E-learning Platforms and E-learning Students: Building the Bridge to Success

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KEYWORD

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Stress

ABSTRACT

E-learning platforms are becoming more and more common in education and with organisations. They are seen as a complementary tool to support learning or, as in many cases, as the primary tool to do it (possibly the only one).

In traditional learning, teachers can easily get an insight into how their students work and learn, and how they interact in the classroom. However, in online learning, it is more difficult for teachers to see how individual students behave.

Affective states and learning styles are determinant in students' performance. Together with stress, these are crucial factor to success. It is believed that the sole use of an E-learning platform can in itself be a cause of stress for students.

Estimating, in a non-invasive way, such parameters, and taking measures to deal with them, are then the goal of this paper. We do not consider the use of dedicated sensors (invasive) such as special gloves or wrist bracelets since we intend not to be dependent on specific hardware and also because we believe that such specific hardware can induce for itself some alteration in the parameters being analysed. Our work focuses on the development of a new module (Dynamic Recognition Module) to incorporate in Moodle E-learning platform, to accommodate individualized support to E-learning students.

1 Introduction

When a student attends an electronic course, the interaction between student and teacher, with all its non-verbal interactions is lost, thus the aware of feelings and attitudes by the teacher becomes more difficult. In that sense, the use of technological tools for teaching, with the consequent teacher-student and student-student separation may represent a risk, as a significant amount of context information is lost. Students' effectiveness and success in E-learning is highly related to their mood to do it, that is, students' emotions like self-esteem, motivation, commitment, and others are believed to be determinant in students' performance. Affective states and learning styles also greatly influence students' learning. Stress is another very important factor.

As the teacher's role gradually loses its substance in an E-learning environment, some issues must be carefully examined, so that the educational processes guided by software applications (e.g. Intelligent Tutoring Systems) will incorporate the best facets of the human experts [ALMEIDA et al, 2008], [RODRIGUES, NOVAIS and SANTOS, 2005].

In our opinion, these issues should be taken into account when dealing with an E-learning environment. In a traditional classroom, the teacher can detect and even forecast some negative situations (e.g. stress), taking appropriate measures for mitigating such situation. When working alone, such actions are impossible, and it is even more difficult to solve inconvenient circumstances.

In that sense, its analysis in an E-learning environment assumes greater importance. Using sensors as in [PETER et al, 2005] could be a solution for detecting stress, affective states and learning styles. However, we believe that the use of visible sensors, induce themselves some sort of stress. In our work, we will try to get useful information from keyboard strokes, mouse movement, accelerometer, touch screen and web cams to generate important information about students' current mood to learn. We are trying to develop an agent based highly modular approach, easily adaptable to other domains and able to estimate students' emotions in a non-intrusive way. Our goal is to develop a dynamic student assessment module that, while making use of context information, will adapt strategies in order to shape the models used by human experts. In fact, teachers frequently make changes in their strategies when detecting significant changes in the state of their students [RODRIGUES, FDEZ-RIVEROLA and NOVAIS, 2011]. With this approach we expect to see the advent of environments whose main objective is to capture context information that can be later used by teachers to achieve better and more satisfactory outcomes when using an E-learning environment (i.e. Moodle).

E-learning

Nowadays, education organizations cannot exclude themselves from information society, being always confronted with new technological challenges. The student population comes from very different social backgrounds, with different needs and expectations. Moreover, society is demanding for more qualified technicians. Schools are, therefore, faced with a new technological paradigm, a new kind of public and new demands from society.

Education organizations have tried to attend to these challenges by investing in organization, management, market research, and in human and technological resources. New pedagogical tools, such as E-learning platforms and Intelligent Tutoring Systems have been also subject of attention.

E-learning systems are software programs that help and provide support to learning. They include personal training systems, usually designed for a certain knowledge domain, known as Tutoring Systems [VANLEHN, 2006], as well as general learning management tools suitable to manage distinct types of learning content, covering several knowledge domains. In this context, an E-learning system should have some basic characteristics such as [CRACIUNAS and ELSEK, 2009]:

- The learning process takes place in a virtual classroom;
- The educational material is available on the Internet and includes text, images, audio and video presentations and links to other online resources;
- The virtual classroom is coordinated by an instructor who plans the activity of the students, discusses aspects of the course using a discussion forum or chat and provides auxiliary resources;
- The learning becomes a social process in which a learning community is created through the interaction and collaboration between the instructor and students;
- Most E-learning systems allow the activity monitorization of the participants, and in some cases also simulations, the work on subgroups, audio and video interaction, etc.

Moreover, there are complementary security concerns regarding some important elements that should be taken into account: authentication, access control, data integrity, content protection, etc.

