E-LEARNING PERSONALIZATION BASED ON DYNAMIC LEARNERS' PREFERENCE

Essaid El Bachari[1], El Hassan Abelwahed[2] and Mohammed El Adnani[3]

[1, 2, 3] Department of Engineering Science, University Cadi Ayyad
elbachari@ucam.ac.ma
abdelwahed@ucam.ac.ma
md-eladnani@ucam.ac.ma

ABSTRACT

Personalized e-learning implementation is recognized one of the most interesting research areas in the distance web-based education. Since the learning style of each learner is different we must to fit e-learning to the different needs of learners. This paper discusses teaching strategies matching with learner's personality using the Myers-Briggs Type Indicator (MBTI) tools. Based on an innovative approach, a framework for building an adaptive learning management system by considering learner's preference has been developed. The learner's profile is initialized according to the results obtained by the student in the index of learning styles questionnaire and then fine-tuned during the course of the interaction using the Bayesian model. Moreover, an experiment was conducted to evaluate the performance of our approach. The result reveals the system effectiveness for which it appears that the proposed approach may be promising.

KEYWORDS

Adaptive Learning, MBTI, Learning Style, Teaching Strategy, Personalization.

1. INTRODUCTION

To day, E-learning has emerged as a new alternative to conventional learning to achieve the goal of education for all. The concept E-learning has numerous definitions and some times confusing interpretations. In our purpose we adopt a definition of E-learning as the use of Internet technologies to provide and enhance students' learning anytime and anywhere. One of its advantages is the learning method which can be more adaptive than conventional learning. Indeed, traditional learning based on "one size fits all" approach, tends to support only one educational model, because in a typical classroom situation, a teacher often has to deal with several students at the same time. Such situation forces each student to receive the same course materials, disregarding their personal needs, characteristics or preferences. Once the teachers learned to provide the detailed, structured instruction the students needed, the class productivity increased. Moreover, it is extremely difficult for a teacher to determine the optimal learning strategy for every learner in a class. And even if a teacher is able to determine all the strategies, it is even more difficult to apply all multiple teaching strategies in a classroom.

Therefore, implementing learning concept in the context of conventional learning is quite difficult due to diverse preferences, prior knowledge, and intelligence of the learners. This problem can be resolved in E-learning system context in which each student can be arranged to receive a teaching strategy which is more fine-tuned to his/her learning style. In our purpose, we define a teaching strategy, called also learning scenario, as the ways a teacher can present instructional materials or conduct instructional activities which called also learning scenarios. On the other hand, Internet offers the perfect technology and environment for individualized learning because learners can be uniquely identified, content can be specifically personalized,

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and learner progress can be monitored, supported and assessed. Existing successful examples from e-commerce system may inspire and help us to build a good personalized e-learning system which can provides learners a new way to break free with the more traditional educational models.

In response to individual needs, personalization in education not only facilitates students to learn better by using different ways to create various learning experiences, but also teachers' needs in preparing and designing varied teaching or instructional packages. However, an important consideration is often being ignored or overlooked in accomplishing a personalized e-learning framework. This consideration concerns a whole-person understanding about key psychological sources that influence how individuals want and intend to learn online. Up to now, developments have focused on technology rather than more important learner-centric issues. Indeed, each learner has a learning style that allows him to learn better and to ignore that can lead to unstable or ineffective online learning solutions. In fact, it is commonly believed that most people prefer some kind of interacting with, taking in, and processing stimuli or information or simply using a visual medium. So to learn effectively and better, learner has to be aware of his preferences that make easy to manage his own way of learning. This information will enable the learner to improve the effectiveness of its approach to learning and to exploit its own resources. Cooper and Miller [11], report that the level of learning style/teaching style congruency is related to academic performance and to student evaluations of the course and instructor. Furthermore, Jungian based psychologists add that people's personality preferences influence the way they may or may not want to become more actively involved in their learning, as well as take responsibility for the self-direction and discipline [13,43,44]. So we may to identify a student's individual learning style and then adapt instruction toward that person's strengths and preferences. In fact, adjusting instruction to accommodate the learning styles of different types of students can increase both the students' achievement and their enjoyment of learning.

In this sense, it is necessary to deploy resources to support the learning process in a way that it not only suits the preferences of a few but all learners. There are many studies on the effectiveness of using teaching strategies based on personality but it's still very difficult to draw a definitive idea on the relationship between them [1, 3, 8-10, 12, 16, 23, 29, 37-39, 50]. Most of these studies rely on Kolb's Learning styles Inventory [33] and Solomon-Felder Index of learning styles [18, 19]. In a review made by Papanikolaou and al. [45], the researchers' effort to design, adaptive E-Learning systems are grouped in the following approaches:

- Personalization of the learning content, based on learners' preferences, educational background and experience
- Personalization of the representation manner and the form of the learning content
- Full personalization, which is a combination of the previous two types.

