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A Dual-Modal System that Evaluates User's Emotions in Virtual Learning Environments and Responds Affectively

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Abstract: Endowing learning systems with emotion awareness features (capture user's affective state and provide affective feedback), seems quite promising. This paper describes a system implementation that provides emotion awareness, both explicitly, by self-reporting of emotions through a usable web tool, and implicitly, via sentiment analysis. Prominent theories, models and techniques of emotion, emotion learning, emotion detection and affective feedback are reviewed. We also present findings from our experiment with university students, validating the explicit mechanism in real education settings. Finally, we set open issues for future experimentation, contributing to the research agenda.

Keywords: Emotion, Mood, Affect, Emotion Awareness, Recognition, Reporting, Measurement, Detection, Affective Computing, Feedback, Sentiment Analysis, Opinion Mining, Collaborative Learning, CSCL
Categories: K.3.1, L.1.3, L.1.4, L.2.0, L.3.0, L.3.1, L.3.5, L.3.6, L.6.2

1 Introduction

During the last decade, Computer Supported Collaborative Learning (CSCL) has been established as a fundamental pedagogical approach in learning, underpinned by the rapid advancements attained in Computer Technology and Network Telecommunications. This new trend premises that new knowledge is constructed through social interaction. However, just because an environment makes it

technologically possible, it does not mean that social interaction will take place. Placing students in groups does not guarantee collaboration [Kreijns et al. 03].

Humans are beings with strong emotions emanating from deep instincts of survival with, as well as, against others [Feidakis et al. 12a]. Emotions strongly influence human's behaviour in social conditions and must be seriously considered when forming collaborations. The embodiment of emotional awareness features (sensing and responding to user's emotions) into CSCL environments could offer a more interactive and challenging approach towards the user's authentic social identity and learning experience [Calvo, 09].

Toward this direction, *Affective computing* [Picard 97] is offering a remarkable amount of research studies that evaluate the role of emotions in various learning contexts [Arroyo 09; Calvo 09; D'Mello 08]. These systems detect and recognise students' emotional states with high accuracy using machine learning algorithms, and provide feedback that has positive impact, not only on students' academic performance, but also on their emotional state. Nevertheless, these systems often employ expensive sensors and complex computer intelligence that require special expertise or extra resources, while they introduce obtrusiveness and invasiveness in the learning process. There is a need for developing emotional intelligent learning systems that take into account the availability of resources in a real education context.

This work presents a system implementation based on previous research [Feidakis et al. 12b] that integrates Virtual Learning Environments (VLEs) with emotion awareness features. The proposed system provides both an explicit and implicit way to evaluate user's emotions. By exploiting an easy-to-use and joyful interface, respondents are able to explicitly report their emotional state and mood, unobtrusively and in parallel with their task. The implicit mechanism lies on opinion mining methodology, involving the lexical analysis of text in order to identify words that are predictive of the affective states of writers. These two channels can be coupled to unfold interesting patterns of individual or group emotional behaviour. In response to the user's emotion recognition, an expressive virtual assistant has been implemented to provide users with feedback enriched with empathetic text, expressive faces and synthesized speech scaffolds.

In the current paper we focus on the self-reporting of emotions. The implicit mechanism, although designed, was not implemented in time. In section 2, we review emotion theories and models in general and specifically in learning, emotion detection practices with respect to time factor and affective feedback strategies. In section 3, we present our system analysis and design together with the applied emotion model. The implemented system, *emot-control* is also described in detail. In section 4, we present a research study, in which emot-control has been customised for Moodle 2 and used, validated and evaluated by University students in the context of a semester course. Finally in section 5, we summarize the key aspects of the paper and set our future steps together with calls for further research.