Investments in E-learning platforms and all the surrounding technology are very expensive; schools cannot afford to have unsuccessful students. As a consequence, the students' careers must be closely followed. Educational institutions should have devices to evaluate their students' learning state, i.e., they should possess means to keep their students' descriptions up to date, that way being able to periodically follow and diagnose the learning paths in order to avoid failures as much as possible. Furthermore, the need to supply the market with effectively qualified personnel favors these evaluations [ALMEIDA et al, 2008].

This evaluation and following should be performed by teachers and psychologists, who access and diagnose the learning paths of the students to detect symptoms of deviations and act accordingly. However, this kind of expertise is not always available, and when it is, it becomes insufficient to address all the needs.

In this context, the lack of some E-learning system providing these features is then obvious. Pedagogical concerns when building such systems are not always present, but some attempts have been made. In [RODRIGUES, NOVAIS and SANTOS, 2005] a framework is proposed to mitigate some of these known
problems.

2 E-learning Platforms

In 2007, it was carried out in Portugal a study titled "Study of Platforms for Distance Training in Portugal", which was funded and conducted by POEFDS DeltaConsultores, Perfil – Psicologia e Trabalho and Instituto Superior de Psicologia Aplicada (ISPA) [DELTACONSULTORES, 2007].

The based survey study was completed by 472 organizations with E-learning platforms installed, among which stands out the Moodle with a share of 57.6% as shown in Figure 1.

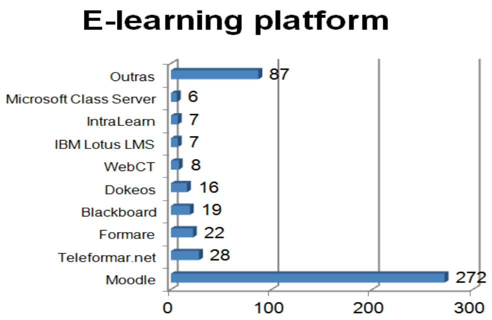

Figure 1- E-learning Platforms installed, 2007

At our Institution (Minho University, Portugal) the option selected was the BlackBoard platform, a proprietary system widely used in the United States. Some examples of implementation and usage tests are documented in [COUTINHO and JUNIOR, 2007].

For [RODRIGUES, OLIVEIRA and PEIXOTO, 2003] Blackboard is "a virtual environment for teaching at a distance, where most of its communication tools are asynchronous, where the teacher can expose text documents, video, audio, etc".

Being a proprietary platform, Blackboard offers advantages in terms of technical assistance and support issues. Evolution is always a thing to keep in mind and with an investment in a platform like this, it must be assured by the developers. However, in addition to the acquisition costs of licenses, limiting change of the internal structure of the platform are negative factors when compared with open source systems.

The environment of the Blackboard platform has tools for teaching and learning online, to create educational communities, providing auxiliary services to these institutions that can be integrated into the academic administrative system of the university itself, or with other platforms and security systems [LUMINITA, 2011]. There are numerous different resources available in the Blackboard platform:

- Contents creation;
- Structuring of contents;
- Provision of notice to students;
- Marking the calendar of events discipline;
- Provision of information team teaching;
- Sending e-mail messages;
- Creation and management of discussion forums;
- Creating synchronous collaboration sessions (chat);
- Job creation platform;
- Document sent to students through digital locker;
- Discipline glossary;
- Creating online tests;
- Management guidelines for notes;
- Etc.

Alternatively, with lower costs and consequently with a smaller investment than proprietary systems, there is the option for Moodle.

Moodle platform is a good example of a LMS/CMS (Learning Management System/Content Management System) that is widely used and for which the number of installations is growing very rapidly. In fact, Moodle is by far the most used E-learning platform in secondary schools in Portugal. Its usage has been widely recommended and encouraged by the official education organizations [VALENTE, 2007].

The Moodle numbers around the world show its popularity among the teaching community, as stated in Table 1.

Registered sites	67,834
Countries	221
Courses	6,576,112
Users	59,977,696
Teachers	1,290,116
Enrolments	40,891,929
Forum posts	106,933,903
Resources	58,168,881
Quiz questions	123,523,979

Country	Registrations
United States	11,760
Spain	5,834
Brazil	4,972
United Kingdom	3,863
Germany	2,893
Mexico	2,726
Portugal	2,090
Colombia	1,808
Australia	1,691
Italy	1,615

Table 1 – Moodle installations worldwide (Source: http://moodle.org/stats/)

In the present and future times when cost containment emerges as a daily imperative, the option for Moodle is rising and the deployment of Moodle in primary and secondary education is unparalleled by other platforms.

