learning Styles (which will be between 0 and 11). The student needs to answer by drawing a circle in the item that he/she agreed; otherwise, it can leave the item without surrounding. On the back of the folio, four columns of numbers belonging to each of the four Learning Styles are presented to define the student's preferred learning profile.

For this work, it was selected randomly 24 questions from the standard questionnaire due to time constraints in the experiment and to avoid boredom in children, each group of 6 questions represents one learning style. It was not used a folio sheet as the standard version; instead, the questions were written in an interactive web system where the student needs to check in a checkbox if he/she is agreed with that question. The score in that similar learning style will be increased, otherwise, if he/she disagrees, the checkbox will be empty, and the score in that learning style will not be modified.

3.2 Artificial Neural Network

It is compounded by three kinds of layers: the input layer, hidden layers, and output layer as it is depicted in Fig. 1. This method comprehends two processes: training and validation. During the training process, the input layer contains the neurons that receive as entry data the CHAEA-JQ answers of the 24 questions. The output layer often also called target layer, holds the percentages of each learning style obtained from the mathematical mini-games based on ADOPTA styles (PLS_{ANN}). The PLS_{ANN} was computed after the student finished playing each mini-game. It measures the percentage

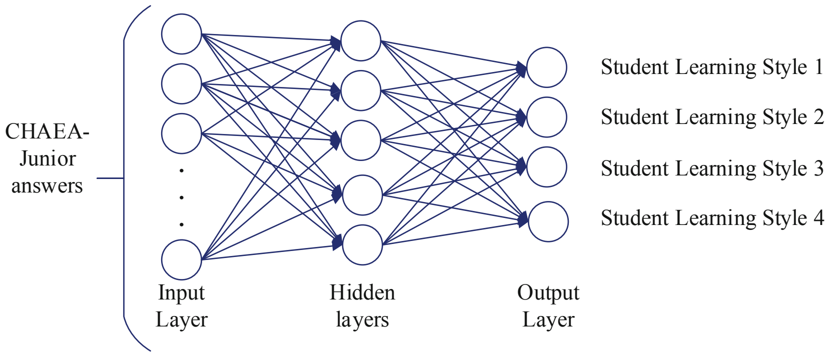

Fig. 1. Top-level architecture of the artificial neural network approach.

of each one by the division between the score obtained in each mini-game and the maximum score between them (which have been applied to the training students' group).

The network learning process takes the input neurons and the expected output neurons, to update the weights on the internal neurons of the one hidden layer until getting the most likely computed output neurons with respect to the target. This process uses the Back-Propagation (BP) algorithm to propagate back the derivative of the error function from the end to the start of the network. The difference between the result from the target and the output of the BP is used as a back-propagation error.

The BP main equation is given by Eq. (1), where o_i is the output of the neuron belonging from the hidden n_i, p represents the synaptic potential, w_{ij} are the synaptic weights between neuron i in the current layer and the neurons of the previous layer with activation $\hat{o}_j$. Therefore, the sigmoid activation function is computed as shown in Eq. (2).

$$o_i = s\left(\sum\nolimits_{j=1}^{n} w_{ij} . \hat{o}_j\right) = s(p) \tag{1}$$

$$s(x) = 1/(1 + e^{-\gamma x}) \tag{2}$$

The BP algorithm objective is to reduce the error obtained by modifying the synaptic weights, to get a minimum difference between targets and network outputs. The error is given by Eq. (3), where the first sum is computed on the p patterns of the data set and the second sum is calculated on the N output neurons. $t_i(r)$ is the target value for output neuron i for pattern r, and $o_i(r)$ is the response network output.

$$E = \frac{1}{2}\sum\nolimits_{r=1}^{p}\sum\nolimits_{i=1}^{N}(t_i(r) - o_i(r))^2 \tag{3}$$

The synaptic weights between two last layers of neurons are computed as shown in Eq. (4), where η is the learning rate and s' is the derivative of the sigmoid function o_i, and the other weights are modified according to deltas (δ) that propagate the error.

$$\Delta w_{ij}(r) = -\eta\left(\partial E/\partial w_{ij}(r)\right) = \eta[t_i(r) - o(r)]s_i'(p_i)\hat{o}_i(r) \tag{4}$$

In the validation process, the input layer receives the CHAEA-JQ answers; meanwhile, the output layer contains the neurons that provide the percentage of the student learning styles which are correlated with ADOPTA playing styles.

