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Learning Behavior Analysis to Identify Learner's Learning Style based on Machine Learning Techniques

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Abstract: Learning styles cover various attributes related to the attitude and the learning behavior of individuals. Research and educational theories confirm that considering learning styles in distance learning environments can improve academic performance and learner satisfaction. The traditional approach to identify learning styles is based on asking students to fill out a questionnaire. This approach is considerably less accurate due to the learners' lack of awareness of their own preferences. Furthermore, learners' learning styles are defined only once. In this study, we propose an automatic approach to identify learners' learning styles based on patterns of learning behavior with respect to Felder and Silverman Learning Style Model (FSLSM), in an online learning environment. Patterns of behavior were analysed based on a data-driven approach. This approach exploits different Machine Learning (ML) techniques to detect the learning styles of learners. To validate our proposals, experiments were carried out in a higher education institution with 73 students enrolled in online courses on the ADLS (Automatic Detection of Learning Styles) system that we implemented. A 9 runs cross-validation was used to evaluate the selected ML techniques. Detection accuracy, recall, precision, and F measure were observed. The findings show the possibility of detecting learning styles automatically based on learning behavior with high performances. Different levels of accuracy were found for the different dimensions of FSLSM. However, Support Vector Machines (SVM) have exhibited great ability in predicting learning styles for all dimensions of FSLSM with an accuracy average of 88%.

Keywords: Learning style, Learning behavior, Behavioral patterns, Online learning environments, Machine Learning (ML), Automatic detection, Classifiers, Felder Silverman's learning style
Categories: I.2, J.4, K.3
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1 Introduction and motivation

The Covid-19 pandemic and home confinement have prompted the adoption of distance learning environments in the educational system. These environments increasingly constitute a vital infrastructure for universities. They allow teachers to provide different representations of knowledge and improve interactions between teachers and learners, and even among learners themselves.

Distance learning environments often provide online tools for assessment, communication, collaboration, uploading learning resources, and various functionalities. In the act of learning, each individual engages in a behavior that can evolve, and that the teacher must take into account. The problem with these environments is that the teacher does not come face to face with his students to know, from their facial expressions, interactions, and questions, whether the content presented is adaptable or not to the learners or whether they have assimilated this content or not. As a result, the analysis of the behavior and activities of learners in a distance learning environment has become a necessity in order to be able to help tutors or teachers to assist their learners.

One of the objectives of current researches in the field of distance learning is to collect a set of data on learners. These data reflect individual differences of learners which are: knowledge; background; experience; goals; interests; ability; motivation; self-efficacy; and also learning style [Kuzgun and Deryakulu, 2004].

Learning styles efficiency in the learning process has been considered since 1970 with the appearance of several models of learning styles. In the literature, several learning style theories exist; Kolb [Kolb, 1984], Honey and Mumford [Honey and Mumford, 1986], Dunn and Dunn [Dunn and Dunn, 1974], Myers-Briggs [Myers, 1962] and Felder-Silverman [Felder and Silverman, 1988].

All models confirm that individual differences are key factors for the development of Personal Learning Environments (PLE) [Chen and Liu, 2008, Kuljis and Liu, 2005]. Learning styles cover several attributes; how a person prefers to interact with others, acquire information, build ideas, and act on ideas [Felder, 1993]. They are tools designed by psychologists to help classify human behavior [Felder, 1993]. Researches confirm that the use of learning styles can improve academic performance and satisfaction of learners [Felder and Silverman, 1988]. Moreover, according to educational theories, learners with a strong preference for a specific learning style might have difficulties in learning if their learning style is not considered by the teaching environment [Graf and Kinshuk, 2008].

The traditional and explicit method of defining learning styles is based on questionnaires developed by psychologists. In these questionnaires, individuals are asked to answer a set of questions corresponding to the learning style model in order to identify their learning styles [Ali et al., 2019]. All psychological questionnaires are introspective in nature [Olry-Louis, 1995]. They suppose at least that the individual knows his own cognitive functioning [Olry-Louis, 1995]. Therefore, the choice associated with each question in the questionnaire implies two constraints: (i) the population to which the questionnaire is addressed must have a general level sufficient to understand questions, and (ii) personal maturity is important for answering questions about their cognitive functioning. In the context of distance learning; learners do not take a lot of time to answer questionnaires on the one hand, and, they do not give great importance to these questions and the consequences of their answers on the other hand. In addition, these instruments consist of a large number of questions that can reach up to 80 questions (Dunn and Dunn: 118 questions, Honey and Mumford: 80 questions) that people must answer in order to define their learning styles.

Given the problems with the explicit method of defining learning styles and the dynamic nature of these styles, the opportunity to automatically detect them has emerged in order to save time and make dynamic adaptation of the learner model easy.

In this work, we are interested in the learning styles, which constitute one of the important characteristics during the modelling of the learner since they can be used to personalize or adapt the learning content, as well to recommend different learning resources. We propose an approach for the automatic identification of the learning styles of learners, based on the investigation of their learning behavior. Consequently, two intriguing questions arise: What model of learning style is appropriate to distance learning environments? How to analyze and interpret the learning behavior of learners in online learning environments to be able to automatically detect their learning styles?

To answer these questions, a bibliographical study was carried out on research analyzing the relationship between learner's behavior in distance learning environments and learning styles [Graf, 2007, Graf et al., 2009, Graf and Kinshuk, 2008, Garcia et al., 2007, Popescu, 2008, Bousbia et al., 2010, Bousbia et al., 2011, Felder and Silverman, 1988]. Felder Silverman Learning Style Model (FSLSM) seems to be the most appropriate for use in distance learning environments [Kuljis and Liu, 2005], FSLSM describes the learning styles of learners in more details [Graf and Kinshuk, 2008], and proposes useful pragmatic recommendations to customise teaching according to the learner's profiles [Popescu, 2008]. This model remains the most widely used by the educational systems [Rasheed and Wahid, 2021, El Aissaoui et al., 2019, Graf et al., 2009, Graf, 2007, Popescu, 2009, Bousbia et al., 2011, Sheeba and Krishnan, 2018, Jena, 2018, Nafea et al., 2019, Kolekar et al., 2017, Paireekreng and Prexawanprasut, 2015]. Therefore, our behavioral investigation is based on this model. Regarding, the second question, we propose quantitative indicators describing the relevant patterns of learner's behavior with the respect to FSLSM. These indicators will be used by a set of different machine learning techniques to automatically detect the learning styles of learners.

Our objective is to propose an automatic approach, which can be used to enrich the learner model dynamically with an important characteristic to personalize and adapt the learning experience.

