Non-Invasive Technology on a Classroom Chair for Detection of Emotions Used for the Personalization of Learning Resources

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Abstract**—**Emotions are related with learning processes and physiological signals can be used to detect them for the personalization of learning resources and to control the pace of instruction. A model of relevant emotions has been developed, where specific combinations of emotions and cognition processes are connected and integrated with the concept of 'flow', in order to improve learning. The cardiac pulse is a reliable signal that carries useful information about the subject's emotional condition; it is detected using a classroom chair adapted with non invasive EMFi sensor and an acquisition system that generates a ballistocardiogram (BCG), the signal is processed by an algorithm to obtain characteristics that match a specific emotional condition. The complete chair system is presented in this work, along with a framework for the personalization of learning resources.

Keywords**—**Ballistocardiogram, emotions in learning, non-invasive sensors, personalization of learning resources.

I. Introduction

In recent years, special attention has been given to the study of emotions during learning. New models have been proposed, which involve a direct relationship between specific learning processes and specific emotions. However, a means for detecting emotional change is needed so that the academic content of a specific lesson or class is better understood. Several physiological data for detecting emotion activation or deactivation have been proposed, such as cardiac pulse variation, body posture analysis, face gestures, pupil size variation, and skin temperature and conductance [1], [2]. The main characteristic of an emotion-aware system capable of interacting with the learner is that it has to be made using non-invasive technology, in order to avoid interference with the learner's normal learning processes. Concepts such as affective learning, firstly used by Picard [3], represent a useful approach to correlate different learning models, signal extraction techniques and the design of new systems involving Human-Computer Interaction (HCI). Another useful way for establishing a framework is to follow the steps proposed by Palacios and Romano [4]: Firstly, a proper selection of the emotional model is made, then selecting the according physiological data and stimulus, and finally the method to extract and analyze the information. Although there is a need for better academic achievement of students using new technologies, the main concern is to improve learning habits, which will allow a specific student to get more involved in her own knowledge acquisition.

In the present work, we analyze several theories that relate learning and emotions, and propose a system involving two different sensing technologies, both non-invasive: a film sensor attached to a regular classroom for detecting cardiac pulses and a force-sensor matrix for analyzing postures and correlate them with emotions.

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II. Learning Models

A. Kort, Reilly and Picard Model

As Picard has introduced the affective learning concept, she proposed a learning model which is based in another important concept called *flow* [5]. Flow is defined as the mental state in which one loses the pass of time due to intense concentration, and generally the information is better processed achieving better results. The relation between flow and emotions can be visualized in Fig. 1. According to the difficulty, or challenge level (*y-axis*) of the material or concept and considering the student skill (*x-axis*), flow can be present if both levels are balanced. However, other emotions can be present if either challenge or skill levels (or both) are not balanced. For example, if the challenge level is high and the skill level is low, then the proposed emotion would be anxiety, as the student does not understand the material being presented to her. On the other hand, if the challenge level is low and the skill level is high, the student will experience boredom.

The flow state has been mentioned by Steels in his book *A Learning Zone of One's Own* [6], where he proposes that schools should pay more attention in providing students with challenging situations that require the application of different skills, as well as presenting material and experiences that help loose the imagination and lead to proper activity involvement. If all the latter are present in the classroom, according to Steels, the learning experience should be optimum.

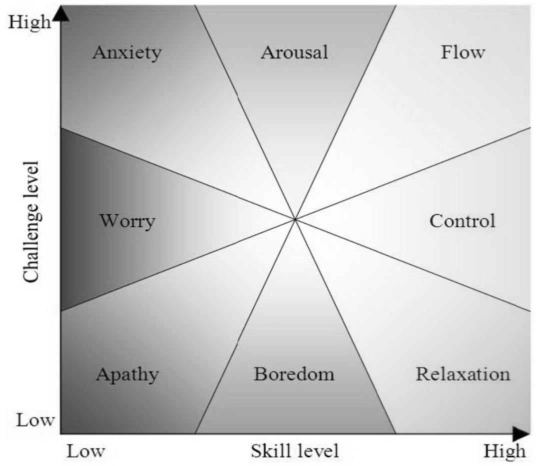

Fig. 1 Concept of flow [6].