2.1 The Moodle Learning Management System

Moodle (Modular Object-Oriented Dynamic Learning Environment) has a number of interactive learning activity components like forums, chats, quizzes and assignments. In addition, Moodle includes a logging module to track users' accesses and the activities and resources that have been followed. With these components, administrators and teachers can extract reports from this data and with appropriate tools the information can be conveniently analyzed. Figure 2 shows a high level view of the Moodle modules.

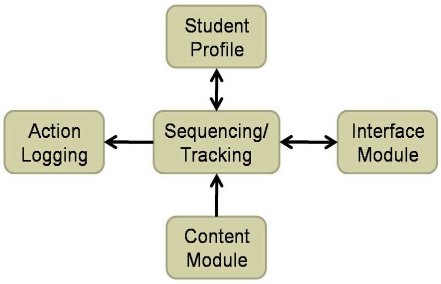

Figure 2- Moodle LMS modules

With that modular design it's easy to enrich the Moodle platform with other plug-ins, designed to meet particular needs of a specific set of users.

Whatever the case, LMS should have some sort of knowledge about the students and their learning processes. This knowledge (i.e. the beliefs the system has about the students), is usually called the Student Model (SM). Without a precise SM a system would simply behave the same way for all students. Additionally, this Student Model must be dynamically upgraded to reflect student's affective states, motivation, etc., to adapt not only to different students, but also to the singular states that a student has when using such a platform.

In this context, a LMS such as Moodle are very successful in E-education, but it does not accommodate full-fledged adaptively [GRAAF, 2007]. Moodle does not provide any of the issues previously discussed, and the need for some module that implements them is crucial to improve student's success.

In next section, some of the important aspects to consider regarding students, their emotions and learning styles in an E-learning platform are subject to a brief analysis. Later, we will present our Dynamic Recognition Module to implement and address such issues in Moodle.

3 E-learning Students

In an E-learning environment, students have several advantages as well as disadvantages. It requires enormous patience, large motivation, self-confidence, dedication and general knowledge of computer use to be successful in E-learning [MEYER, 2003]. E-learning can be a focus of frustration for some individuals, for instance, when the organization is supporting the course and requiring its employees to learn, an understated premise is implicit that if they don't learn some negative consequences may arrive. Even now, not everyone is comfortable using a computer or is willing to adapt to change. Those who chose to use E-learning must realize that they will only get out what they put into it, that is, enormous effort is needed in order to get good results. Students´ learning styles and behavior types also affect their success when using E-learning [MEYER 2003]. In addition, [HUANG, 2002] found that there are several other factors that alter the success of E-learning, such as age and gender.

E-learning students in most cases are not monitored with strategies to ensure that they are really learning. In fact, there is no definite way (yet) of measuring the amount of knowledge that the students gained from E-learning. In this context, it is needed human interaction for manually acquire such information, or the existence of some dynamic module able to gather it in an automatic way, which is the core of this work.

Another problem is the different learning styles of the students. Not all of them are self-motivated and self determined to handle online courses [MEYER, 2003]. As previously mentioned, affective states and learning styles can greatly influence E-learning students' performance. Stress can also play an important role in E-learning, by itself or by influencing the learning styles, as stated in [VAUGH et al, 2012], where a relationship between stress and learning styles was established. Also in [ZHAI and BARRETO, 2008] affective states are found to have an intrinsic relation with stress in E-learning systems.

3.1 Affective States in E-learning

Most of the E-learning systems focus attention towards knowledge acquisition or cognitive processing.
When

building such a system, affective states (such as motivation and emotion), are considered only in terms of how the content is structured and presented. To make learning efficient and to deliver personalized content, adaptive systems are based on students' goals models, knowledge, and preferences. Thus, a student model that integrates the cognitive processes and motivational states would lead to more efficient and personalized adaptation [COCEA, 2007]. Transforming a non-affect sensitive E-learning system into a system that includes the user affective states requires the modelling of a cycle known as the affective loop. The affective loop encompasses detection of a user's affective states, appropriate actions selection for decision making, and the synthesis of appropriate affective state by the system [D'MELLO, 2008].

As previously commented, affection influences the learning performance and decision making. This means that students who become caught in affective states such as anger or depression do not process and absorb information efficiently. From this, it can be inferred that a user's affective state has a major role in improving the effectiveness of E-learning [WEIMIN, 2007].

Emotion, mood and affective attitude are different things but strongly related and influence each other. An emotion is "composed" by a facial expression, a feeling (the conscious experience of the emotion) cognitive processing aimed at evaluating the situation in terms of personal relevance, physiological change and action readiness. It is a short but intense episode. In contrast, mood refers to the presence of moderate levels of affect. Mood is not consciously attributed to a causal factor (e.g. I can feel frustrated for half a day not knowing why). An affective attitude is an affective association coupled with a thing or person whilst an emotion is an evaluation of a thing or person in terms of personal relevance [BROEKENS et al, 2010].