Until now, most of researches emphasize only on the first aspect (personalisation of the learning content) to build a personalized e-learning framework and a few focus on the second aspect (personalisation of the teaching strategies). In fact, we believe that it is of great importance to provide a personalized system which can automatically adapt to learners' learning styles and intelligently recommend online activities with the full personalization which is a combination of the first and the second aspect. Since that the problem is not how to create electronic learning materials (what we teach), but how to locate and utilize the available information in personalized way (how we teach). In this sense, our work is new and significantly different from the previous efforts done by others in the field.

This article is structured as follows: the next section discuss the related work cited in literature. Section 3 we present our adaptive teaching taxonomy based on MBTI model easy to implement to build a framework which can facilitate and personalize the learning process, so that students have a better assimilation of knowledge. The MBTI model was selected as the preferred model to profile students and create personalized learning environment. In our system, learners are first clustered based on his/her learning style. After this, a personalized learning experience (adaptive educational content and scenario) is provided by the system. The development of the prototype, LearnFit framework is discussed in section 4. In section 5 the results and the evaluation of our research are presented and the conclusions and future work are discussed in the last section.

2. RELATED WORK

In the past decades, various issues concerning adaptive learning have attracted the attentions of many researchers from the fields of computer science and education. In the meanwhile, various ways of measuring learning styles were proposed to assist instructors or educational researchers to more realize the characteristics of learners. In the following subsection, relevant studies addressing learning styles and the Myers-Briggs Type Indicator model are given.

2.1. Learning styles

Many researches have long tried to relate personality profile of learners' to teaching and learning style. Keefe in [30] described the learning style as both a student characteristic and an instructional strategy. As a student characteristic, learning style is an indicator of how a student learns and likes to learn. As an instructional strategy, it informs the cognition, context and content of learning. It can also be defined as the way a person collects processes and organizes information. Thereby, the learning style provides educators an overview of the tendencies and preferences of the individual learner.

There are many models of learning styles existing in literature. Individual learning styles differ, and these individual differences become even more important in the area of education. Honey and Mumford [26] defined a learning style as being 'a description of the attitudes and behavior which determine an individual's preferred way of learning'.

Several studies show that students learn in different ways, depending upon many personal factors and everyone has a distinct learning style [40, 41]. These researches show also that matching users' learning styles with the design of instruction is an important factor with regard to learning outcome. A number of experiments indicate that the user's performance is much better if the teaching methods are matched to the preferred learning styles.

Therefore, when an instructor's style matches a learner's learning style; this affects the learner's experience and ability to do well. Until today, a lot of research works has been done about learning styles and developed a good deal of learning style models but there does not seem to be any agreement of acceptance of any one theory [33]. There have been several models for defining and measuring learning styles, proposed, such as Kolb's questionnaire [34], Honey and Mumford's questionnaire [26], Keefe's questionnaire [30], The Myers-Briggs Type Indicator's questionnaire [43], Felder and Solman [18, 19] proposed a psychometric questionnaire ILSQ. Therefore, in our study, we adopted the MBTI model as one the well-known source information for personalization.

2.2. MBTI learning style model

The Myers-Briggs Type Indicator (MBTI), developed by Katharine Briggs and Isabel Myers, is based on the work of C.G. Jung, a psychiatrist who studied human behaviors for many years. The MBTI functions as a tool to help people understand themselves and their behaviors. It describes personality preferences rather than measuring skills or abilities and purports that all preferences are equally important. It has been well documented and researched in hundreds of scientific studies over the past forty years [43, 44]. The Myers-Briggs Type Indicator reports a person's preferences on four scales as presented in Table 1.

Table 1. Basic definition of the four MBTI dimensions

Preferences	**Definition**
Extraversion or Introversion	Where a person prefer to focus their attention
Sensing or Intuition	The way a person prefer to take in information
Thinking or Feeling	How a person deal with the external world
Judging or Perceiving	Where a person prefer to focus their attention

The various combinations of these preferences result in a total of sixteen personality types and are typically denoted by four letters to represent a person's tendencies on the four scales as shown in Table 2.

Table 2. MBTI types

ISTJ	ISFJ	INFJ	INTJ	ISFJ
ISTP	ISFP	INFP	INTP	ISFP
ESTP	ESFP	ENFP	ENTP	ESFP
ESTJ	ESFJ	ENFJ	ENTJ	ESFJ

For example, ENFJ stands for Extroversion, Intuition, Feeling, and Judging. This does not mean that a person possesses only four preferences, but that the four preferences show a greater presence than their counterparts.

The MBTI assessment can not only indicate the learner's preferences, but also indicate, how clear in expressing the preference for a particular pole over its opposite.