4 Experimental Setup

4.1 Data Preparation

Experiments were carried out over collected data of 100 students between 11 and 12 years old from seven-grade primary education of the school "Teodoro Gómez de la

Torre" (Imbabura-Ecuador), which were divided randomly into two data sets, 80% for training and 20% for testing phase. Both methods CHAEA-JQ and ANN were evaluated on the testing set.

4.2 Quality Metrics

The ability to identify the learning styles that have a student was measured through metrics such percentage for learning style recognition for CHAEA-JQ (Pls_{JQ}) and ANN (Pls_{ANN}). Pls_{ANN} corresponds to the output of the network in Eq. (1), while Pls_{JQ} for each learning style is given by Eq. (7), which takes into account the Sumatory of Each Learning Style $(SELS_L)$, and the Sumatory of all questions related to the Learning Styles (SLS):

$$SELS_L = \sum\nolimits_{j=1}^{6} q_j^L \quad \begin{matrix} q_j^L = 1\,\mathit{if\ it\ is\ check\ the\ checkbox} \\ q_j^L = 0\,\mathit{if\ it\ is\ not\ check\ the\ checkbox} \end{matrix} \tag{5}$$

$$SLS = \sum\nolimits_{j=1}^{24} q_j \tag{6}$$

$$PLS_{JQ} = SELS_L / SLS \tag{7}$$

4.3 Experiment Description

To assess the quality achieved by CHAEA-JQ and Artificial Neural Network approaches to identify students learning styles, several experimental tests have been performed in a testing group of children by answering the questions in the CHAEA-JQ and by answering mathematical questions in math mini-games based on ADOPTA playing styles.

To test CHAEA-JQ, each student answered 24 questions in an interactive web-system. The answers were captured in the system, with 1 corresponding to agree (checked checkbox) and 0 corresponding to disagree (empty/unchecked checkbox). An example of data captured in one student will be 1 0 1 …… 11111, where each number represents the answer of the 24 questions.

By using (PLS_L), it can be found the percentage of learning style with the CHAEA-JQ. An example of one student is 0.00 | 0.50 | 0.17 | 0.33, where each value represents learning styles percentage in the questionnaire, like 0.00 it means the percentage of the Activist learning style, meanwhile 0.50 represent the Reflector learning style.

To determine the percentage of all the styles to learn by using ANN, each student played four mathematical mini-games based on the four ADOPTA playing styles with 32 mathematical questions each one. The mini-games are Competitor (shooting rockets to the correct answer), Dreamer (pressing a puzzle piece to the correct answer), Logician (pressing a card to the correct answer) and Strategist (jumping an avatar and shooting bubbles to the correct answer). The goal of the mini-games is to solve basic mathematical operations (sum, subtraction, multiplication, and division) according to the rules in each mini-game. If the student answers the question correctly, the score is increasing at one point in that mini-game; otherwise, there is not a score increment. After the student finished playing the four mini-games, the data was captured in the system. An example of the scoring results of one student could be 120 | 100 | 130 | 200, where each value represents the score in one of the mini-games. For instance, 120 represent the score of the Competitive style correlated to the Activist learning style; meanwhile, 200 represent the score of the Strategist style correlated to the Pragmatist learning style.

Then, it is calculated the percentage of the learning style based on the scores from the mini-games, dividing the score of each game by the sum of the scores of all the mini-games, obtaining results as 0.22 | 0.18 | 0.24 | 0.36. The binary answers from the CHAEA-JQ were used as input in the ANN, and the target was the percentage calculated from the mathematical mini-games based on ADOPTA playing styles as explained before. In that way, both techniques with a testing set of 20 students were evaluated finding the error between the percentages in the learning styles calculations. Therefore, the error (ε) between both methods for the four Learning Styles (N = 4) was calculated by the Eq. (8).

$$\varepsilon = \frac{\sum_{1}^{N}\left[abs\frac{(Pls_{ANN} - Pls_{JQ})}{Pls_{JQ}}\right]}{N} \tag{8}$$

For the training and testing processes, ANN uses $\eta = 0.05$ and $\gamma = 1/2$, using 1000 for the maximum number of iterations as the parameters that best fit the model in different experimental tests. Besides, different architectures were used with the calculation of the Mean Square Error (MSE), the best performance was achieved by the architecture with one hidden layer of 10 neurons.

5 Results and Discussion

This section depicts and discusses the achieved precision to recognize the learning styles for each analyzed method. The average of the results of the percentage reached by all styles that own every student of the testing group has been computed for the Pls_{JQ} and Pls_{ANN} metrics. The overall results are summarized in Table 1, where the existing relation between Learning Styles and ADOPTA Playing Styles is shown in the first column.