In this work, we will use the term mood in order to determinate or name a student's particular state of mind or emotion, that is, a particular inclination or disposition to learn something.

Several parameters can be used to describe students' affective states, motivation and interest. Confidence, effort and confusion are highlighted among the possible factors influencing a student's motivation [QU, WANG and JOHNSON, 2005]. Moreover, the motivational model presented by [DE VICENTE and PAIN, 2002] includes variables related to trait (control, challenge, fantasy, and independence) and state (confidence, sensory interest, cognitive interest, effort, and satisfaction).

In [KHAN, 2010a], four methods to infer student´s affective states are proposed: (*i*) verbal approach, where a questionnaire or self report instrument is presented to the student, (*ii*) nonverbal approach, where psycho-physiological instrument measures physical states through the use of sensors, (*iii*) intrusive approach, through the use of intrusive instruments to measure affective states (although these instruments influence a student's normal affective state and may thus lead to misinformation), and (*iv*) non-intrusive approach, where the affective state is identified through interaction with the system.

Another model, known as OCC, is frequently referred also as the standard cognitive appraisal model that provides a clear and convincing structure of the eliciting conditions of emotions and the variables that affect their intensities. This psychological model is popular among computer scientists that build systems able to reason about or incorporate emotions [ORTONY, CLORE and COLLINS, 1990].

3.2 Learning Styles

The idea that student's learn differently is valued and probably has its origin with the ancient Greeks. For many years, it has been noticed that some students prefer certain methods of learning more than others. The particular student learning style can aid educators in planning small-group and individualized instruction. [GRASHA, 1996] has defined learning styles as "personal qualities that influence a student's ability to acquire information, to interact with peers and the teacher, and otherwise participate in learning experiences". There are probably as many ways to teach as there are to learn.

Learning styles specify a student's own way of learning. Someone that has a specific learning style can have difficulties when submitted to another learning style [FELDER, 1988]. When the presenting instruction style matches the student's learning style, the process is maximized, that is, the student learns more and better. Based on literature, we can establish that the consideration of learning styles in a learning environment influences a student's learning. Nowadays, learning styles are being investigated in order to incorporate them into adaptive online learning environments [GRAF and KINSHUCK, 2006].

Adaptive online learning environments are ideal for generating learning style based instructional material in large classes, as they do not have the same limitations as human instructors due to the lack of resources and time for focussing on individual students. One popular learning style inventory largely used in distance learning research is the Kolb Learning Style Inventory (LSI). Kolb's LSI measures student learning style preference in two bipolar dimensions [KOLB, 1986].

ther several learning style theories exist, for instance, Honey and Mumford [HONEY and MUMFORD, 1982] and Felder-Silverman learning style model [FELDER, 1988]. The later seems to be the most appropriate for use in E-learning systems [CARVER et al, 1999]. Most other learning style models classify learners in few groups, whereas FSLSM describes the learning style of a learner in more detail, distinguishing between preferences on four dimensions. In [GRAAF and KINSHUCK, 2006] a very interesting work is proposed to automatically detect learning styles through student modelling.

Learning Style	Characteristics
Active	Tries things out, works within a group, discusses and explains to others.
Reflective	Thinks before doing something, works alone.
Sensing	*Learns from and memorizes facts, solves problems by well-established* methods, patient with details, works slower.
Intuitive	Discovers possibilities and relationships, innovative, easily grasp new concepts, abstractions and mathematical formulation, works faster.
Visual	Learns from pictures, diagrams, flow charts, time lines, films, multimedia content and demonstrations.
Verbal	Learns form written and spoken explanations.
Sequential	Learns and thinks in linear/sequential steps.
Global	Learns in large leaps, absorbing material almost randomly.

Table 2 – Learning styles adapted from [SHAHIDA, 2008]

Currently, two approaches are used for identifying learning styles, namely the use of questionnaires and the use of data from students' behaviour and actions in an online course. Shute and Zapata-Rivera [SHUTE and RIVERA, 2008] identify at least two problems associated with questionnaire based information. Students may provide inaccurate data either purposefully (e.g. a desire to present themselves in a more prominent way) or accidentally, due to not knowing their own characteristics. A second problem is that when completing the questionnaire during the online learning process, it consumes time, and students tend to provide invalid data in order to shortcut to contents quickly. As previously stated, Felder and Silverman developed an Index of Learning Styles (ILS) Questionnaire that is widely used to identify learning styles explicitly (Table 2).

An approach based on the actions and behaviour of the students during their interaction with the system for learning may be used. No additional effort is needed by students in these approaches in order to obtain information about their learning styles. In fact learning styles are inferred by the system from the student's actions, being the information captured that way free from uncertainty. In [KHAN, 2010a] a concept for identifying learning styles and affective states using different approaches is proposed.