According to Fig. 2, Kort, et. al [7] propose a 4-quadrant model, in which each quadrant represents a different stage in the learning process. When one complete cycle, including all four quadrants, is achieved, flow state is present and hence learning is carried out in an effective way. In the horizontal axis, called affect axis the emotions can be classified as negative or positive; in the vertical axis, called learning axis, the gaining of learning is considered. In this model, emotions like satisfaction, curiosity, deception, frustration, hope or confusion are treated. Moreover, the model proposes different affect axes which consider different ranges of emotions (Fig. 3).

B. Other Theories

Several theories and work from different authors that attempt to explain the relationship between learning and specific emotions are presented in Table I**Error! Reference source not found.**. The control-value theory presented by Pekrun explains the relation between emotions experienced by the student and her academic achievement [8], [9]. The theory defines specific emotions according to an academic domain. The classification criterion is given by the valence of the emotion (positive – negative) and the activation level, which depends on the value or importance that the student gives to the situation according to the emotional state. Experiments involving German students were carried out in order to evaluate the proposed emotions [8].

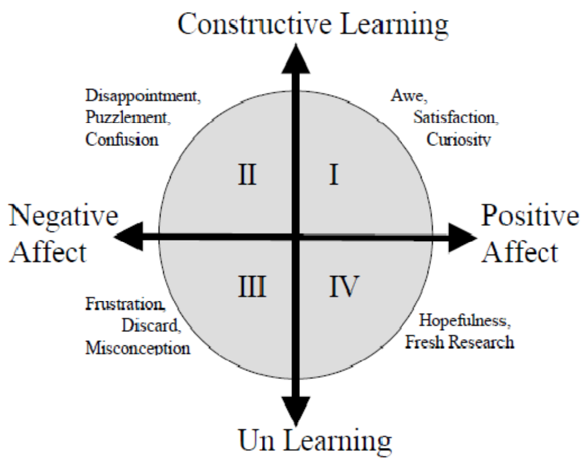

Fig. 2 Relationship between affect and learning gaining as described in [7].

Chaffar and Frasson [10] proposed a model based on Gagné's theory, and relate emotions with every cognitive process. Gagné's theory proposes a model based in expected responses that begins with an external stimulus and ends with an answer, or response, from the subject. The response can be seen as an attitude or behavior change towards knowledge gaining.

Axis	-1. 0	-0. 5	0		+0. 5	+1. 0
Anxiety-Confidence	Anxiety	Worry	Discomfort	Comfort	Hopefulness	Confidence
Ennui-Fascination	Ennui	Boredom	Indifference	Interest	Curiosity	Fascination
Frustration-Euphoria	Frustration	Puzzlement	Confusion	Insight	Enlightenment	Euphoria
Dispirited-Enthusiasm	Dispirited	Disappointed	Dissatisfied	Satisfied	Thrilled	Enthusiasm
Terror-Excitement	Terror	Dread	Apprehension	Calm	Anticipatory	Excitement
Humiliated-Proud	Humiliated	Embarrassed	Self-conscious	Pleased	Satisfied	Proud

Fig. 3 Different axes from Kort, Reilly and Picard's Model **[7]**.

TABLE I
SUMMARIZATION OF DIFFERENT LEARNING THEORIES AND WORK RELATED WITH EMOTIONS.

Author(s)	Work/Theory	Emotions relevant for learning
Kort [7]	4 quadrant affective model	Curiosity, confusion, frustration, hopefulness…
Craig [11]	Constructivist Learning Framework (AutoTutor [9])	Boredom, Confusion, Flow
D'Mello [12]	AutoTutor	Boredom, Engagement (flow), Confusion and Frustration
Mota, Picard [13]	Posture Analysis	High, medium, low interest level, taking a break
Pekrun [9]	Control-Value Theory	Activity Emotions Enjoyment Anger Frustration Boredom
Boekaerts [14]	Self-Regulation Model	Positive Affect Joy Contentment At ease Secure Negative Affect Feeling worried Tensed Irritated Displeased
Chaffar and Frasson [10]	Cognitive processes associated with emotions	*Attention*: Negative emotions and joy. *Acquisition*: Depends on emotional content of academic material. *Retrieving*: Depends on student's emotional state. *Organizational Response*: Induce positive emotions, e.g., joy.