2 Theory and Background

2.1 Emotion Research

Despite the few attempts to understand and define *emotion*, *feeling, affect* or *mood*, scientists are still lacking from a widely acceptable definition. *Emotion* "is usually an intense experience of short duration - seconds to minutes - and the person is typically well aware of it" [Zimmermann 08, p. 47]. *Affect* is "a synthesis of all likely effects of emotion" [Davou 00, p.125]. *Feeling* "may have various levels of intensity, and its duration depends on the length of time that the representation of the object remains active in the mind of the individual" [Davou 07, p.5]. *Mood* tends to be "subtler, longer lasting, less intensive, more in the background, giving the affective state of a person a tendency in positive or negative direction" [Zimmermann 08, p. 48].

There are two different approaches usually followed in emotion research: the *information processing* and the *interactionist* [Calvo et al. 09]. The *information processing* approach treats emotion as an entity similar to information that is communicated from one person to another. Models and theories that fall into this category use a label approach with a limited set of categories, either pictorial or verbal, for users to identify their emotions. On the other hand, [Boehner et al. 07] posit an *interactional approach* that sees emotion as constructed through interaction and expression. They focus on emotion as a social and cultural product, not as a measurable, biological fact. In fact, they skip the emotion recognition process; the translation of input and output signals to specific emotion information. Success of such a system is measured by whether users find the system's responses useful for interpreting, reflecting on, and experiencing their emotions.

With regards to emotion as an information, [Scherer 05] has distinguished three major schools in emotion research: the *basic emotion* (patterns are equivalent to basic emotions that can be easily recognised universally e.g. fear, love, anger, happiness), the *emotion dimension* (quantifies emotion using various dimensions, e.g., arousal, valence, intensity etc.), and the *eclectic approach* (use of verbal labels that seem appropriate to the aims of a particular study e.g. academic emotions).

Darwin was perhaps the first to systematically identify and categorize a comprehensive range of basic emotions in connection to the primitive instincts of survival [Darwin 1872]. His classification included over thirty different emotions that were further categorized into seven groups, clustering similar emotions together [O' Regan 2003].

Ever since, most researchers on emotions agree on the existence of two types of human emotions: *Primary* and *Secondary*. *Primary* emotions are evoked by a stimulus, e.g., fear in sudden noise. *Secondary* or social emotions such as embarrassment, jealousy, guilt, pride are those that arise later in an individual's development when systematic connections are identified between primary emotions and categories of objects and situations [Damasio 94].

In their Facial Action Coding System (FACS), [Ekman and Friesen 78] classified six basic emotions (anger, disgust, fear, joy, sadness, and surprise) based on their mapping to facial expressions. If we recall from our experience, an angry or happy face can be easily recognized in contrast to love or compassion that are hardly inferred by human facial expressions. The existence of universal expressions for some emotions has been interpreted as an indication that these six emotions are basic in the

sense that they are innate, overcoming cross-cultural boundaries [Calvo and D'Mello 10].

[Ortony et al. 88] have proposed 5 basic (anger, fear, happiness, joy, love) and 14 secondary emotions, in their *OCC* (Ortony, Clore, and Collins) model. They view emotions as reactions to situational appraisals of events, actors, and objects. [Plutchik 01] created a wheel of emotions that consisted of 8 basic emotions arranged as four pairs of opposites (joy-sadness, trust-distrust, fear-anger, surprise-anticipation), and 8 advanced emotions each composed of 2 basic ones.

[Parrot 01] enriched the above classifications adding a third type. He used a tree structured list with three layers, namely primary (love, joy, surprise, anger, sadness, and fear), secondary or feelings (e.g., affection, pride, irritation, suffering, horror, et al.) and tertiary (e.g., desire, relief, annoyance, depression, shock, et al.).

In a different approach, [Russell 80] has suggested a *circumplex model of affect* deploying *valence* and *arousal* dimensions instead of emotion labels, projecting user's affective state in a two-dimension emotional space. Russell's model offers a solution towards the quantification of emotions according to the different dimension or variables adopted each time. [Hascher 10] has referred to several indicators identifying the quality of an emotion that are often used to quantify emotions:

- Arousal (deactivating/activating)
- Valence (negative/positive)
- Intensity (low–intense)
- Duration (short–long)
- Frequency of its occurrence (seldom–frequent)
- Time (retrospective like relief, actual like enjoyment, prospective like hope).