The rest of this paper is organized as follows: in section 2, we present the literature review of approaches on automatic detection of learning styles. In section 3, we describe the process followed by the proposed approach. Section 4 is reserved for the carried out experiment. Section 5 presents and discusses the obtained results using a system that we have implemented, and which adopts the proposed approach. Finally, the general conclusion, limitations, and future works are presented in section 6.

2 Literature Review

Identification of learning styles can be carried out in two ways: collaborative and automated [Graf, 2007]. The collaborative method is based on asking students to fill out a questionnaire. Automated learning styles detection is realized by analyzing the interaction of the students with the e-learning environments, in the form of behavioral patterns [Popescu, 2008].

2.1 Learning Behavior for Automatic Detection of Learning Styles

Learners with different learning styles have different behavior and also different needs during the learning process [Popescu, 2008]. Learning behavior of a student in e-learning environments refers to a student's observable response to a particular stimulus in a given domain. The exploitation of these observables or traces provides knowledge about the activity which we call learning indicators [Bousbia et al., 2010]. Learning indicators are variables that indicate the mode, the process or the quality of the considered 'cognitive system' activity, the patterns or the quality of the interaction product, and the mode or the quality of the collaboration. A lot of researches investigate learning behavior based on learning indicators to automatically identify the learning style of learners [Rasheed and Wahid, 2021, El Aissaoui et al., 2019, Dutsinma and Temdee, 2020, Nafea et al., 2019, Sheeba and Krishnan, 2018, Jena, 2018, Garcia et al., 2007, Graf and Kinshuk, 2008, Popescu, 2009, Bousbia et al., 2011]. These researches differ regarding learning environments, the type of traces and indicators, the learning style considered, and the used method. The researchers associated with each style model a set of actions or behavior patterns that can be followed in the learning platform to be able to detect the learning. Learner observable behavior, analyzed in previous studies, includes navigational, temporal, and performance indicators. Recent researches exploit other types of patterns for the automatic detection of learning styles. [Zhang et al., 2021] verified the effectiveness of using electroencephalogram (EEG) features to recognize learning styles. [Nugrahaningsih et al., 2021] investigate the accuracy of eye-tracking technology in identifying learning styles. A survey of learning style detection methods using eye-tracking and machine learning in multimedia is presented in [Wibirama et al., 2020].

2.2 Felder and Silverman Learning Style Model (FSLSM)

FSLSM distinguishes between the preferences of learners on four dimensions: Processing; Perception; Understanding; and Input. Each dimension defines two opposite learning styles [Felder and Silverman, 1988].

- **Information processing (Active/Reflective):** how the learner prefers to process information: through physical activity and discussion (active), or through reflection and analysis (reflective);
- **Information perception (Sensing/Intuitive):** this dimension is concerned with the type of information that the learner prefers to perceive: examples and facts (sensing); or abstract or theoretical concepts (intuitive);
- **Information input (Visual/Verbal):** the format of representation and encoding of information preferred by learners: video, image, demonstration, diagram (visual); or verbal: audio and text (verbal);
- **Understanding process of information (Sequential/Global):** how learners progress to understand: sequential with small steps in a linear order (sequential); or global with large steps in random order (global).

2.3 Learning Styles Automatic Detection Techniques

In the literature, two main approaches were identified for the automatic detection of learning styles from learning behavior in an online course: data driven and literature based.

2.3.1 Data Driven Approach

The data driven approach is characterized by the use of Artificial Intelligence (AI) techniques in the detection of learning styles. This approach uses sample data to build a model that imitates a learning style instrument. The built model can be very accurate due to the use of real data. However, a representative dataset is crucial to build an accurate classifier because the approach strictly depends on the available data [Graf, 2007, Feldman et al., 2015]. Among the AI techniques used, we cite: Decision Tree [Rasheed and Wahid, 2021, Dutsinma and Temdee, 2020, Sheeba and Krishnan, 2018, Jena, 2018, Maaliw III, 2016, 2016, Liyanage et al., 2016, Bousbia et al., 2011, Cha et al., 2006]; Neural Networks [Hasibuan et al., 2019, Khan et al., 2019, Kolekar et al., 2017, Paireekreng and Prexawanprasut, 2015]; Support Vector Machines (SVM) [Rasheed and Wahid, 2021, Paireekreng and Prexawanprasut, 2015, Amir et al., 2016]; Bayesian Network [Liyanage et al., 2016, Garcia et al., 2007, Bousbia et al., 2011]; Hidden Markov Model (HMM) [Cha et al., 2006]; and K Nearest Neighbors (KNN) [Rasheed and Wahid, 2021, Bousbia et al., 2011]. In [Troussas et al., 2020], KNN classifier was combined with SVM and Naïve Bayes classifiers based on the majority voting rule for automatic identification of students' learning styles. Under the paradigm of fuzzy-logic, we can cite the work presented by El Aissaoui and his colleagues [El Aissaoui et al., 2019]. In this work, the authors present an automatic approach for detecting students' learning styles based on web usage mining. For large-scale online education, [Zhang et al., 2020] proposed a learning style classification approach, based on the Deep Belief Network (DBN) to identify students' learning styles.

2.3.2 Literature Based Approach

The literature based approach uses the behavior of learners to get hints about their learning style preferences and then applies a simple rule-based method to calculate learning styles from the number of matching hints [Graf, 2007, Feldman et al., 2015]. This approach has the advantage that it is generic and applicable to data gathered from any learning course [Graf, 2007]. However, the approach might have problems in estimating the importance of the different hints [Graf, 2007]. Seven of the works examined [Nafea et al., 2019, Khan et al., 2019, Graf et al., 2009, Graf et al., 2008, Ahmad et al., 2013, Dung and Florea, 2012, Amir et al., 2016] used literature based approach.

Much research has proven the effectiveness of using learning styles in education. Some examples of systems that provide courses that fit learners' individual learning styles are eTeacher [Schiaffino et al., 2008], CS383 [Carver et al., 1999], TANGOW [Paredes and Rodriguez, 2004], INSPIRE [Papanikolaou and Grigoriadou, 2003]. The problem with these systems is that the use of questionnaires to identify learning styles makes dynamic adaptation of the learner model very difficult. In addition, for systems that have adopted an automatic process for the detection of learning styles, the proposed approaches have not been evaluated or evaluated through simulation [Alkhuraiji et al., 2011, Ahmad and Shamsuddin, 2010]. For the approaches that have been evaluated on real data, these approaches are strongly linked to the educational systems in which they have been integrated.

In our work, we propose an automatic approach to identify learners' learning styles, based on patterns of learning behavior with respect to FSLSM. The patterns that were chosen for the prediction of learning styles are related to the functionalities commonly used in education systems (courses, exercises, self-assessments, forums, chat, examples, summary outlines, overviews, etc.). The learning features are obtained from a learning platform that we have implemented and made available to students.