III. DETECTION OF EMOTIONS

The models described so far propose a relationship between emotions and learning processes without taking into account the variability from person to person. The relation between emotions and learning is an important aspect for establishing an individualized learning architecture; however, every person learns in a different way and hence, the information the subject needs to process to increase his abilities varies according with his emotional state and physiological conditions. In recent years, non-invasive sensing technologies for HCI systems have been of particular interest since in real interaction scenarios, the emotions can be very spontaneous o could be non-authentic due to invading devices attached to the body. According to the learning model proposed by Chaffar and Frasson, the different cognitive processes and their relation with emotions were taken in order to define the way in which the emotions can be detected. As a resume, Table II presents those variables and signals related to emotions and later two types of non-invasive technology adopted for this particular project are explained.

A. EMFi Sensor and BCG Analysis

There is a direct relationship between a physiological change e.g., cardiac rhythm or respiration, and emotions. As a first approximation and as a part of a prototype, a system involving a sensor attached to a classroom chair is proposed. Due that it is necessary to use non-invasive technology; the sensor is in contact with the subject only when he is in a sitting position. The sensor is made with thin electromechanical films that have a voltage output depending on the distance between the layers proportional to the force applied [15]. This type of sensor has been used in previous work for acquiring a signal known as ballistocardiogram (BCG) which carries cardiac information [16], [17], [18], [19]. The cardiac pulse is taken from the blood pressure of the femoral artery when the subject is sitting on the sensor attached to the chair.

TABLE II
EMOTIONS RELATED WITH PHYSIOLOGICAL SIGNALS AND SENSING TECHNOLOGY.

Cognitive Process	Emotions	Variables /Sensing Technology
Attention	Curiosity (+)	Cardiac pulse[1] / EMFi sensor Posture analysis / Force sensors
Concept construction - idealization	Boredom (-)	Facial recognition / Camera Posture analysis / Force sensors
Memorization - retrieval	Happiness (+) Satisfaction (+)	Facial recognition / Camera Cardiac pulse[1] / EMFi sensor
Objective evaluation - response	Curiosity (+) Satisfaction (+) Deception (-)	Posture analysis / force sensors Facial recognition / Camera