[Schutz et al. 09] differentiate emotions as *state* (situation specific) versus *trait* (apply to a broader context*)* that follow three different forms:

- Core affect (moods like feeling blue),
- Emotional episodes (state emotions like sadness), and
- Affective tendencies (trait emotions like being depressed).

2.2 Emotion Learning

In literature, "emotion learning" and "emotion in learning", although quite common, they usually point to different directions.

Emotion learning usually refers to the flourishing of social and emotional competencies (*emotional awareness, empathy, self-efficiency, self-motivation)* and is mainly ascribed by the term *emotion intelligence* (EQ). The early emotional intelligence theory was originally developed during the 1970s and 80s by the work and writings of psychologists Howard Gardner, Peter Salovey and John Mayer. In his homonymous book, [Goleman 95] presents convincing evidence that the emotional intelligence quotient (EQ) is just as important in academic success as cognitive intelligence that is measured by the Intelligence Quotient (IQ) or SAT scores.

In the last three decades, there have been hundreds of school-based programs that have been developed to assist people in gaining control of their emotions. These programs are better classified under the more general label *Social and Emotional*

Learning-SEL (e.g. *PATHs*[1], *Resolving Conflict Creatively*[2], *Self Science*[3], *6Seconds*[4]). Their main objective is to establish effective social and emotional learning as an essential part of education from preschool through high school. And in spite of the pedagogical progress that has been attained in SEL, there are no experimentally adequate CSCL applications that exploit SEL practices to foster students' EQ [Feidakis et al. 11a].

From another point of view, research studies do not interpret *emotion learning* as enhancing one's emotional competences, but as "*learning that considers and shows respect to learner's emotions*". Learning environments that fall into this category, are equipped with special tools that capture student emotions and based on emotion theory and experience take appropriate actions that provide the learner with cognitive or emotional scaffolds [Arroyo 09; D'Mello 09; Woolf et al. 07] in an attempt more to improve his/her academic performance and less to support them emotionally.

In general, there are no adequate empirically proven strategies to address the presence of emotions in learning [Hascher 10]. Theoretical background has been built upon theoretical foundations of pedagogy and recommendations made by pedagogical experts [D' Mello et al. 08]. And despite the evidence of the positive effects of positive mood and emotions, there are no clear rules such as: positive emotions foster learning, and negative emotions are detrimental [Hascher 10].

For almost two decades, Pekrun and his team examined the impact of the so-called academic emotions [Pekrun 92; Pekrun et al. 11 - see Table 1]. According to their findings, positive mood fosters holistic, creative ways of thinking. Harmful effects can only be expected in situations, where students are in a good mood and the learning topics are of less importance to them. In this case, the positive emotion might detach them from learning [Hascher 10].

	Valence	
Activation	**Positive**	**Negative**
Activating	Enjoyment	Anxiety
	Pride	Anger
	Hope	Shame/Fault
Deactivating	Relief	Boredom
		Hopelessness

Table 1: Academic emotions [Pekrun et al. 11]

In their *Learning Cycle* model, [Kort et al. 01] have suggested six possible emotion axes (anxiety-confidence, ennui-fascination, frustration-euphoria, dispirited-enthusiasm, terror-excitement, humiliated-proud) that may arise in the course of learning together with a four quadrant model, relating phases of learning to emotions [Figure 1]. "A typical learning experience involves a range of emotions, cycling

[1] http://www.prevention.psu.edu/projects/paths.html

[2] http://www.ncrel.org/sdrs/areas/issues/envrnmnt/drugfree/sa2lk16.htm

[3] http:/www.selfscience.net

[4] http://www.6seconds.org/

students around this four quadrant cognitive-emotive space as they learn. It is important to recognize that a range of emotions occurs naturally in a real learning process, and it is not simply the case that the positive emotions are the good ones. The negative half is an inevitable part of the learning cycle. Our aim is to help students to keep orbiting the loop, teaching them to propel themselves, especially after a setback." (p.3-4)