3 Proposed Approach for the Automatic Detection of Learning Styles

The objective of our work is to provide a new approach based on the analysis of the learning behavior of learners, in an online learning environment, to automatically detect their learning styles. To answer our second question posed in the introduction, an analysis of learner behavior was carried out to identify relevant and distinctive learning patterns between dimensions in FSLSM (sub-section 3.1). Sub-section 3.2 describes the indicators developed from the patterns of the proposed behavior model. The proposed indicators are transmitted to machine learning classifiers to enable automatic detection of learning styles. Figure 1 below illustrates the process followed by the proposed approach.

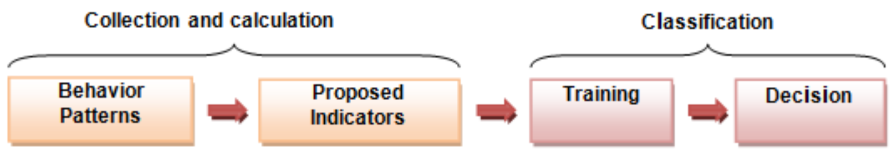

Figure 1: The Process Followed by the Proposed Approach.

3.1 Learner's Behavior with Respect to FSLSM

The proposed approach is based on the investigation of learning behavior in an online learning system according to FSLSM. Our investigation is based on predefined patterns which on the one hand are related to the FSLSM and on the other hand, based on commonly used features in e-learning environments. The incorporated features include different Learning Objects (LO): courses; outlines; overviews; exercises; self-assessment (test); forum discussion; and chat discussion. Figure 2 shows the modeling of learner's behavior based on FSLSM.

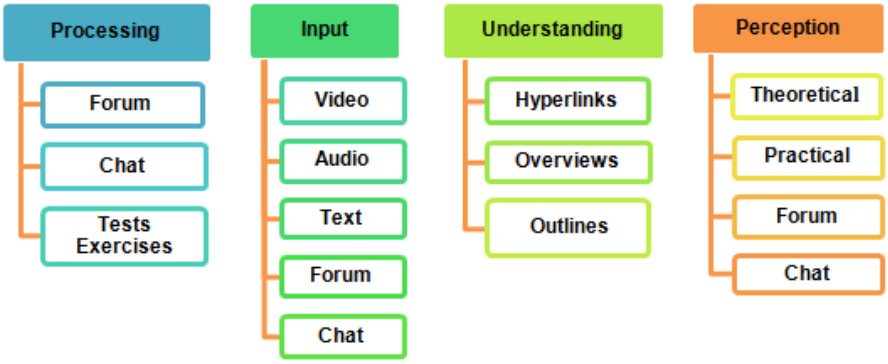

Figure 2: Learner's Behavior Modeling based on FSLSM.

This modeling was adopted by the ADLS (ADLS: for Automatic Detection of Learning Styles) system. In fact, the proposed approach has been integrated in this system. Figure 3 illustrates the general architecture of this system.

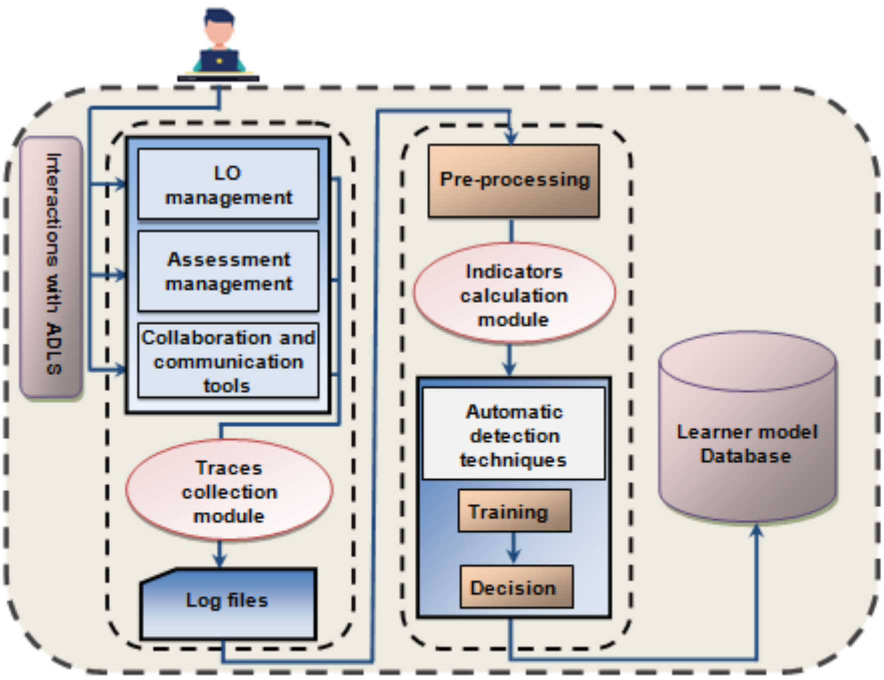

Figure 3: Learning Styles Detection System.

Table 1 summarizes the features as well as the related patterns to each feature targeted by our model of learner behavior. The symbol × indicates that the pattern quoted in the row is relevant for the dimension of FSLSM mentioned in the column.

Patterns		**Active Reflective**	**Sensing Intuitive**	**Visual Verbal**	**Sequential Global**
Forum	No participation	×	×		
	Number of views	×	×		
	Number of Posts	×	×		
	Time Spent in Forum			×	
Chat	No participation	×	×		
	Number of discussions	×	×		
	Number of views	×	×		
	Time Spent in Chat			×	
Learning Objects (LO)	Number and duration of consultation of the verbal objects visited (Audio, pdf, power point, text, hypertext)	×	×	×	
	Number and duration of consultation of visual objects visited (video, graphics, demonstrations, diagrams)	×	×	×	
	Time spent in course outlines				×
	Number of visits to course overviews				×
	Number and duration of exercises done	×	×		
	Number of learning objects revisited		×		
Hyperlinks	Linear route of the hypertext course (next-previous buttons)				×
	Global route of the hypertext course				×
Tests	Number of tests done	×	×		
	Number of modifications in the tests done		×		
	Time spent in a test		×		

Table 1: Learner's Behavior Patterns.

3.2 The Proposed Indicators

Based on patterns of the learning behavior with respect to FSLSM, presented in Table 1, we have identified 15 indicators on which the proposed automatic learning style detection approach is based. The proposed indicators are classified into three groups according to three criteria:

- Indicators taking into account **the consultation time** of the learning objects;
- Indicators taking into account **the frequency of visits** of the learning objects;
- An indicator taking into account **the navigation behavioral** of the learner.