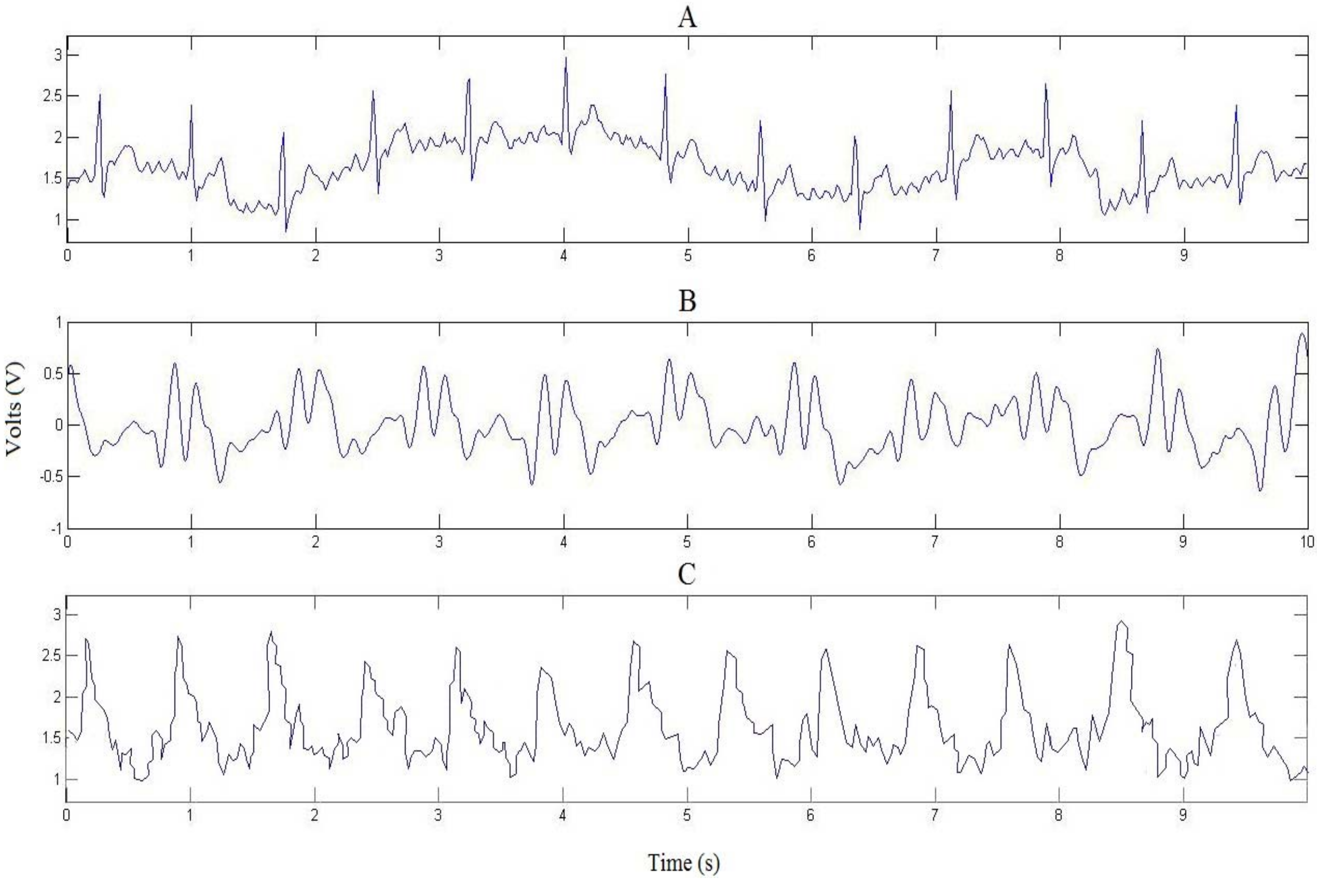

Fig. 4 Relationship between different cardiac signals, A) Normal subject ECG signal, B) Normal subject BCG signal and C) normal subject cardiac pulse taken from an oxymeter.

Moreover, it has been demonstrated that through BCG signal acquisition, emotional changes can be detected [20], [21]. Additionally, electronic filters are implemented to have a more reliable noise-reduced signal.A comparison between a conventional electrocardiogram (ECG), a BCG and an oxymeter signal (blood pressure taken from the tip of the finger) is shown in sensorFig. 4. As can be seen, the signal acquired with the EMFi (Fig. 4-B) is consistent and has low noise, thus providing very useful information as the ECG shown in Fig. 4-A. The mayor disadvantage of EMFi sensors is the high sensitiveness to sudden abrupt changes in movement. However, the pulses can be detected when the movement is kept minimal. The oxymeter signal can be seen in Fig. 4-C and shows the pulses corresponding to a 10 second time frame, as well as the other two signals.

B. Force Sensors and Posture Analysis

Another important aspect considered in this work is the system's ability to distinguish between different sitting positions and relate them to emotions. There has been previous work in this field [13], where commercial systems specially designed for posture analysis are used. In the present work, however, a lower number of piezoresistive sensors is considered. The idea is to set enough number of sensors on the chair such that a good resolution of the signal is obtained. This type of devices varies their resistance according to the force that is being applied on them, and if connected to an operational amplifier, voltage changes can be observed. The piezoresistive sensors are very thin thus providing the necessary manageability for the present application. The complete system including both EMFi and piezoresistive Flexiforce sensors attached to a classroom chair is shown in Fig. 5.

According with each posture, a particular activation of the corresponding sensors is expected. The area that is covered by the complete sensor system correspond to the seat and back of the chair, as depicted in Fig. 5. Mota and Picard [13] carried out experiments involving children sitting on regular chairs. Adult coders observed the resulting video-clips and established a group of postures shown in

Table III. The system used by Mota and Picard, however, is much more sophisticated and commercial.

Another useful approach for analyzing postures is given by Kamiya et. al, where a matrix sensing system is proposed. In this work, nine postures were extracted after the sensors' information was processed: normal, leaning backward, leaning forward, leaning right, right leg crossed, leaning right with right leg crossed, leaning left, left leg crossed, leaning left with left leg crossed [22]. Nonetheless, this work does not correlate the postures with emotions.

TABLE III
POSTURES AND RELATIVE EMOTIONS

Emotions	Postures	Main Sensing Area
Medium Interest /	Sitting on the edge, leaning forward left/right	Front part of seat
High Interest / Happiness / Anxiety / Curiosity	Sitting upright	Seat and Back (whole)
Low Interest / Anger	Slumping back	Upper part of back and front part of seat
Boredom	Leaning back right/left	Back part of seat and right/left area of back

Fig. 5 System with both types of sensors attached. An EMFi sensor and 17 force sensors are shown.