3.3 Stress

Another important factor is stress. Stress can play a relevant (usually negative) role in education, even more in E-learning. Stress can alter the learning style.

Following the approach of [PALMER et al, 2003] stress can be defined as "when the perceived pressure exceeds your perceived ability to cope". Stress represents an abnormal condition that disrupts the normal functions of the body or mind. In other words, human stress is a state of tension that is created when a person responds to demands and pressures [GARDELL, 1982].

Stress is thus always perceived; a situation is stressful for an individual – not for all individuals. Given a particular situation, one student may feel it like a stressful one, whilst another student may feel it like an enjoyable situation. No two people are affected in exactly the same way, or to the same degree, but it is likely that in some part of life we experienced some stress situation. Indeed, stress is now considered as the second greatest cause of absence from work in the EU (back pain is the greatest) [BT, 2002]. Stress can affect the body, thoughts, feelings, and behaviour of a person. Stress adds challenge and opportunity to life. Without stress life would be dull, but too much stress can seriously affect your physical and mental health. Thus, stress can greatly influence E-learning students, by acting in their affective states and learning styles, usually in a negative way.

In terms of health, it is important to find the optimal level of stress that can be managed effectively. In E-learning systems, it is also very important to manage stress, and keep it within controllable levels. Stress and the way people respond to it is unique to each of us, and thus, for each E-learning student. What one person may find relaxing, another will find stressful.

For example - public speaking is routine for some people, whilst others view it as a difficult task and are extremely uncomfortable with it. The key to stress reduction is the identification of those strategies that fit to a person as an individual. This becomes a critical factor in E-learning environments. Treating each student as an individual in such environments would be a major step to improve academic success.

The best way to deal with unhealthy stress is to recognise it, and when stress is growing above some perceived acceptable level, take some appropriate actions. Events themselves are not necessarily stressful; it is the way in which each individual interprets and reacts to an event that induces stress.

3.3.1 Signs of stress

The signs of stress can be divided into four categories. For each category a person can experience some symptoms. Table 3 shows that symptom for each category [MELINDA et al, 2012].

Not all of these symptoms are prone to be detected in an E-learning environment, especially if we assume that no intrusive sensors will be used to detect such situations. A few ones though can be detected, and the way to do it will be further discussed.

Table 3 – Stress categories

Thoughts	Feelings	Behaviour	Physical symptoms
Self-criticism; Difficulty in concentrating or making decisions; Forgetfulness or mental disorganization; Preoccupation with the future; Repetitive thoughts, Fear of failure.	Anxiety; Irritability; Fear; Moodiness; Embarrassment.	Stuttering or other speech difficulties; Crying; Acting impulsively; Nervous laughter; Snapping at friends Teeth grinding or jaw clenching; Increased smoking, alcohol or other drug use; Being prone to more accidents; Increased or decreased appetite.	Tight muscles or muscle spasms, Cold or sweaty hands; Headaches; Back or neck problems; Sleep disturbance; Stomach pain and diarrhoea; Frequent colds and infections; Tiredness; Rapid breathing or pounding heart; Trembling; Dry mouth.

Despite all the existing work, it is still a challenging task to develop a practical human stress monitoring system. Several difficulties can be enumerated including (*i*) the expression and the measurements of human stress are person-dependent and even time or context dependent for the same person, (*ii*) the sensory observations are often ambiguous, uncertain, and incomplete, (*iii*) the user stress is dynamic and evolves over time and (*iv*) the lack of a clear criterion for feasible stress states greatly increases the difficulty of validating stress recognition systems.

In an E-learning environment, the ability to recognize common stress symptoms and, ideally, the real causes, is crucial to understand the underlying factors that conduct the students' success. Our current work focuses on modelling a system that is able to recognize human stress from its external symptoms. Therefore, we aim to develop a non-invasive real-time system that monitors students' stress in an E-learning environment like Moodle.

4 Dynamic Student Assessment Module

As stated before, affective states and learning styles greatly influence E-learning students' performance, with stress having an enormous importance in those two factors, thus in E-learning performance too. To mitigate such problems, several research studies have been carried out. In [RODRIGUES, FDEZ-RIVEROLA and NOVAIS, 2011] a framework was proposed where the goal was to obtain an external module to be linked to Moodle platform, enabling the detection of student's affective states together with learning styles in order to really know each student and presenting contents accordingly. The affective module will be responsible for gathering all this information, and derive students mood (referred to as students particular state of mind or emotion, that is, a particular inclination or disposition to learn something) in order to present relevant clues for a personalization and recommendation module.

In Figure 3, the Dynamic Student Assessment Module is presented. Not detailed in this work is the Personalization and Recommendation Module that will be subject of future work.