3.2.1 Time Indicators

We calculate 8 indicators providing information on the time devoted to learning objects and activities (course, exercises, overviews and outline, forum, test). The first two indicators (ITS_{Ver}, ITS_{Vis}) provide information on the presentation methods preferred by the learner to receive the information (visual or verbal). The indicators ITS_{Tho} and ITS_{Pra} relate to the types of resources preferred by the learner (theoretical or practical). Tables 2, 3, and 4 describe the 8 proposed indicators.

Indicator	Description
ITS_{Ver}	Time spent in verbal LO versus time spent in all LO
ITS_{Vis}	Time spent in visual LO compared to the time spent in all LO
ITS_{Tho}	Time spent in the theoretical LO compared to the time spent in all types of LO: theoretical and practical
ITS_{Pra}	Time spent in practical LO compared to the time spent in all types of LO: theoretical and practical
ITS_{Test}	The degree of the prudence of the learners during the tests, by comparing the time planned for the assessment with the time spent
ITS_{Course}	The course consultation time: by comparing the time planned for the consultation of the courses to the time spent
$ITS_{Ov/Ot}$	Time to consult overviews and outlines: comparing the time expected to consult overviews and outlines to the time spent
ITS_{Forum}	The degree of interactivity in the collective activity: according to the average time spent in the forums

Table 2: Time Indicators.

3.2.2 Consultation Frequency Indicators

We calculate 6 indicators based on the frequency of access to LO and learning activities.

Indicator	Description

IFQ_{Test}	The degree of certainty of the learner according to the number of trials in self-assessment, the higher the number of trials, the more the learner is more cautious and less certain.
IFQ_{Com}	The degree of interactivity in the collective activity of the learner: taking into account the average rate of posts and discussion in the communication tools (forums and chat).
$IFQ_{Revisit}$	The rate of LO revisited
$IFQ_{Ov/Ot}$	The visit rate of overviews and outlines taking into consideration the average number of accesses to these two objects
$IFQ_{Test/Exe}$	The rate of tests and exercises done by the learner: taking into account the average number of exercises and tests done
$IFQ_{Posts\ vs\ Views}$	The rate of posts versus views indicates the way of participation in the collective activity: passively by accessing the forum to read the messages or positively by posting messages on the forum

Table 3: Consultation Frequency Indicators.

3.2.3 Navigation Indicator

The navigation (browsing) indicator: we calculate a single indicator that provides information on the navigation behavioral of learners when browsing the learning content.

Indicator	**Description**
$\boldsymbol{INV}$	The type of access to the learning objects: sequential with the next and previous buttons, or random with a big jump

Table 4: Navigation Indicator.

The calculation formulas associated with all the proposed indicators are presented in tables: A.1, A.2, and A.3 in appendix A.

3.3 Relating Behavior Patterns with Proposed Indicators

After the modeling of the learners' behavior based on FSLSM and calculating the proposed indicators, the objective of our third step of the learning styles detection process is to relate the proposed indicators to the four dimensions of the FSLSM. Based on the description of the FSLSM and the related works found, we have proposed new relationships between the learning patterns of each learning style and the indicators proposed previously. Table 5 shows this association.

Dimension	**Used Indicators**	**Behavior Patterns**

Information processing (Active/Reflective)	IFQ_{Com} $IFQ_{Revisit}$ $IFQ_{Test/Exe}$ $IFQ_{Posts\ vs\ views}$	**Active learners**: - Have tendencies for collective activities - Post more messages in the forums - Do more tests and exercises **Reflective learners:** - Work less in groups - Participate passively by reading posts on communication spaces - Spend more time in the course
Information perception (Sensing/Intuitive)	IFQ_{Com} IFQ_{Test} $IFQ_{Revisit}$ ITS_{Course} ITS_{Test} ITS_{Tho} ITS_{Pra}	**Sensing learners:** - Prefer practical resources - Participate more in collective activities - Are careful - Are less certain **Intuitive learners:** - Prefer theoretical resources - Work faster
Understanding process of information (Visual/Verbal)	IFQ_{Com} ITS_{Vis} ITS_{Ver} ITS_{Forum}	**Visual learners:** - Learn best from what they see (video, graphics) **Verbal learners:** - Prefer words - Use more communication tools (Forum, chat)
Information input (Sequential/Global)	$IFQ_{Posts\ vs\ Views}$ $ITS_{Ov/Ot}$ INV	**Sequential learners**: - Understand with small steps in a sequential order **Global learners**: - Understand with large jumps in random order - Spend more time in overviews and outlines

Table 5: Relating Behavior Patterns with the Proposed Indicators.

3.4 Automatic Detection of Learning Styles

The objective of this step is to classify the behaviors of learners in classes using the calculated indicators as being relevant patterns for a set of classifiers.

Automatic classification approaches go through two phases: the training phase and the decision phase.

3.4.1 Training

The goal of this step is to estimate a model from the indicators proposed and the relationship between behavior learning and learning styles. A data file, which contains the calculated indicators, for each of the four dimensions, is created. Each file is one of the parameters passed to training programs. Model files are generated at the end of training (Figure 4). Figure 5 shows an excerpt from the training base.

Figure 4: The Training Phase.

Figure 5: Part of the Sensing / Intuitive Training Matrix

3.4.2 Decision

The last step in our automatic learning style detection process is the decision. Six techniques used in Machine Learning (ML) were chosen for the classification, more precisely:

- Logistic Regression (LR) ;
- Linear Discriminant Analysis (LDA);
- K-Nearest Neighbors (KNN);
- Classification and Regression Trees (CART);
- Gaussian Naive Bayes (NB) ;
- Support Vector Machines (SVM).

The output classes of classifiers are the learning styles of the learners according to the FSLSM. For each dimension of the learning style, we have two output classes. For example, for the information processing dimension, the two output classes are Active and Reflective (Figure 6).

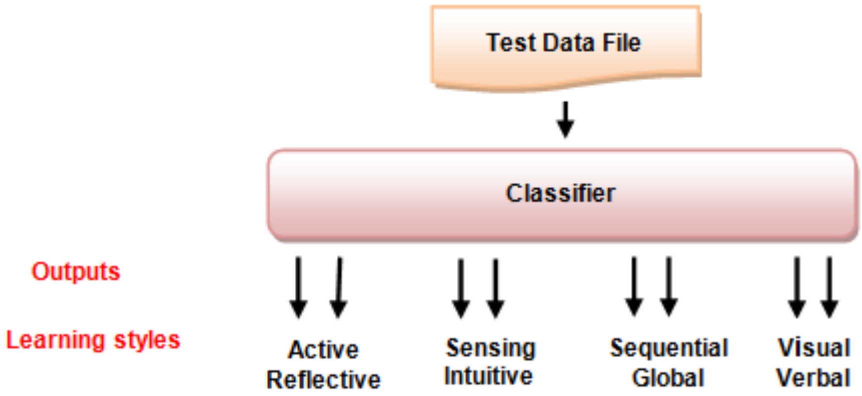

Figure 6: The Decision Phase.