IV. PERSONALIZED LEARNING ARCHITECTURE

We have explained the ways in which an emotional condition, including the level of concentration and the motivation of the learner, impacts the learning process. Concerning cognitive aspects during a learning task, there are aspects such as the difficulty in a task that has an impact in the emotional process [6]. Difficulty is associated with the contents of learning activities presented to students, and their student's previous experience, e.g., the student's skills and concepts, as well as the timing for doing it. The student requires previous contextual and specific knowledge to comprehend new ideas and learn; it follows then, that a student who does not have an adequate previous knowledge will have more difficult to comprehend new concepts, and may experience boredom or an excess of frustration. To avoid undesired emotional states during the learning process, not only should the environment e.g., ventilation, noise, illumination, among others, should be appropriated, but also the cognitive content, the timing of the activity, and the order in which its elements or concepts are presented.

Learning encompasses the acquisition of concepts, detailed explanations through computational approaches about the cognitive processes involved can be found in works such as those of Anderson [25], Newell [26], Ramirez [27] and Wang [28]. The computer learning processes considered for this work are described in a previous publication of Ramirez and Valdes [29].

In order to personalize learning resources, adaptation is needed, where an adaptation operation requires an object to adapt, a criterion of adaptation and an information source. Each learning technology has different attributes and therefore is subject to different types of adaptation, a list of learning technology adaptations is presented in [30] where among others types, adaptation of order and presentation are described. In this work, the object to be adapted is the learning flow, the criterion is the necessity for the complexity to be ad hoc to the student's abilities, and the information source is a student profile of the student´s knowledge, i.e., the knowledge the student already has. To present the student's knowledge in an orderly computable way, a model for knowledge representation called Memory Map MM [29] was developed. As its name states, MM presents a formal representation of what a student knows pinpointing his concepts and skills, the concepts and skills measured through several evaluation tools that should match the learning objectives of learning activities.

Through these granular concepts and skills a direct mapping can be established between the student profile's concepts and skills, and the activities learning objectives of a given learning flow. Such mapping lets us know what the student knows, and what the learning activity should teach her next. Therefore we can also know what previous concepts or skills are required for a particular student to perform successfully in the learning activity.

There are two possible times for these adaptations: design time and execution time. In the design time, a whole personalized course can be planned for each student in attending to his specific needs. In execution time the learning flow is constantly altered in reaction to his learning profile and his emotional condition, here is where most advantage can be obtained. The real time emotional condition feedback and learning flow adaptation enables new features such as content correction based on emotional condition and learning design based on emotional condition.

Storing the emotional feedback provided by the chair, and comparing it to the timeline of a learning flow, enables a mapping between the emotions and the content, hence correlation and perhaps causality can be established between them, the discovery of new patterns that are hard to observe for long periods of time in a direct way. This can represent a significant advancement for learning design methods.

Personalized learning systems such as Paquette's TELO app [24], could greatly benefit from the incorporation of such technology if we aspire to go beyond course design and into real-time adaptation of a learning environment.