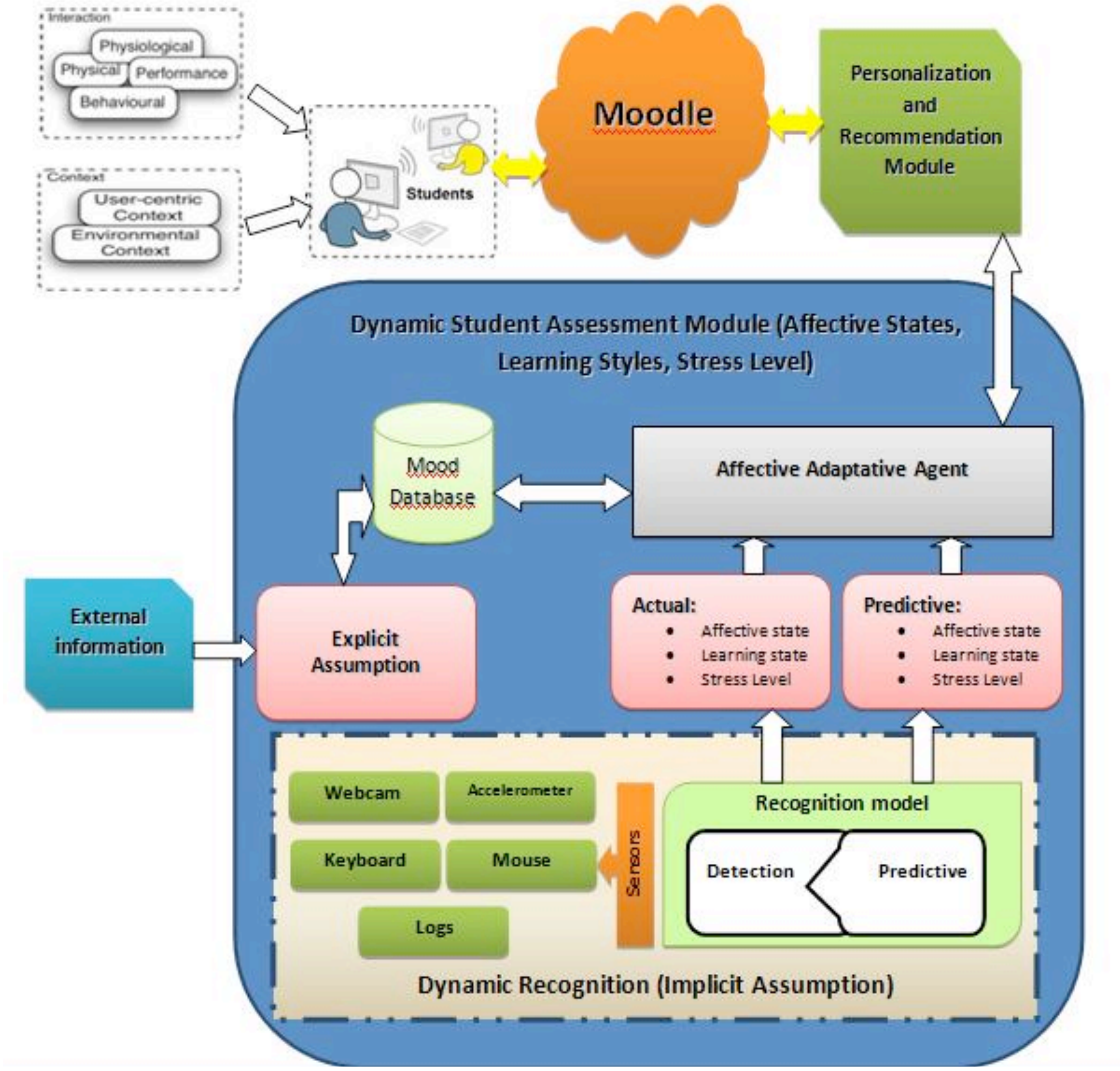

Figure 3 – Dynamic Student Assessment Module

The Dynamic Student Assessment Module has two sub-modules: explicit assumption and Dynamic Recognition (implicit assumption), whose function is to detect student's mood, maintaining that information (actual and past) in the mood database. This information will be used by another sub-module, the affective adaptative agent, to provide relevant information to the platform and to the referred personalization module. This enables that actual students mood information can be displayed in Moodle platform, and may be used to personalize instruction according to the specific student, thus enabling Moodle to act differently to different students, and also to act different to the same student, according to his/her past and present mood. Here, we refer to mood as the actual "willing" of the student to learn, which incorporates his/her affective state, learning style and level of stress.