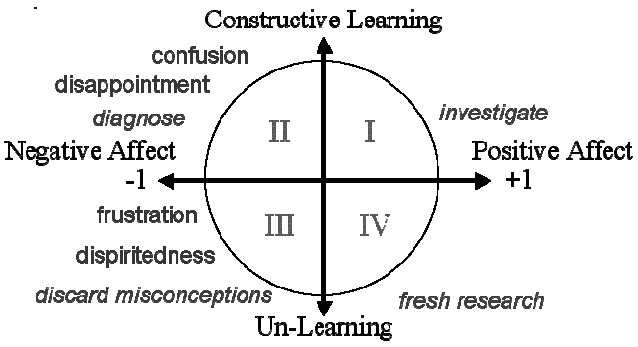

Figure 1: Learning Cycle Model [Kort et al. 01, p.3]

2.3 Emotion Detection

In line with the above emotion theories, a variety of tools and methods has been developed to capture user's emotions. In the paragraphs that follow, we review different tools and methods used to capture the respondent's emotions. In our analysis we adopted the following criteria [Feidakis et al.11b]:

- *Objectiveness*: Relates to the degree of consciousness when an emotion is experienced i.e. physiological emotion signals are considered more objective than self-reporting that is based on user's subjective experience.
- *Obtrusiveness*: User's experience of the medium i.e. sensors that are attached in the human body (EMG or EOG) have been reported as obtrusive. Emoticons or animations constitute a more student-friendly way to express emotions.
- *Invasiveness*: Realistic use in education setting, i.e. the standard PC equipment (webcams for recording facial expressions, measuring keyboard pressure or mouse clicks from log files) considered non-invasive in contrast with the use of extra equipment (professional cameras or artificial labs) or long questionnaires for self-report.
- *Task relevance*: Measurement is applied in parallel with user's task (real-time) without interrupting the learning process. Task irrelevance is the main flaw of self-reporting.
- *Cost* of possible special equipment.
- *Special expertise* to run the equipment
- *Universality*: Text and speech interfaces are tied to language and cultural barriers.

The tools found in the literature to capture the user's emotion signals or affective state can be grouped into three areas [Feidakis et al.11b]: *Bio-physiological, Motor-Behavioural* and *Self-Report*:

- *Self-Report* (1st person, subjective report using verbal or pictorial scales or questionnaires, etc.)
- *Bio-physiological* (use of sensors to capture biometric signals e.g., electromyogram-EMG, electrodermal activity-EDA, electrocardiogram-EKG or ECG, electrooculogram-EOG, blood volume pulse-BVP, etc.)
- *Motor-Behavioural* (observation or capturing of motor-behavioural activity e.g., facial expressions, voice intonation, body posture, sentiment analysis of text input, mouse and keyboard logs etc.)

There is not a concrete measurement tool that fully qualifies all these design requirements. Sensors are more precise but cost more money and time. Self-reporting on the other hand is free of charge but often subjective and out of context. Multimodal integration (combination of the three methods) seems the only way to provide scientifically adequate emotion detection.

A fundamental criterion to select the appropriate detection method is the *availability of resources.* Most computers on a lab or portable devices are equipped with a camera that can be used for facial expression recognition. Text is also an important modality for sensing emotion because the majority of computer user interfaces today are textually-based [Valitutti et al. 2004].

Self-reporting is the only way to measure user's subjective feelings, although users are often reluctant to disclose their inner feelings to researchers in order to avoid embarrassment [Wong 06]. These tools originate from Clinical Psychology and employ verbal and non-verbal descriptions of emotions. Usually, they are cost-free or inexpensive.