Our goal is to verify the performance of each algorithm against the learning patterns used.

4 Experiment

To validate our proposals, we conducted an experiment. This section describes the participants involved, the experiment methodology, and data analysis.

4.1 Participants

The proposed approach was tested on a sample of students from the University of 8 Mai 1945, Guelma (Algeria). The learners involved in this experiment are enrolled in the first year of a computer science master's degree (two specialties; CS: Computer Systems and ICST: Information and Communication Systems and Technologies) and in the third year of Information Systems (IS). The total number of students is 73. Data of 25 students out of 73 was used for testing, while data from the remaining 48 students was used for training.

4.2 Methodology

At the beginning, the 73 learners involved in the experiment completed the ILS (Index of Learning Styles) questionnaire [Felder and Soloman, 1996] to get their learning styles. This tool is made up of 44 questions, 11 questions for each dimension. This questionnaire determines the dominant learning style for each learner. The 73 registered learners can attend, on the designed system (ADLS), three online courses: "Expert systems"; "Artificial intelligence techniques"; and "Compilation"[1]. The experiment was conducted during semester 1 of the 2020-2021 academic year.

4.3 Data Analysis

During the experiment, all traces of students interacting with ADLS system are recorded in log files. The log files were stored in XML format for pre-processing. The pre-processing is applied to the log files, to eliminate unnecessary traces and keep only useful traces serving as relevant patterns for the automatic learning style detection process. The patterns kept during the pre-processing correspond to patterns presented in table 1 of sub-section 3.1. These patterns were then processed by the ADLS system to compute the values of indicators described in sub-section 3.2. Learners' learning styles are evaluated by the ILS questionnaire. The results obtained from this questionnaire and the indicators values are used to build the classifier models.

5 Results and Discussion

5.1 ILS Questionnaire Results

Table 6 summarizes the ILS questionnaire results for the 73 students for the four dimensions of FSLSM: Active/Reflective; Sensing/Intuitive; Visual/Verbal; and Sequential/Global.

FSLSM dimension	**Number of learners**
Active	46 (63%)
Reflective	27 (37%)
Sensing	37 (51%)
Intuitive	36 (49%)
Visual	43 (59%)
Verbal	30 (41%)
Global	44 (60%)
Sequential	29 (40%)

Table 6: ILS Questionnaire Results.

5.2 Learning Style Prediction Results

In what follows, we present the results obtained after using the six chosen classifiers (Tables 8, 9, 10, and 11). The programming language used is Python. This choice is justified by the wealth of its libraries in the field of machine learning. The results were obtained after 9 runs cross-validation by applying: recall; precision; accuracy; and F1-score metrics (see (1), (2), (3), and (4) below).

Recall: the classifier's ability to correctly classify instances.

[1]Compilation: is a subject taught to the students of the third year of "Information Systems" (Computer Science specialty, in Guelma University, Algeria). It presents the main steps to implement compilers of programming languages.

$$Recall = \frac{Number\ of\ correct\ positive\ prediction}{Total\ number\ of\ prediction\ that\ should\ be\ retreived} \quad (1)$$

Precision: the classifier's ability to find only the relevant instances.

$$Precision = \frac{Number\ of\ correct\ positive\ prediction}{Number\ of\ retrieved\ prediction} \quad (2)$$

Classification accuracy: indicates the percentage of correctly classified instances placed in the correct category.

$$Accuracy = \frac{Correct\ Predictions}{Total\ number\ of\ predictions} \quad (3)$$

F1-score: The harmonic mean of precision and recall.

$$F - score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (4)$$

The parameter model used to train our machine learning classifiers is presented in table 7.

	Active Reflective	**Sensing Intuitive**	**Visual Verbal**	**Sequential Global**
LR	C=10.0, penalty = l2 solver=liblinear	C=1, penalty = l2 solver=liblinear	C = 1 penalty = l1 solver=liblinear	C=10.0 penalty = l1 solver=liblinear
LDA	Shrinkage = 0.001 solver = lsqr tol = 0.001	Shrinkage = 1.0 solver = lsqr tol=0.001	shrinkage = 0.001 solver = lsqr tol=0.001	shrinkage = 0.001 solver = lsqr tol=0.001
KNN	Metric= euclidean K=1	metric=euclidean K=2	metric= euclidean K=3	metric=euclidean K=1
CART	max_leaf_nodes = 6 min_samples_split= 3	max_leaf_nodes = 6 min_samples_split = 3	max_leaf_nodes =2 min_samples_split = 2	max_leaf_nodes = 2 min_samples_split = 2
NB	var_smoothing = 0.08697490026177834	var_smoothing = 0.001	var_smoothing = 0.001	var_smoothing = 0.001
SVM	C = 0.0001 degree=2 gamma=1000, kernel=polynomial	C = 0.0001 degree=1 gamma=1000 kernel=polynomial	C = 0.01 degree=1 gamma=1000 ernel=polynomial	C = 0.01 Degree = 1 Gamma =1000 Ernel=polynomial

Table 7: Model Parameter Values.

Tables 8, 9, 10, and 11 present the obtained results.

Algorithm	Precision	Recall	Accuracy	F1-score
		Active/Reflective		
LR	0.89	0.89	0.88	0.88
LDA	0.89	0.89	0.88	0.88
KNN	0.92	0.92	0.92	0.92
CART	0.81	0.81	0.80	0.80
NB	0.84	0.82	0.80	0.80
SVM	0.96	0.96	**0.96**	**0.96**

Table 8: LS Classification Results for Information Processing Dimension.

Algorithm	Precision	Recall	Accuracy	F1-score
		Sensing/Intuitive		
LR	0.88	0.88	0.88	0.88
LDA	0.88	0.88	0.88	0.88
KNN	0.81	0.81	0.80	0.80
CART	0.92	0.92	0.92	0.92
NB	0.97	0.95	**0.96**	**0.96**
SVM	0.88	0.88	0.88	0.88

Table 9: LS Classification Results for Information Perception Dimension.

Algorithm	Precision	Recall	Accuracy	F1-score
		Visual/Verbal		
LR	0.88	0.88	**0.88**	**0.88**
LDA	0.80	0.80	0.80	0.80
KNN	0.80	0.80	0.80	0.80
CART	0.80	0.80	0.80	0.80
NB	0.84	0.85	0.84	0.80
SVM	0.80	0.80	0.80	0.80

Table 10: LS Classification Results for Information Input Dimension.