Each student interacts with Moodle from his/her own real environment, when attending a course. This environment is equipped with sensors and devices that acquire different kind of information from the student in a non-intrusive way. While the student conscientiously interacts with the system and takes his/her decisions and actions, a parallel and transparent process takes place in which this information is used by the Dynamic Student Assessment Module. This module, upon converting the sensory information into useful data, allows for a contextualized analysis of the operational data of the students. This contextualized analysis is performed by the Dynamic Student Assessment Module. Then, the student profile is updated with new data, and the teacher responsible for that course receives feedback from this module. Moreover, the student gets useful information
about

his/her levels of stress, for instance, he/she can get the information to have a coffee break due to high level of detected stress, or in advance, when the predictive level of stress is too high the student could get the information to do something else for a while.

We are not developing all the modules from scratch. Instead of this, various research works have been done in areas as facial recognition, keyboard and mouse stress detection that can be used here. Many research in log analyses for student characterization is also widely available [FDEZ-SAMPAYO et al, 2009]. The rest of the system sub-modules are explained next.

4.1 Explicit Mood Assumption

One of the easiest ways (but not the most accurate) of knowing a student's mood to achieve a certain class is by posing explicit questions to the student. Surprisingly, this may not be the most accurate way, not always the answers obtained reveal the accurate state of the student. However, we can still use questionnaires as a way of gathering some useful information. An explicit mood assumption agent could periodically pose some questions, preferably in a visual way, for the student to upgrade his/her mood to the system. In this context, several research works have been carried out to detect student mood explicitly [BROEKENS et al, 2010].

4.2 Dynamic Recognition (Implicit Mood Assumption)

The aim of this sub-module is to monitor the interactions between the student and the system in order to infer the students' mood, doing so without being intrusive, that is, without the student being aware of the analysis being performed. Agent technology is used to monitor five key aspects: facial analyses, mouse analyses, keyboard analyses, accelerometer analyses and log analyses. As web cams tend to be widely standard equipment in computers, the goal is to use it to try to infer emotions from the user. Mouse movements can also predict the state of mind of the user, as well as keyboard entries. With newer devices like Tablets and Smartphone's, accelerometers become widely available, giving us the change to detect a stressed user. Finally, analysing the past interactions of the student through the logs files of Moodle turns possible to infer some of the information we are looking for.

4.2.1 Webcam

As stated previously, and being widely recognized from psychological theory, human emotions can be classified into six archetypal emotions: surprise, fear, disgust, anger, happiness, and sadness. Facial motion plays a major role in expressing these emotions. Several automatic emotion recognition systems have explored the use of facial expressions to detect human affective states [COHEN et al, 2003], [PANTIC and ROTHKRANTZ, 2000].

The main idea is to extract affectively relevant features from an image. In order to establish student current emotions, features like mouth angle and face movements are used. Doing this implicitly makes more difficult to deceive the system, as the student is not aware of the on-going analyses.

4.2.2 Keyboard, Mouse and Accelerometer

The way a user types may indicate his/her state of mind and level of stress. Pressing the keyboard hard and rapidly could mean an altered state, anger for instance, while taking too much time may mean sadness. The same occurs with mouse movements. Also if the user moves the device rapidly causing high accelerometer readings (in case of tablets or smartphones) could mean an altered state, impatience or high stress. A system that monitors users' behaviour from standard input devices, like the keyboard or the mouse is proposed by [ZIMMERMAN et al, 2003]. Analyzed features include: the number of mouse clicks per minute, the average duration of mouse clicks (from the button-down to the button-up event), the maximum, minimum and average mouse speeds, the keystroke rate (strokes per second), the average duration of a keystroke (from the key-down to the key-up event) and performance measurements. [GEORGE et al, 2008] included keyboard stroke information in order to improve the accuracy of visual-facial emotion recognition.

The level of stress of the students assumes greater importance due to its correlation with affective states, learning styles and the E-learning students' success. The focus is on devices capable of acquiring data related to stress. The following sources of information (from now on designated sensors) acquired from the respective devices are:

- **Touch pattern** - the touch pattern represents the way in which a student touches the device and represents a variation of intensity over a period of time. This information is acquired from touch screens with support for touch intensity.
- **Touch accuracy** - a comparison between touches in active controls versus touches in passive areas (e.g. without controls, empty areas) in which there is

no sense in touching. This information is acquired from touch screens.