For example, in Figure 1, E is showing a greater presence, on a clear level, over its opposite I and N is showing a greater presence, on a moderate level, over its opposite S. F is showing a greater presence, on a clear level, over its opposite, T. Lastly, J is showing a greater presence, on a moderate level, over its opposite, P.

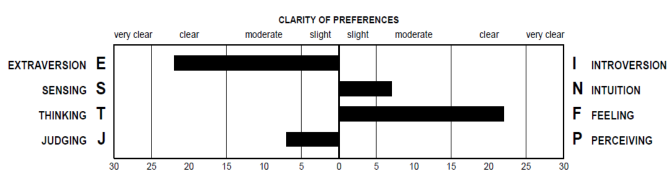

Figure 1. The strengths of MBTI type preferences.

2.3. Classification of students based the dominant type

Bayne [2] asserts that one of the four preferences, sensing, intuition, thinking or feeling, usually dominates the others. In fact, we all have an aspect of our personality which dominates or governs us. It gives direction to the personality and shapes the motives and goals for learners. This is called the dominant Process. For example, a person uses the dominant type the most and feels most comfortable when using it. There is also an auxiliary or secondary process which should be the second in strength and is the necessary assistant to the dominant. As with the dominant type, the auxiliary is readily used and a person will unconsciously shift back and forth between the two. If the learner is Extravert, then this guiding preference is most typically used in an open/easily apparent manner, dealing with the outside world. However the leaner is introvert, then this guiding preference is most typically used internally and more privately in reflection and consideration. Figure 2 shows the dominant and auxiliary preferences for each MBTI types.

ISTJ #1 Dominant S #2 Auxiliary T	**ISFJ** #1 Dominant S #2 Auxiliary F	**INFJ** #1 Dominant N #2 Auxiliary F	**INTJ** #1 Dominant N #2 Auxiliary T
ISTP #1 Dominant T #2 Auxiliary S	**ISFP** #1 Dominant F #2 Auxiliary S	**INFP** #1 Dominant F #2 Auxiliary N	**INTP** #1 Dominant T #2 Auxiliary N
ESTP #1 Dominant S #2 Auxiliary T	**ESFP** #1 Dominant S #2 Auxiliary F	**ENFP** #1 Dominant N #2 Auxiliary F	**ENTP** #1 Dominant N #2 Auxiliary T
ESTJ #1 Dominant T #2 Auxiliary S	**ESFJ** #1 Dominant F #2 Auxiliary S	**ENFJ** #1 Dominant F #2 Auxiliary N	**ENTJ** #1 Dominant T #2 Auxiliary N

Figure 2. Dominant and auxiliary preferences in each type (*Source*: [44]).

To design and develop sixteen teaching styles for the same course can be a complicated task for educational designers to meet the needs of learners. Myers, looking from a Jungian perspective breaks the groupings into four function types, focusing on the dominant type in the pattern, looking at "what the types have in mind" [31]. Therefore, in our approach only the dominant preference is selected not only because it has been approved by Myers but also because it's easy to deal with four students' categories than sixteen.

Table 3. The four Learners' classification based on MBTI

	Dominant preferences	**Myers Briggs type**
Sensory Types	$\widehat{S}$	ISTJ, ISFJ, ESTP and ESFP
Intuitive Types	$\widehat{N}$	INFJ, INTJ, ENFP and ENTP
Feeling Types	$\widehat{F}$	ISFP, INFP, ESFJ and ENFJ
Thinking Types	$\widehat{T}$	ISTP, INTP, ESTJ and ENTJ

Table 3 shows our suggested learners' classification according to the dominant preference for each MBTI type. For example, $\widehat{S}$ denotes a set of all learners which have ISTJ, ISFJ, ESP or ESTP types. In the following section, we use this classification to suggest a correspondence between teaching style and class learning style and thereafter to design and implement our learning system.

3. ADAPTIVE EDUCATIONAL EXPERIENCE

Teaching strategy refers to ways of presenting instructional materials or conducting instructional activities. Teaching strategies are the elements given to the students by the teachers to facilitate a deeper understanding of the information. The emphasis relies on the design, programming, elaboration and accomplishment of the learning content. Teaching strategies must be designed in a way that students are encouraged to observe, analyze, express an opinion, create a hypothesis, look for a solution and discover knowledge by themselves [20].

The strategies that teachers choose to use in their practice are usually determined by the learning theory they use. Historically, there have been three main theories of learning, behaviorism, cognitivism and constructivism. In the context of e-learning, a major discussion in instructional theory is the potential of learning objects to structure and deliver content. It is extremely difficult for a teacher to determine the optimal learning strategy for every student in a class. Even he is able to determine all strategies, it is even more difficult to apply multiple teaching strategies in a classroom.