Algorithm	Precision	Recall	Accuracy	F1-score
		Sequential/Global		
LR	0.66	0.67	0.64	0.64
LDA	0.55	0.55	0.52	0.52
KNN	0.69	0.70	0.68	0.68
CART	0.88	0.91	**0.88**	**0.88**
NB	0.37	0.36	**0.40**	**0.36**
SVM	0.88	0.91	**0.88**	**0.88**

Table 11: LS Classification Results for Understanding Process of Information Dimension.

According to the results presented in the tables 8, 9, 10, and 11, the rates for recall, precision, accuracy, and F1-score obtained for the six classifiers used, varied between 80% and 97% for the first three dimensions (information processing, information perception and information input), and between 36% and 91% for the last dimension (understanding process of information). For this last dimension, we notice that NB classifier got the worse results (precision = 37%, recall = 36%, accuracy = 40%, F1-score = 36%), while the best classification rates were reached by the SVM and CART classifiers (precision = 0.88, recall = 0.91, accuracy = 0.88, F1-score = 88%). The low rates obtained by the other classifiers may be due to the limited number of discriminative patterns (three patterns) used to identify the sequential and global learners.

Figures 7, 8, 9, and 10 show a comparison between the six classifiers used, based on precision for the two styles of each dimension.

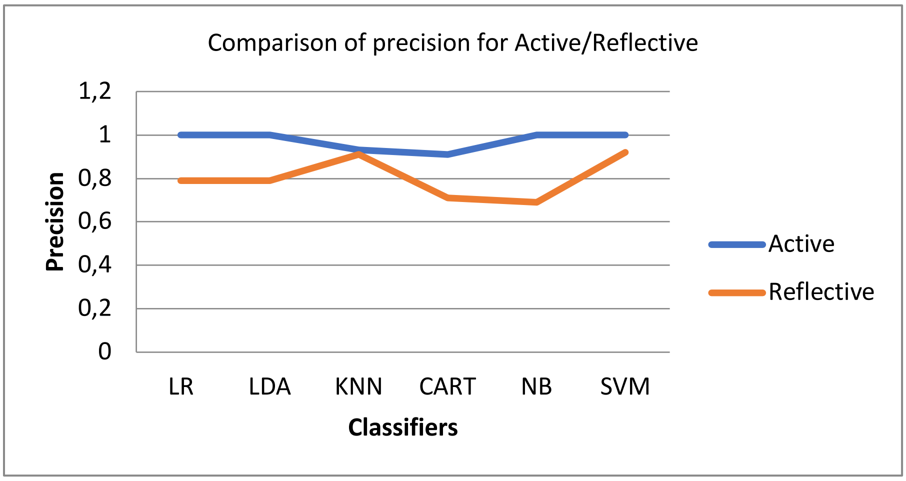

Figure 7: Comparison of Precision Values for Information Processing Dimension.

For *information processing dimension*, we note that the six classifiers learned "active learners" better than "reflective learners". For example, SVM achieved the best result (active: precision = 1), while the worse ones are obtained by the CART classifier (precision = 0.71). This is due to the stronger presence of active learners (46 learners: 63%) than reflective ones (27 learners: 37%) (The number of learners for each style is represented in table 6).

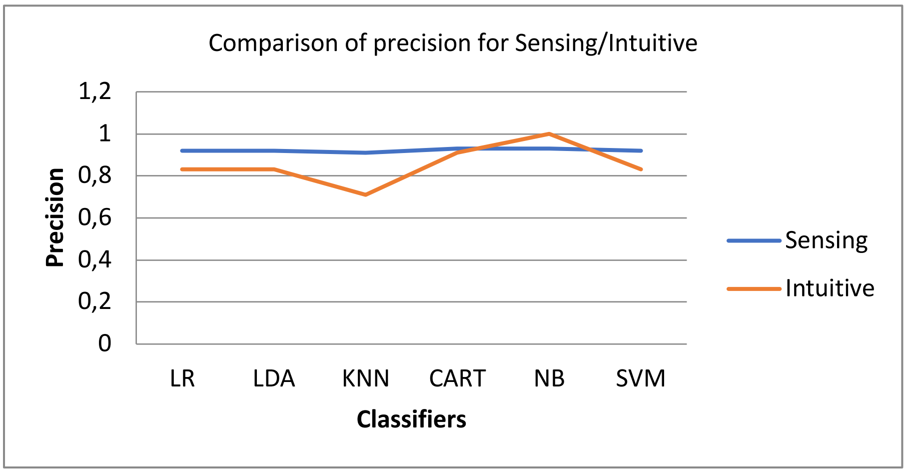

Figure 8: Comparison of Precision Values for Information Perception Dimension.

Concerning *information perception dimension*, classifiers learned "sensing learners" better than "intuitive learners"; except for the NB classifier which learned "intuitive learners" better than "sensing" ones (sensing: precision = 0.93; intuitive: precision = 1). We note that the CART classifier learned learners of both styles with balanced precision (sensing: precision = 0.93; intuitive: precision = 0.91). We mention that the number of sensing and intuitive learners is balanced (sensing learners: 37 (51%); intuitive learners: 36 (49%)) (c.f. table 6).

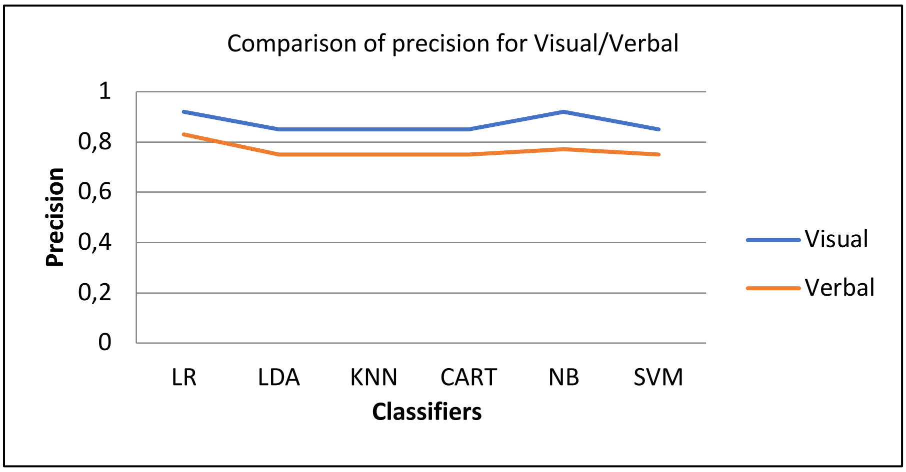

Figure 9: Comparison of Precision Values for Information Input Dimension.