Table 1. Average of percentages learning styles based on CHAE-JQ and ANN

Learning Styles/ADOPTA playing styles	Pls_{JQ}	Pls_{ANN}
Activist/Competitive	18.82%	23.44%
Reflector/Dreamer	**32.45%**	**29.91%**
Theorist/Logician	22.33%	26.70%
Pragmatist/Strategist	26.39%	20.07%

The results depicted in Table 1 show that Reflector/Dreamer is the most dominant learning style in the students that have achieved the highest percentage value for both CHAEA-JQ and ANN approaches. It describes that the majority of the students follow the traditional educational system, and have a higher tendency to prefer to listen to the people opinion and consider the problem in different ways to obtain conclusions.

It is essential to mention that the results found in the CHAEA-JQ have a variance of $\sigma^2 = 34.25\%$. The variation in this technique states a considerable difference in the dispersion between the data. The reason is the highest percentage found in the Reflector/Dreamer learning style with a value of 32.45% in comparison with the other learning styles. This predominance in this learning style denotes the psychological evolution in children by following a traditional educational system, where the students need to adapt to that learning style since their early stages of life. Being this tendency to this learning style to preferred to listen first, and then act to conclude, to create solutions; with a tendency to be thoughtful and cautious. The students with a higher-level Reflector/Dreamer learning percentage do not learn when they are forced to take a leadership position in a group and doing tasks without prior preparation. The CHAEA-JQ could slight differ if the 24 questions were selected different from the 44 questions and if the questionnaire could be presented with graphical representation in each question. It could produce an increase or decrease in the learning style percentage in the student, but the main improvements could be made by boosting interactivity in the questionnaire to amuse the students to answer the question self-aware because even that the survey is the most common approach, the student could lie in it producing an unreliable classification. Also, the ANN approach has a variance $\sigma^2 = 17.91\%$, meaning that the spread of the data is more uniform as is seen in Table 1 starting from the lowest percentage style which is 20.07% in Pragmatism/Strategist learning style until the highest value with 29.91% which was stated before. It is related in the amount of data that was collected because according to the input in the network and the scoring in the mini-games, it could drastically improve the learning style percentage prediction that will be discussed in the next paragraph.

In Table 1 is shown that the results were not fit in the rest of the learning styles, by comparing the CHAEA-JQ with ANN approach. It is because of the data gathered from the mechanics in the game, such that in the Activist style related to the Competitive playing style, the students, attracted by the game, shoot to an answer randomly without trying to solve the question correctly. On the Pragmatist style related to the Strategist playing style, the students were confused in jumping the avatar precisely to throw away bubbles to the correct answer, and in the Theorist style, related to the Logician Style, the students were confused with pressing the card center in the right answer selection. Those behaviors generated outcome where the students could not answer some questions. In fixing it some components in the game, the data gathering could be more effective in the prediction of learning styles percentages. Also, the reliability in learning style detection can be enhanced by amplified the sample size.

However, it is interesting to note that the automatic method based on ANN is not too far from the CHAEA-JQ results, which in the past has been characterized by its excellent reliability and validity, with just an error $\varepsilon = 18.9\%$.

6 Conclusion

In Ecuador there is an inefficient personalized education in teaching math to students in the primary education level, being an indicator one of the lowest scorings in the international mathematical examination called PISA in comparison with developing countries. By lack of accessibility to excellent and personalized training in teaching math to children and the motivation that takes part in it. The use of ICT has been an advantage, but the customized content to each student according to its learning style is still a challenge. However, finding the most optimal method to learning style detection to the student it can be a useful tool to diminish this problem.

As an overall conclusion, by the comparison between the two methods: CHAEA-JQ questionnaire and ANN, it was found that the ANN provides percentages close to the most effective traditional one (CHAEA-JQ) to recognize the most dominant learning style, and obtain an average error $\varepsilon = 18.9\%$ for identifying all of them. To have better recognition and in the future could be used to provide content related to the learning style of the student by using mathematical mini-games based on ADOPTA playing styles to increase the mathematical skills in Ecuadorean students.

To obtain better results in the learning style recognition it must be considered the environment in which the experiment is taken place, i.e., the computational resources equipment because the CHAEA-JQ and the mini-games were implemented in a Web system. The sample size should be acknowledged to enhance the results in the experiment. The gathered data to enhancement in this work can be done by improving the game mechanics, adapting dynamic tutorials in the game and animated avatars in each question in the CHAEA-JQ. Some data that can be collected in future works is the emotional state for the student after it finishes to play each game to be used in the ANN.

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