Several researchers have used the Myers-Briggs Type Indicator (MBTI) to determine preferred teaching styles in relation to distance education [14], willingness to use technology in teaching [22, 47], and willingness to embrace innovation and change [25].

Ehrman in [14] builds upon the previous work of Lawrence [36] to chart preferred teaching models of the four scales of the MBTI. Properties of each learner's preference presented in Table 4, pertaining to education and learning, were collated from the literature [4, 13, 14, 24, 43].

Table 4. Myers-Briggs Type Indictor preferences

Learners' group	Preferred learning characteristics	Electronic Media
$\widehat{S}$	– Uses traditional curriculum and step by step – Likes using past experiences and standard ways to solve problems. – Enjoys applying what is already known by giving examples and details. – May ignore and not trust their inspirations. – Likes suggestions that are straightforward and feasible. – Are inclined to follow an agenda. – Likes to do practical things and prefers realistic applications. – Seldom makes errors of facts.	– Chat – E-mail – Forums – Animation – Online learning – Communities – Pictures – Podcast – Internet research – Simulation – Webblog – Wikis
$\widehat{N}$	– Focuses on conceptual understanding and the use of self-instructional methods for teaching. – Likes solving new and complex problems. – Enjoys learning new skills more than using them. – Willing to follow their insights and relies on imagination. – Likes novel and unusual suggestions. – Prefers change and proceeds with bursts of energy to follow global schemes. – Likes to do innovative things. – May make errors of facts.	– E-books – E-mail – Forums – Lectures – Online learning – Communities – Pictures – Recorded live events – Simulations – Tutorial systems – Wikis – Written text (Documents)
$\widehat{F}$	– Uses simulations and case studies together with small group work for teaching.	– Chat – E-mail

	– Uses values to reach conclusions. – Works best in harmony. – Tends to be sympathetic and has difficulty providing criticism. – Feels rewarded when people's needs are met. – Seeks involvement with people. – Presents points of agreement first. – Is sociable and friendly.	– Forums – Online learning – Communities – Pictures – Recorded live events – Simulations
$\widehat{T}$	– Uses teacher-directed instructional approaches and peer tutoring. – Uses logical analysis to reach conclusions. – Can work without harmony. – Is firm-minded and has little trouble giving criticism. – Feels rewarded when task is done. – Seeks involvement with tasks. – Presents goals and objectives first. – Tends to be brief and concise.	– Chat – E-mail – Forums – Animation – Online learning – Podcast – Internet research – Simulation – Webblog – Wikis

In the next session, we summarize the general setup of our proposed framework LearnFit before presenting it in detail.

4. SYSTEM ARCHITECTURE

Our proposed framework LearnFit is an Add-On to the popular Moodle Learning Management System to provide adaptivity learning experience. The tool is a web-based application having two tiers and has been implemented with PHP, MYSQL Server, CSS and AJAX on Linux environment. In spite of the fact that this system is designed and implemented as a general adaptive learning management for different courses and disciplines, the first completely implemented and tested version was for a programming language course suitable to design to help learners in learning. The main propose of LearnFit sytem is to recommend useful and interesting materials prepared within appropriate course to learners based on their preferences in e-learning context. Figure 3 shows the high-level system architecture of the proposed framework. Most classical studies include three main models to achieve the goal of individualized instruction: Domain Model, Pedagogical Model and Learner Model. Some developed systems using these three models are EDUCE [5, 6], INSPIRE [45] and PROTUS [32]. Our general purpose framework may be viewed as being comprised of at least the following three elements.

1. Domain Model: Consist of concepts and the relations that exist between them. Typically the domain model gives a domain expert's view of domain.

2. Learner Model: Consists of relevant information about the user that is pertinent to the personalisation of the learning style

3. Pedagogical Model: includes two parts :

    - Adaptive Engine Model: Consists of set of rules or triggers for describing the runtime behaviour of the system as well as how the domain model relates to the user model to specify adaptation.

- Revised Strategy Model: Consists to determine whether a given resource is appropriate for a specific learning style or not.

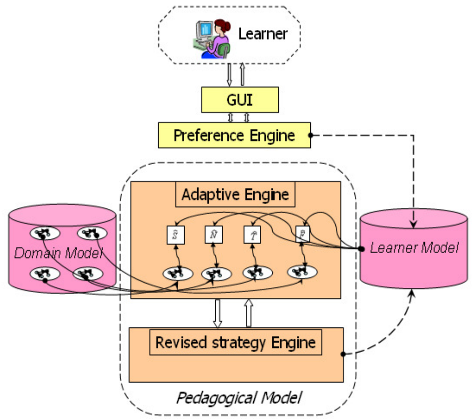

Figure 3. System Architecture of LearnFit

These three elements are described in detail in the following sub-sections.