Concerning the *input information dimension*, classifiers learned better "visual learners" (precision = 0.92 achieved by LR and NB classifiers) than "verbal learners" (precision = 0.75 achieved by the SVM, CART, and LDA classifiers), as there are more visual learners (43 learners: 59%) than verbal learners (30 learners: 41%) (c.f. table 6).

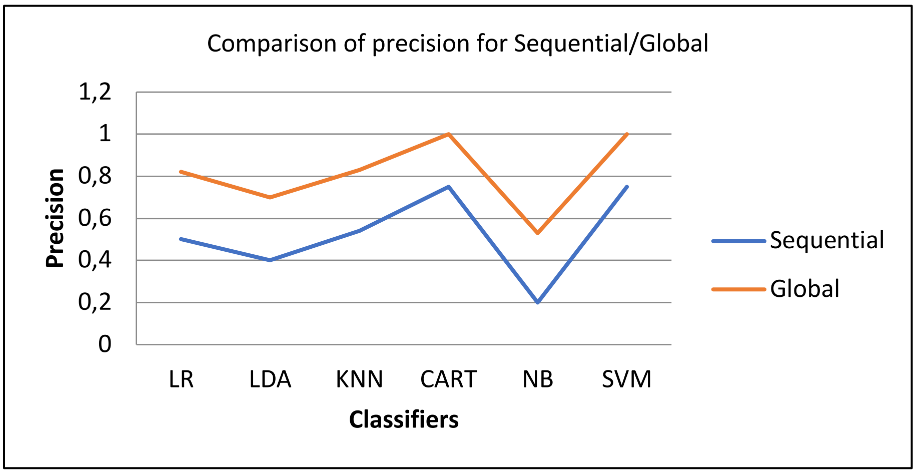

Figure 10: Comparison of Precision values for Understanding Process of Information Dimension.

For *the understanding process of information dimension*, the six classifiers learned better "global learners" (precision = 1 achieved by the SVM and CART classifiers) than "sequential ones" (precision = 0.75 obtained by the SVM classifier). This is due to the stronger presence of global learners (44 learners: 60 %) than sequential ones (29 learners: 40%) (c.f. table 6).

Figure 11 shows a comparison between the six classifiers based on classification accuracy.

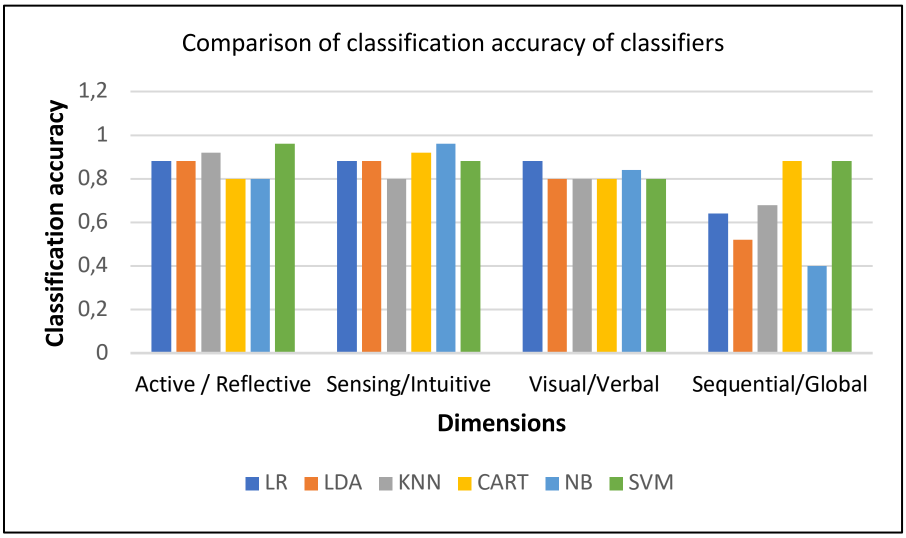

Figure 11: Comparison of Classification Accuracy for the Six Classifiers.

The achieved results for classification accuracy vary between 40% and 96%. Figure 11 shows that the SVM and NB classifiers attained the highest accuracy classification for the two dimensions "information processing" (96%) and "information perception" (96%). The worse accuracy classification was achieved by the NB classifier (40%). In general, it is clear that all the classifiers, apart from the SVM and CART classifiers (accuracy = 0.88), obtained a low accuracy classification (between 40% and 68%) for the "understanding process of information" dimension, compared to other dimensions where the accuracy classification varies between 80% and 96%. This may be due to the insufficient number of patterns, taken into consideration for this dimension, for the classification.

From the results obtained from the carried out experiments, we can say that the learning patterns chosen for the first three dimensions are able to predict the learning styles of the learners with higher precision. For the "understanding process of information" dimension, other patterns should be taken into account to improve predictions. In addition, we can conclude that the SVM classifier has exhibited great ability in predicting learning styles.

Finally, the conducted experiment led us to confirm the possibility of detecting learners' learning styles by analysing learning behavior in online learning environments.

5.3 Comparison between Our Approach and some Related Works

In section 2, we studied the literature about research works involved in the automatic detection of learning styles. Table 12 presents a comparison between our approach and some of the research works that we studied.

	E-learning environment	**Learning style model used**	**Learning styles detected**	**Patterns used**	**Detecti-on methods used**
Our approach	ADLS system	FSLSM	Active/Reflective Sensing/Intuitive Visual/Verbal Sequential/Global	Frequency and visit duration of LO, trials on tests, navigation behavioral, participation in collaborative tasks	LR, LDA, KNN, CART, NB, SVM
[Rasheed and Wahid, 2021]	/	FSLSM	Active/Reflective Sensing/Intuitive Visual/Verbal Sequential/Global	Frequency and visit duration of LO, trials on tests, navigation behavioral, participation in collaborative tasks	LR, LDA, KNN, NB SVM, DT[2], RF[3]
[Zhang et al., 2021]	/	FSLSM	Active/Reflective	EEG features	SVM, BPs[4]
[Zhang et al., 2020]	StarC: free MOOC platform	MOOCL-S[5]	Active/Reflective Sensing/Intuitive Visual/Verbal Sequential/Global Social/Alone	Frequency and visit duration of LO, trials on tests, navigation behavioral, participation in collaborative tasks	DBN[6]
[Troussas et al., 2020]	Leareglish	FSLSM	Active/Reflective Sensing/Intuitive Visual/Verbal Sequential/Global	Personal and cognitive student's characteristics (age, gender, prior academic performance)	Multi-classif-ier: KNN, SVM and NB
[El Aissaoui et al., 2019]	E-learning platform of Sup'Manage-ment Group	FSLSM	Active/Reflective Sensing/Intuitive Visual/Verbal Sequential/Global	Frequency of visits to LO	Fuzzy C-Means

Table 12: Comparison between Our Approach and the Systems Studied

[2] DT: Decision Tree
[3] FR: Random Forest
[4] BPs: Backpropagation neural networks
[5] MOOCLS :a learning style model suitable for MOOC built by the authors
[6] DPN: Deep Blief Network

6 Conclusion and Future Works

This paper introduced an automatic approach to identify learners' learning styles according to the Felder and Silverman Learning Style Model (FSLSM). The proposed approach investigates the learning behavior of students in online learning environments. It relies on three major steps. Firstly, an analysis of learner behavior was carried out to identify relevant and distinctive learning patterns between dimensions in FSLSM. Secondly, we identified indicators on which the proposed automatic learning style detection approach is based. These indicators take into consideration; the consultation time of the learning objects, the frequency of visits of the learning objects, and the navigation behavioral of the learner. We explored the relationships between the learning behavior and learning styles, through the proposed indicators. In the third step, proposed indicators were transmitted to machine learning classifiers to enable automatic detection of learning styles.