Self-reporting is considered intrusive, usually interrupting the learning process. However, the use of non-verbal interfaces that employ short and less time-consuming answers can obtain *brevity* in response, minimizing the disruption of associated task performance. For instance, emoticons and mannequins are student-friendly and used quite often to add emotion information in posts. Unfortunately, the number of labelling tools that can be easily customised is still limited, i.e. Self-Assessment Manikin-SAM [Lang 80], Geneva Emotion Wheel [Scherer 05], AffectButton [Broekensm and Brinkman 09], GTrace [Cowie and McKeown 10].

With regard to text input, automatically mining the opinion or emotions expressed in a text is a complicated Natural Language Processing (NPL) task, one for which a range of strategies rooted in different approaches have been used. One type of strategy is based on information recovery techniques [Read 04; Turney, 02], which firstly identify a text's polarity and then its affective content. Such techniques are used to recover texts discerningly, based on their polarity.

A second strategy type uses supervised learning and classification techniques, such as support vector machines [Corina and Vapnik 05] or latent semantic analysis [Deerwester et al. 90], to develop statistical models for classifying texts according to emotions [Leshed and Kaye 06]. The drawback to supervised learning is that relatively large quantities of manually tagged samples are required for model development [Caballé et al. 09].

A third type of strategy is based on the use of an affective dictionary that contains words with a significant element of emotion in the language under analysis. These words may act as 'triggers' for expressions of emotion. The recovery of such expressions of emotion can be enhanced using lexico-semantic resources like WordNet [Miller et al. 90] and multilingual linguistic resources like FreeLing [Carreras et al. 04].

2.4 Time points

The user's affective state can be evaluated into three time points [Feidakis et al. 12b]:

- *Before the task*: We are interested in the respondent's mood and disposition before accomplishing a specific learning task. Positive mood fosters holistic, creative ways of thinking [Pekrun et al. 11]. On the other hand, negative mood create a pessimistic perceptual attitude, diverting the learner's attention to aspects irrelevant to the task, activating intrusive thoughts that give priority to a concern for a well-being rather than for learning [Boekaerts 93]. Groups and roles in subsequent collaborative tasks can be based on the prospective assessment of the respondents' affective state.
- *In parallel with the task*: The respondent's affective state is monitored together with his/her learning performance. Physiological or behavioural methods or non-verbal self-reporting can be applied to measure user's emotions without interrupting the learning flow.
- *After the task*: Retrospective emotion measurement refers to the evaluation of the respondent's affective state right after the task (i.e. after a quiz or test) or in deferred time. The latter is aiming at annotating past sessions (e.g. forums, chats etc.) with emotion information by exploiting *observation* (i.e. observe motor-behaviour signals in video files or images) or *sentiment analysis & opinion mining* techniques (classify posts based on their affective content).

2.5 Affective Feedback

Once the learner's affective state is detected or recognised, next step is what to do with this valuable information. The user needs to see some interaction from the system that corresponds to his/her feelings.

Affective feedback design is aiming at sending appropriate affective or cognitive scaffolds to the user, in response to their affective state detection, ensuring their emotional safety and their engagement in the learning process. Computer mediated affective feedback strategies are classified in *parallel-empathetic* (exhibit an emotion similar to that of the target), *reactive- empathetic* (focus on the target's affective state, in addition to his/her situation) or *task-based* (supplementary to empathetic strategies) [Robison et al. 09]. Common tools include dialogue moves (hints, prompts, assertions, and summaries), immersive simulations or serious games, facial expressions and speech modulations, images, imagery, cartoon avatars, caricatures or short video-audio clips [D'Mello et al. 08; D' Mello et al. 09; Robison et al. 09].

Unfortunately, there are few studies that exploit computer mediated affective feedback strategies, and their impact on users' task performance or affective state.

Furthermore, the number of tools and strategies to design expressive avatars in response to learner's emotion detection is quite limited. [Fabri 06] has found that emotional expressiveness in avatars increases involvement in the interaction between users in Virtual Collaborative Environments (VCEs), as well as their sense of being together. This has a positive effect on their subjective experience.