4.1. Domain Model

A domain model contains the knowledge about the curriculum structure and it's built on a conceptual network of concepts. Each course includes an outline at the beginning, presenting all chapters with finally a conclusion summarizing the highlights of the course.

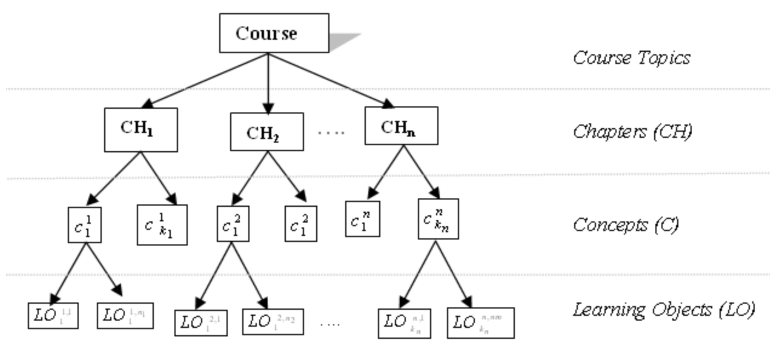

Figure 4. Structure of our domain model

A chapter can be represented as a tree of learning units or concepts (Figure 4). A learning unit holds one unit of knowledge and presents different aspects of it with different types of learning object which constitutes multiple external representations such presentations, questions, activities, examples, exercises, glossary [45]. In this research, the selected domain is "Introduction PHP Programming", one topic which is currently being taught at FSSM, UCAM Morocco. Five units of this course were adopted to develop an adaptive teaching style approach that is: C1: "Functions", C2: "Strings", C3: "Arrays", C4: "Objects" and C5: "Databases". Figure 6 shows the structure of our suggested domain model.

4.2. Learner Model

The model represents various learner characteristics (identity, preferences, etc…), which can be used to adapt the content and the teaching styles.

This component stores all user-related data, i.e. the users' profiles, including personal information, preferences. It enables the system to deliver customized instruction, on the basis of the individual student's, or the student group's, learning style. In our work, we consider only preferences to represent learner profiles since they are effective parameters in human activities such as learning and also teaching. Figure 5 shows the structure of the learner's profile according to MBTI tool. The learner profile is composed of two parts. The first part, is contains the name, age, educational level and languages. The second describes his learning style according the MBTI test and which can be defined as followed:

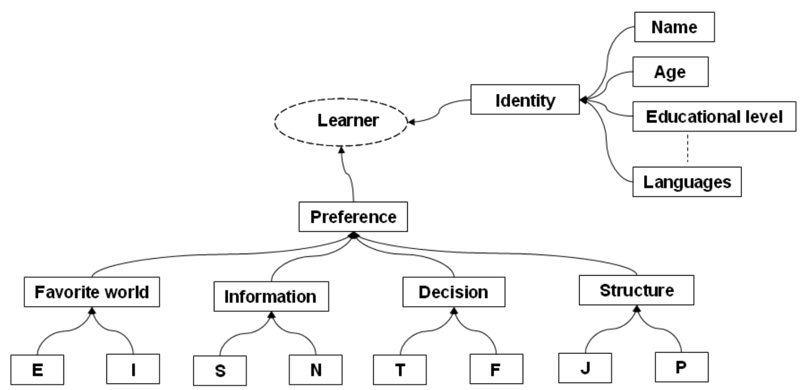

Figure 5. Learner's profile

The learner profile is composed of two parts. The first part, is contains the name, age, educational level and languages. The second describes his learning style according the MBTI test and which can be defined as followed:

$$U = \left\{ u \in [0,1]^8 \,/\, u = (u_E, u_I, u_S, u_N, u_T, u_F, u_J, u_p) \right\} \tag{1}$$

Each component u_i of the vector u element of U represents the priori probability of preference at ith MBTI dimension. Using the MBTI questionnaire we may explicitly evaluate the U value for each learner on numerical values in an interval [0, 1] such that 0 indicates a minimal satisfaction and 1 indicates a maximal satisfaction.

4.3. Pedagogical Model

The pedagogical model represents the teacher's knowledge of how to teach each concept. Teacher can use also different strategies to teach the same concept. As it was mentioned in previous section, personality plays an important role in learning processes, and learners with different personalities need special learning style. This cognitive knowledge guides the teacher into making good decisions when choosing learning goals for a learner and re-structuring LO(s) to achieve these learning goals.

Teaching strategies (TS) are the elements given to the students by the teachers to facilitate a deeper understanding of the information. The emphasis relies on the design, programming, elaboration and accomplishment of the learning content [20]. The main objective is to facilitate the student's learning. Our pedagogical model has two main intelligent axes: adaptive strategy module and revisited strategy module. In the following sub-sections, theses parts will be described.