- **Touch intensity** - the intensity of the touch represents the amount of force that the student is putting into the touch. It is analyzed in terms of the maximum, minimum and mean intensity of each touch. This information is acquired from touch screens.
- **Touch duration** - this represents the time span between the beginning and the end of the touch event. This data is acquired from devices with touch screens.
- **Amount of movement** - the amount of movement represents how and how much the student is moving inside the environment. An estimation of the amount of movement from the video camera is built. The image processing stack uses the principles established by [CASTILLO et al, 2011] and uses image difference techniques to calculate the amount of movement between two consecutive frames [FERNÁNDEZ-CABALLERO et al, 2010] .
- **Acceleration** - the acceleration is measured from accelerometers in mobile devices. It is useful for building an estimation of how much the student is moving and how he is doing it (e.g. is the student having sudden movements?). Moreover, information from the accelerometer is used to support the estimation of the intensity of touch.
- **Mouse movement** – the amount of mouse movement represents the pattern in which the student moves the mouse (e.g. low amplitude quick movements of the mouse may indicate a high level of stress). These data are acquired from the mouse.
- **Mouse clicks** – the amount of mouse clicks and its frequency is useful for building an estimation of how much the student is moving around the screen and where he/she clicks. It is similar to the first four topics enumerated (pattern, accuracy, intensity and duration). These data are acquired from the mouse.
- **Keyboard strokes** – frequency and intensity of the use of the keyboard. Frequently backspaces may indicate frequent errors, high keyboard stroke may suggest experienced user (student) as opposed to low keyboard strokes. Stroke intensity (if keyboards allow it) may also be considered. These data are acquired from the keyboard.

4.2.3 Log Agent

Moodle has an activity logger to register users' accesses (i.e., user ID, IP and time of access) and the activities and resources that have been accessed. From the log, Moodle is able to generate, for each student, activity reports. In [KHAN, 2010b], learning styles and affective states information are gathered from students' interactions in a web-based learning management system. The students' behaviour on features that are commonly used in Moodle is analysed. Those commonly used features include content objects, outlines, exercises, self assessment tests, examples, discussion forums for assignment related queries, discussion/peer rating forums related to the content objects, and assignments. Considering information from all these features, the students' learning styles as well as affective states can be identified using a rule-based approach.

In the proposed system, we expect to realize that sensor values are influenced by stress in a significant way. Thus, changes in the level of stress result in changes in the readings from the sensors. When a student is stressed, he/she touches the interface in a different way, performing different movements with less touch accuracy, and so forth. An E-learning environment built with these devices and the described functionalities could provide information about the context and state of the student, his/her affective state and learning style.

We aim to accurately measure the influence of stress in a non-invasive and non-intrusive way of E-learning students by analyzing key features in their interaction with technological devices. This work has been done in other research fields [CARNEIRO et al, 2012], [NOVAIS et al, 2012].

In our work, we are using non-invasive techniques because we believe that it is the best way to do it. We believe that more intrusive techniques like body sensors, heart monitors, etc. are not well accepted by users. Another interesting point to refer is that using this kind of technologies (web cam, mouse and keyboard analysis) makes our solution cheaper, versatile and virtually undetected by users, making the inference from interactions more reliable.

A prototype of this system is being developed, aiming to produce a module to incorporate in Moodle that dynamically recognizes stress, learning styles and current affective states in E-learning students. A test group of secondary school students will be used to obtain and validate the data obtained by the sensors. First, they will be confronted with some questions with absolutely no constraints (no time limit, internet available, etc.), that is, perfectly stress free. Secondly, the same group will be submitted to some recognized stress factors such as time limit, noise, etc. Finally, we will analyse the data obtained and hopefully, validate the assumptions of our work.

5 Conclusions

Throughout this paper, we have introduced the importance of E-learning platforms for organizations to cope with present society challenges. Nowadays, the optimization of resources leads towards the massive use of E-learning platforms with all the widely known problems that come with it. In such a situation, students' success rises as a critical issue nowadays.

The importance of students' individual characteristics, as the way they learn and the mood in which they do it, outstands as a crucial learning factor. Nevertheless, as stated, E-learning platforms do not take into account these issues.

Affective states, learning styles and stress (that influences the former two) were identified as the major factors that can contribute to students' failure. Starting with some previous work regarding an affective module to incorporate in Moodle, a Dynamic Student Assessment module system was proposed to detect and predict such items in students. Detecting affective states, learning styles and stress levels will enable our recommendation module to do more effective recommendation namely in terms of content presentation. The work here proposed uses all around available technology to act as sensors, that is, detection is made via non-intrusive ways. The use of implicit methods to do this is emphasised as the student does not need to be aware of the on-going analyses, thus the probability of diseasing the system gets lower. Keyboard, mouse, touch screen and accelerometer are used to extract students' data about their interactions with the platform. Massive amounts of data are obtained this way, and we aim to estimate an optimal level of stress for a given student, for instance, detecting and predicting variations and acting accordingly. A prototype is being developed to be tested in secondary students. Research carried out in other fields suggests that our work is heading the correct way. After this work has been validated, we expect to develop a module to be incorporated in Moodle.

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