In *AutoTutor* [D' Mello et al. 09] the authors have used a variety of heuristic policies to respond to student's emotion. Instructional feedback is varied according to type (explanation, hints, or worked examples) and timing (immediately following an answer or after some elapsed time). The affective tutor's responses to student affect are produced based on a table of affective responses e.g. when frustration is detected: (1) *Empathetic response*: "That was frustrating. Let's move to something easier" (2) *Give students control:* "Would you like to choose the next problem? What kind would you like?"

[Woolf et al. 07] developed an agent tutor that personalises the choice of hint type for individual students based on their cognitive profile, gender, spatial ability, and math fact retrieval speed. They used a variety of heuristic policies to respond to student's emotion and they measured how feedback variables interact to promote learning in context (characteristics of the learner, aspects of the task). [Wang et al. 08] implemented a model of "socially intelligent tutoring" that achieved significant learning improvements, based on politeness theory in an online learning system.

[Robison et al. 09] report on the results of two studies that were conducted with students interacting with affect-informed virtual agents, evaluating somehow the agents' response to both positive and negative affective states. They support that positive emotions (flow, delight, boredom) appear to be particularly susceptible to the quality of feedback given. On the contrary, for particularly negative emotions such as frustration, the risk of inappropriate delivery is not large enough to warrant extreme caution when providing responses. Nevertheless, we can never be entirely certain that the dynamic affect-adaptive tutoring systems are delivering useful affective feedback. "There will always be some risk of unintentional negative consequences when attempting to intervene to modify student affect" [Robison et al. 09, p.5].

3 System Design

In line with the design issues, methods and tools mentioned in the previous section, we have designed an emotion aware system that is able to detect students' emotions, implicitly (sentiment analysis) and explicitly(self-reporting), and based on fusion logic, it produces affective responses using a virtual affective agent.

3.1 Emotion Model

Our first design requirement, "*what* we want to measure," necessitates the specification of the emotions of interest, in e-learning context. Much of the research on basic emotions is of little relevance to the developers of computer learning environments [Calvo and D'Mello 10], which focus more on learning-centred emotions such as *confusion*, *frustration*, *boredom*, *flow*, *curiosity*, and *anxiety*.

Academic emotions *(enjoyment, anxiety, pride, anger, hope, shame/fault, relief, boredom, hopelessness*) [Pekrun et al. 11] provide a starting point. A reasonable

argument would be if *boredom* or *relief* corresponds to the definition of emotion that was set in our paragraph 2.1. *Anger, anxiety, shame/fault* are considered emotions, while *boredom* and *enjoyment* are better understood as *states*. *Pride* and *hope* are not easily reported in e-learning situations.

The *Learning Cycle* [Kort et al. 01] provides more options together with an escalation in intense. The *cycle* form offers a nice metaphor highlighting that positive emotions are not the good ones and the negative half, is only a part of the cycle. Students must learn to keep orbiting the loop, and come up again after a setback. Russell's *Circumplex Model of Affect* (1980) offers a solution towards the quantification of emotions, suitable for statistical measurements. Again, emotion labels like *afraid* or *miserable* are not easily met in e-learning situations.

In our model, we have tried to provide both a rich-informative way for emotion expression and an interactive way for mood report. We have deployed a two-dimension emotion space defined by the emotion dimensions of *valence* (negative/positive, x-axe) and *activation* (deactivate/ activate, y-axe), evaluating 14 emotional states (*inspired, excited, interested, relaxed, curious, confused, anxious, embarrassed, indifferent, bored, tired, angry, desperate, neutral* – the *neutral* state is to initialize or reset the system) that represent different values in the *valence* and *activation* axes. Mood is measured in 5-likert scale (*sad, unhappy, neutral, happy, very happy*).