4.3.1. Adaptive Strategy Module

Like we explain below at the beginning, the system ask learner the way he want to start his learning smart strategy or ad-hoc one. The ad-hoc one allows learners to use a teaching experience without using learning style. The ad-hoc learning experience can be one of the four proposed courses. If the learner selects the smart strategy, the new learner signs up by using the registration form in order to initial personal profile. Each profile stores personal information provided by the learner, i.e.: the name, age, educational level and languages and other meaningful attributes. When learners are registered, the system finds deals with detecting and storing the learning style in student model. In fact, the learner need to answer a psychological questionnaire which maps a set of 60 questions representing learning preferences and styles based on MBTI tools. The result indicates a preference of one of the four teaching styles. These styles are stored in student model which will be used for the first initial learning experience.

When a learner is logged in a session is initiated based on its learning style and an educational experience is recommended to him/her. It also includes a part for testing the acquired knowledge for each lesson. The test contains several multi-choice questions and code completions task

The order of logical arrangements of the tool when used by a student is given in Figure 6.

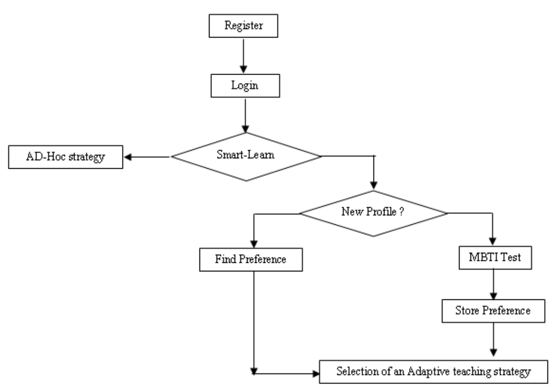

Figure 6. The flow chart of LearnFit system

This extension deals with the decision unit, an adaptive teaching strategy will be selected according to learner's psychology. For that we used a simple one-to-one correspondence illustrated in the following diagram (Figure 7).

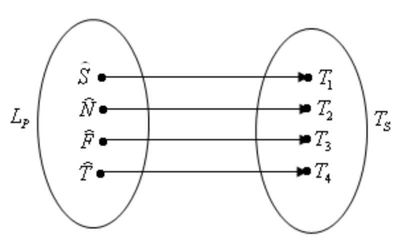

Figure 7. Diagram of selection a Teaching Strategy

L_P : denotes a set of the learners' profile categories presented in section 2 and T_S a set of their corresponding teaching strategies designed as follows.

Teaching strategy T_1: Sensing students rely heavily on their five senses to take in information. They like concrete facts, organization, and structure. They are good at memorization, usually realistic, and relatively conventional. They often have difficulty with theory. Brightman in [4] suggested the Application-Theory-Application (ATA) approach (Figure 8). Teacher starts by presenting an Application. The students attempt to analyze and solve the problem without the benefit of the upcoming course's theory. Therefore, the teacher present the chapter's theory or ideas, and then applies it to the original application. Afterwards the teacher presents additional applications to make easy the learning process.

Teaching strategy T_2: Intuitive students see the world through intuition. They want to know the theory before deciding that facts are important. They are creative, innovative, and work with bursts of energy. Also Brightman in [4] suggested for intuitive students the Theory-Application-Theory (TAT) (Figure 8). Teacher start by presenting the chapter's theory or idea before application related. The students attempt to analyze and solve the problem using the course's knowledge. The teacher can reuse the theory to facilitate the learning process. This approach (TAT) is used for the traditional educational model. Intuitive students like also the TAT approach.

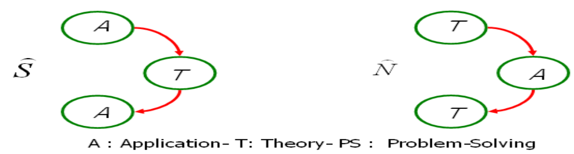

Figure 8. Teaching styles suggested for S and N classification

Teaching strategy T_3: Thinking students emphasize logic and objectivity in reasoning. They follow their head rather than their heart, value truth over tact, and sometimes appear blunt and uncaring about the feelings of others. They excel in inductive reasoning, logical problem solving, case studies, planned interactive activities and tests to progress. We may suggest for thinking students the approach T-A-PS (Figure 9). Teacher start by presenting the chapter's theory or idea before examples related. The students attempt to analyze and solve the practical exercises using the course's knowledge. Afterwards the teacher presents additional applications based logic and problem-solving.

Teaching strategy T_4: Feeling students follow their heart rather than their head. They decide on the basis of their feelings, personal likes and dislikes. Feeling types are often found in social work, elementary school teaching, and other helping professions. They feel rewarded when they can help others. We can suggest for feeling students the same scenario in collaborative context (Figure 9). In fact, the feeling type learners may prefer group exercises and working with small group. Problem-solving (also cases studies) and Collaborative Learning may be a good teaching style for this type of learners (Figure 9).