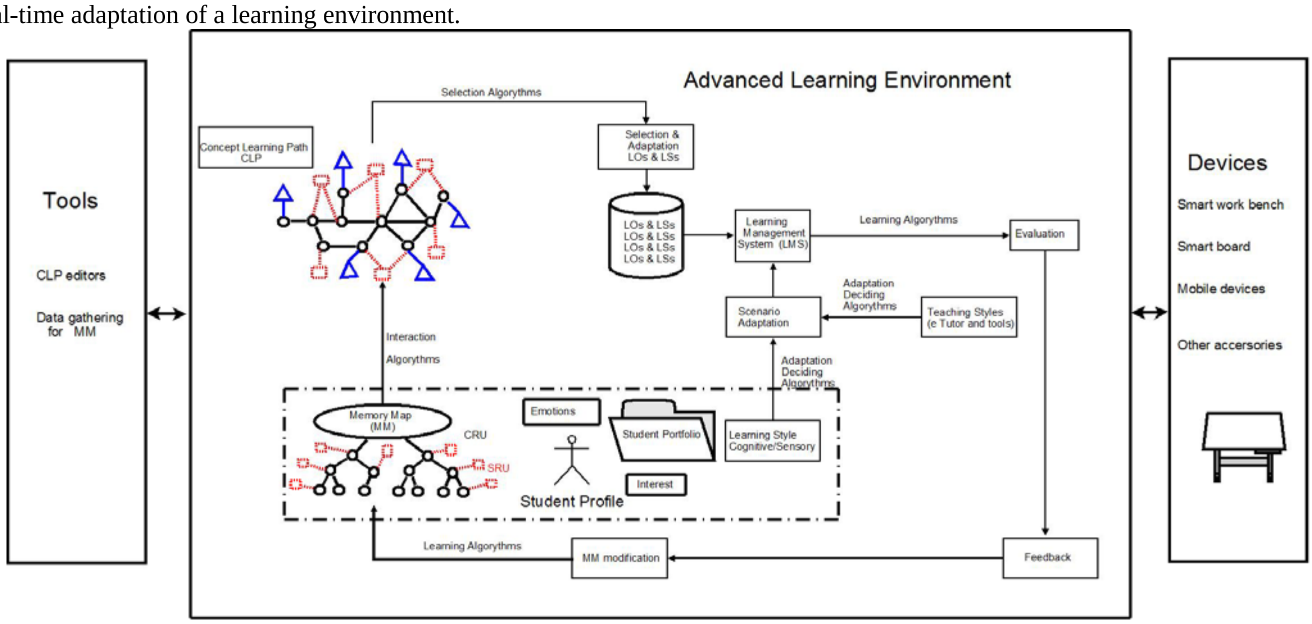

Fig. 6 Adaptive Learning Environment Components.

Assuming an ideal isolated environment, negative emotional conditions can be predicted and avoided through preemptive adaptations. For example, if a student is presented with very advanced content that she is unable to understand, it is probable that she will experience frustration and anxiety; on the other hand, if she is presented with basic content which she already knows, she'll probably experience apathy or boredom. There should be a different adaptation for each case: On the first one, a previous learning activity to develop the required skills before entering the scheduled learning activity should be introduced in her learning flow; on the second one, the learning activity can be skipped or eliminated. A third option in both instances would consist of changing the difficulty level of the activity to better suit the student's current level, if the educational model of instruction or the curricula allows such.

Detection of emotional condition and the according reaction in the learning flow adaptation can also be used to check if a previous adaptation or learning flow structure is adequate. For example, if an emotional condition suggesting frustration is detected in a student while performing an activity, her MM would be checked to verify that she indeed has the required skills for the activity. If it is determined that the content is too advanced, assistance would be provided in the way of an AI tutor or a distress signal could be emitted to her professor.

A. An Advanced Learning Environment

Emotional detection tools, such as the non-invasive sensors equipped chair, and the personalized learning architecture are components of an Advanced Learning Environment (ALE). ALE contains other components as shown in Fig. 6, all of which are designed to work together under a constructivist paradigm. Components interact to create a wide variety of adaptations, e.g., learning personalization in physical, emotional and knowledge context. ALE is a model for a state of the art adaptive classroom, its main components are: the special workbench presented in this paper which additionally to sensing a few emotions, will also has a embedded computer and other accessories; A student's profile containing a record emotional responses, a MM, a record of personal interests, learning style and project evidence encased in an IMS E-portfolio; A Leaning Management System LMS capable of performing real time modifications of the Learning Flow [30]; and personalization algorithms.

V. Conclusion and Future Work

Several theories that relate emotions with learning were reviewed and summarized in Table I. For the recent project, the model proposed by Chaffar and Frasson seems to be adequate in order to establish a framework within the model and the physiological data. However, the concept of flow is important for the research, as it provides a way for inducing the emotions that provide the best way for achieving a high level of learning success.

A system involving two types of non-invasive technology was presented and preliminary tests for establishing a correlation between physiological signals and emotions are being carried out.

The study of the cardiac pulse along with the flow concept presented showed how to detect emotions such as curiosity, boredom, happiness, satisfaction and deception; and their corresponding cognitive processes such as attention, concept construction and idealization, memorization retrieval and objective evaluation.

Further work is required for the integration of both technologies and the processing of the information, e.g., developing an optimum algorithm capable of identifying the current emotional state and relate it to academic content. Other means of detecting physiological signals via non-invasive technology are also desirable, such as face gestures.

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