The proposed approach was integrated into an online learning environment that we implemented called ADLS (for Automatic Detection of Learning Styles). In addition to features commonly used in e-learning environments, the ADLS system tracks and analyzes the actions of its learners.

To validate our proposals, tests were carried out on 73 students from the University of 8 Mai 1945, Guelma (Algeria). Recall, precision, accuracy, and F1-score were used as evaluation metrics to assess the classification results achieved by the six classifiers used. The results of the experiment confirm that is possible to deduct learning styles, automatically, based on learning behavior analysis.

The proposed approach is always under evaluation in order to have as much evidence as possible on the actions of learners. The first results achieved are promising despite the fact that the sample used for the experiment is small, which limits the number of traces resulting from the interactions of learners with the system.

This research opens the doors for Personal Learning Environments (PLE). As future works, we propose to take into consideration the predicted learning styles to personalize the learning experience of the learners taking into account their preferences and characteristics. In addition, we intend to exploit different techniques used by artificial intelligence, including Learning Analytics (LA), clustering, and predictions to analyze learning data to improve the performance of distance learning in general.

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Appendices

Appendix A.

Indicator	Formula
ITS_{Ver}	$ITS_{Ver} = (\frac{TS_{LO\ Ver}}{TS_{LO\ Ver/Vis}}) \times 100$ With: $TS_{LO\ Ver}$: time spent in verbal LO $TS_{LO\ Ver/Vis}$: time spent in verbal and visual LO
ITS_{Vis}	$ITS_{Vis} = (\frac{TS_{LO_{Vis}}}{TS_{LO_{Ver/Vis}}}) \times 100$ With: $TS_{LO\ Vis}$: time spent in visual LO $TS_{LO\ Ver/Vis}$: time spent in verbal and visual LO
ITS_{Tho}	$ITS_{Tho} = (\frac{TS_{LO_{Tho}}}{TS_{LO_{Tho/Pra}}}) \times 100$ With: $TS_{LO_{Tho}}$: time spent in theoretical LO $TS_{LO_{Tho/Pra}}$: time spent in theoretical and practical LO
ITS_{Pra}	$ITS_{Pra} = (\frac{TS_{LO_{Pra}}}{TS_{LO_{Tho/Pra}}}) \times 100$ With: $TS_{LO_{Pra}}$: time spent in practical LO $TS_{LO_{Tho/Pra}}$: time spent in theoretical and practical LO
ITS_{Test}	$ITS_{Test} = \frac{TS_{Test}}{TP_{Test}}$ With: TS_{Test}: time spent in the test TP_{Test}: time planned to the test
ITS_{Course}	$ITS_{Course} = \frac{TS_{Course}}{TP_{Course}}$ With: TS_{Course}: time spent in the course TP_{Course}: time planned to the course
$ITS_{Ov/Ot}$	$ITS_{Ov/Ot} = \frac{TS_{Ov} + TS_{Ot}}{TP_{Ov\ /\ Ot}}$ With: TS_{Ov}: time spent in the overviews TS_{Ot}: time spent in the outlines $TP_{Ov\ /\ Ot}$: Time planned to overviews and outlines
ITS_{Forum}	$ITS_{Forum} = \frac{TS_{Forum}}{Av\_TS_{Forum}}$ With: TS_{Forum}: time spent in the Forum $Av\_TS_{Forum} = \frac{Total\ time\ spent\ in\ the\ forum}{Number\ of\ learners}$

Table A.1: Time Indicators Formulas.

Indicator	Formula
IFQ_{Test}	$IFQ_{Test} = (\sum_{i=0}^{n} {}^{1}/_{Number\ of\ trails} / _{N}) \times 100$ N: Number of the tests done
IFQ_{Com}	$IFQ_{Com} = \left(\frac{N\_P_{Forum}/Av_{NP} + N\_D_{Chat}/Av_{ND}}{2} \right) \times 100$ With: N_P_{Forum}: Number of the posts in the Forum N_D_{Chat}: Number of the discussions in the chat $Av_{NP} = \frac{Number\ of\ Posts\ in\ the\ Forum}{Number\ of\ learners}$ $Av_{ND} = \frac{Number\ of\ Discussions\ in\ the\ chat}{Number\ of\ learners}$
$IFQ_{Revisit}$	$IFQ_{Revisit} = \left(\frac{Number\ of\ LO\ revisited}{Number\ of\ LO\ visited} \right) \times 100$
$IFQ_{Ov/Ot}$	$IFQ_{Ov/Ot=} \frac{N\_A_{Ov/Ot}}{Av\_A_{Ov/Ot}}$ With: $N\_A_{Ov/Ot}$: Number of accesses to overviews and outlines $Av\_A_{Ov/Ot} = \frac{The\ total\ number\ of accesses\ to\ overviews\ and\ outlines}{Number\ of\ learners}$
$IFQ_{Test/Exe}$	$IFQ_{Test/Exe} = \frac{N_{Test/Exe}}{Av_N}$ With: $N_{Test/Exe}$: Number of tests and exercises done $Av_N = \frac{The\ total\ number\ of\ tests\ and\ exercises\ done}{Number\ of\ learners}$
$IFQ_{Posts\ vs\ Views}$	$IFQ_{Posts\ vs\ Views} = {}^{N\_Acc_{Forum}}/_{N\_P_{Forum}}$ With: N_Acc_{Forum}: Number of accesses to the forum N_P_{Forum}: Number of posts in the forum

Table A.2: Frequency Indicators Formulas.

Indicator	Formula
INV	$INV = \begin{cases} 0 \\ 1 \end{cases}$ 0: if the route is linear using the next-previous buttons 1: if the route is random using the summary associated with the course

Table A.3: Navigation Indicator Formula.