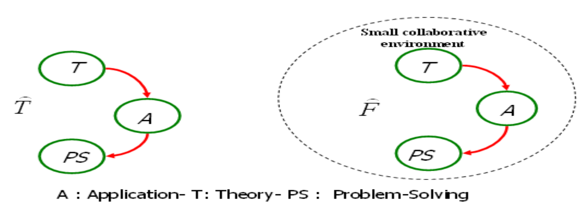

Figure 9. Teaching styles suggested for T and F classification

4.3.2. Revisited Strategy Module

Recent researches indicate that learning styles of an individual can vary depending on the task or the learning content [35, 48, 52]. Hence, it seems counter-productive to lock the learner into a fixed learning style profile after the initial assessment. Thus, it is important to estimate the dynamic learning style during the learning achievements. Our revisited strategy module implements a probabilistic decision model to adjust the basic learning style and classify a teaching strategy as "appropriate" or "not appropriate" for a specific learning style. The decision model used is the Dynamic Bayesian Network (DBN) which is quite similar to a Recommender System (RS) that tries to present to user the information items he/she is interested in. For more details about the probabilistic decision model see [7, 21, 28, 32, 47, 43]. A DBN is a model to describe a system that is dynamically changing or evolving over time which enables to monitor and update it as time proceeds.

In our model we consider three kinds of variables:

- A variable to represent the student's LS: The student belongs to only one of the four categories using only the Dominant Type Dimension (DTD). The set of possible values is given by :

$$DTD = \left\{ \tilde{S},\ \tilde{N}, \tilde{T}, \tilde{F} \right\} \tag{2}$$

- A variable representing the Teaching Style (TS) suggested for that learning style which includes the following values :

$$TS = \left\{ T_1, T_2, T_3, T_4 \right\} \tag{3}$$

- Variables to represent the selected learning objects: For each concept the system matches the learning style with adequate teaching style by using one or more learning objects. We use IEEE-LOM [27] standard to characterize resources, defining the most important elements of the learning object metadata. We use one variable for each LOM attribute that we consider significant for our approach. These variables are: Learning Resource Type (LRT), Format (F), Interactivity Type (IT) and Semantic Density (SD). Their possible values is given below :

$$\begin{aligned}
LRT &= \{\ exercise,\ simulation,\ diagram,\ slide,\ narrative-text,\ exam,\\
&\qquad \exp eriment,\ lecture\ \}\\
F &= \{text,\ image,\ audio,\ video,\ application\}\\
IT &= \{active,\ \exp ositive,\ mixed\}\\
SD &= \{very-low,\ \ low,\ \ medium,\ \ very-high\}
\end{aligned} \tag{4}$$

To define the DBN's parameters we set the a priori distribution of the nodes representing the LS according to the score obtained by learner in the MBTI test at the first connexion (Figure 10). The arcs represent the relationships between the teaching style and the factors determining it.

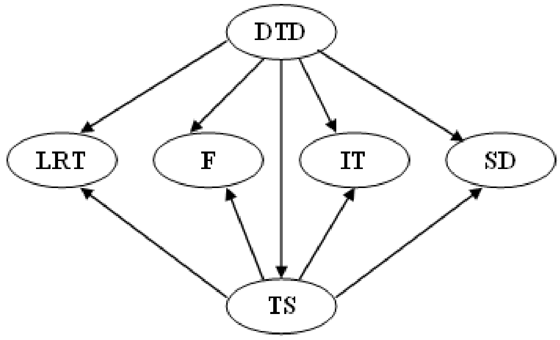

Figure 10. Bayesian networks representing the decision model

Regarding the conditional probability tables (CPTs) that represent the relationships between the dimensions of the LS, the TS and thereafter the online delivery learning objects, we estimated these CPTs taking into account the matching tables defined by the expert of the system. For more detail about this approach see [15].

5. EXPERIMENTS AND EVALUATION

We have set up experimentation to compare our approach with a classical one that doesn't use an adaptive teaching style, by measuring the student understanding after learning process. We conducted a research on LearnFit's effectiveness in learning five units of the course "Introduction PHP programming". Our main research question was:" Does the teaching strategies based student's preferences affect the learning outcome?" In fact the null hypothesis was that adaptive teaching using learner's personality has no effect on learning. Participants for this experimentation, were drawn from a pool (n= 48) of Computer Information Systems Master's Degree students at FSSM, UCAM Morocco in fall 2008 and 2009. In fall 2008, the course included 24 students (the control student). In fall 2009 the students count was also 24 students (the experimental group). The difference between the groups was that the control group used the traditional teaching style which basically is based on T-A-T approach, whereas the experimental group used our proposed framework. Indeed, in the treatment group had to study the same five units designed in four ways: $\widehat{S}$, $\widehat{N}$, $\widehat{F}$ and $\widehat{T}$'s strategy. Four versions of subject material have been implemented in LearnFit to provide personalized learning environments for students witch different learning styles. When students enter LearnFit for the first time, they are asked to take a learning style test based on MBTI's approach. This psychological questionnaire maps a set of 60 questions representing learning preferences and styles. The questionnaire calculated and stored the preferences in student model. The framework then determines the MBTI's classification and stores the preferences in student model for all future connexions. Figure 11 provided the questionnaire results:

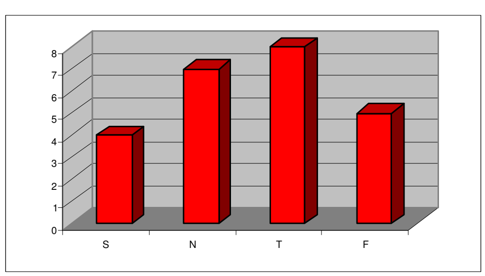

Figure 11. MBTI questionnaire results for the experimental group

The sessions were arranged at the beginning of the course and during eight weeks of experimentation, the students studied the learning material using one of those approaches in the same conditions. The student achievement was measured at the end of the experience using a post-test which consisted of a 60 questions Multiple-choice Quiz related to the presented subject mater and scores for this experience were calculated on the scale of 0 to 20. The time reserved answering was 45 minutes.

The results were analyzed with a two-tailed and independent t-test which is appropriate for this research design conducted to investigate any difference achievement between the two groups. Also Kolmogrov-Smirnov-test was used to check the distributions of the gathered data. Indeed In, we aim to analyze the dependant variable posttest score which used as an indicator for representing the student learning efficiency. Table 5 presents the results of T-Student test.

Table 5. Results of T-Student test in experimental and control group

Group	**N**	**Mean score**	**Standard deviation**	**T**	**P**
Experimental Group	24	14.52	2.05	-4.53	.02
Control Group	24	12.02	3.5		

An analysis on Table 4 shows that students in the experimental group have significantly higher post-test score than those in control group and there are a significant difference in learning achievement and performance ($T = -4.53$ and $P < .05$). This supports our hypothesis about of the effect of using adaptive teaching styles based on learners' profile to improve the learning achievement. The results seem to support earlier studies which concluded that using learning styles matching with the learners' psychology is helpful to students in enhancing both learning efficacy and efficiency [1, 17, 49, 51].

6. CONCLUSION

Personalized learning occurs when e-leaning systems make deliberate efforts to design educational experiences that fit the needs, goals, talents, and interests of their learners. In this work, we conducted a research on the effects of student's psychology to improve their learning performance. We propose a personalized e-learning system LearnFit which can which takes the dynamic learner's personality into account. In this system some modules for personality recognition and selecting appropriate teaching strategy are used to achieve the learning. The results indicate that placing the learner beside an appropriate teaching style matching with learner's preference lead to improvement and make the virtual learning environment more enjoyable. Although the innovative approach presented in this article has demonstrated is benefits, it also depicted the limitation of actual application. The major difficulty is to develop four versions of the same course to meet the personalization of learning process. Finally, the evaluation results show that students understood the process and liked being involved in it, in spite the fact that it was not a simple task. Finally, this study's results should be carefully interpreted as MBTI is only one of many popular personality assessment instruments and our approach can be altered in many different ways.

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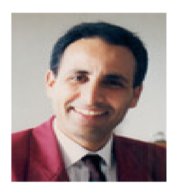
Authors

Dr. Essaid El Bachari is an Associate Professor in the Department of Computer Science at Cadi Ayyad University, Marrakech in Morocco. He received his PhD degree in Mathematics from Paris VI University France in 1998. His first dissertation concerned Mathematical Modelling and Analysis in nonlinear elasticity and image recognition. He is responsible for the development and presentation of open learning courses, which include the investigation of various modes of course presentation and tutor development. He is also the Executive Manager CRU which is responsible for promoting the use and adoption of international eLearning.

Dr. El Hassan Abdelwahed is Professor of Computer Science at Cadi Ayyad University, Morocco since 1993. He received PhD in Computer Science and Robotics from Montepellier II University in 1991. His main research interests are in Ontology, Interoperability, Context, Web services and E-learning. He also was Program Chair of the IEEE conference ICWIT10 and has served on the program committees of number of national and international conferences.



Dr. Mohamed El Adnani received his PhD Degrees in Computer Science from Clermont Ferrand University France in 1994. He is presently a Professor in the Department of Computer Science at the University of Cadi Ayyad Marrakech in Morocco. Most of his scientific activities are devoted to computer science especially e-learning, spatial data base and engineering. He has been general chair and co-PC Chair of number of international conferences. He is the author of numerous publications related to his research interests.