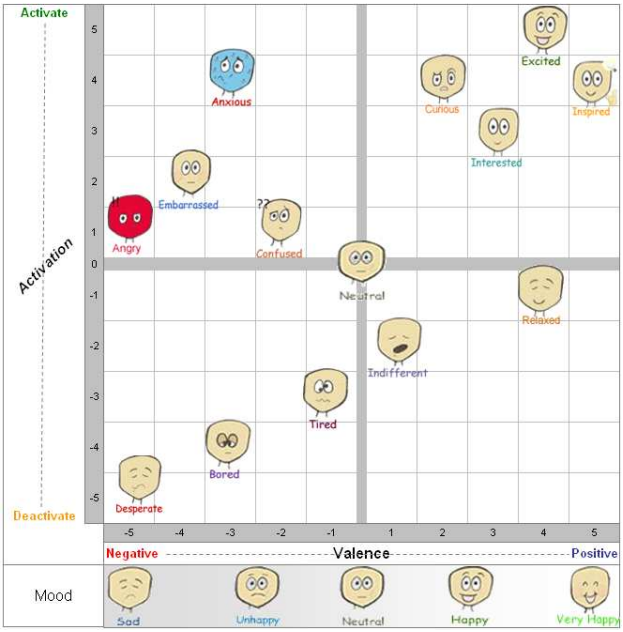

Figure 2: Emotion model

The position of each emotion on the two axes derives from Russell's model [Russell 80], as well as, our preliminary experimentation [Feidakis et al. 12a, Feidakis et al. 12b]. It is not standard but only indicative of the place of the respective emotion

label in relevance to the valence and activation dimensions, as well as the other emotions. For instance, curiosity is considered the same activating emotion as anxiety, but of the opposite valence. Hence, curiosity is more possible to transit to excitement while anxiety to anger.

This model constitutes an updated version of the model described in [Feidakis et al 12a]. Our main objective is to evaluate the proposed model into e-learning and CSCL tasks and mine for possible affective sequences and patterns that lead to increased task performance and fruitful collaborations, through time (i.e. per day, per time, per task phases). Certainly, the proposed models constitute a first attempt to encompass human emotions, with respect to learning. However, it is difficult to set the district lines among different emotion labels that pervade real life. It is our ambition to test and inform our model with findings from experimentation in real education settings, enriched by the exchange of empirical data among expert teachers, in which trends and beliefs considering students' emotions will be evaluated.

3.2 Emotion Report

For our experiments, we have designed and implemented an emotion reporting tool: the *Emot-control* ("emot" is the latin root of the word "emotion" and means "moving away"). *Emot-control* is a cross-platform, language-free, open-source tool that has been programmed in PHP-JavaScript-MySQL. We have used special, coloured emot-buttons with appropriate labels to project specific emotions, based on existed emot-icons and using emotion colours [Feidakis et al. 12b]. Additional text boxes have been provided for respondents to report other emotions than the default ones.

So far, we have experimented on different interfaces, evaluating usability in emotion reporting [Figures 3-6], customising the control to satisfy different requirements (front-end or back-end integration, communicating with MySQL or through JSON services, use of text labels or not, etc.). In version 3, emot-control has adopted the shape of a spiked circle, in accordance with the *Learning Cycle* [Kort et al. 01] and the *Geneva Emotion Wheel* [Scherer 05], giving the impression of an emotion circle, involving a range of emotions that usually appear in a learning experience. In our last version 4 [Figure 6], the emotion label "*Embarrassed*" was replaced by "*Tired"*, due to infrequent reports after experimenting in real CSCL settings. Moreover, by removing the text from images, the emot-control became more language-free so that it can be easily translated in different languages (currently it supports English, Greek and Catalan). For the mood report, we developed a more interactive interface in which different mood selection corresponds to different emot-control background colour, in analogy with the background role that mood plays toward emotions.

3.3 Sentiment Analysis

For the implicit emotion detection, we have designed a system that automatically detects fragments of text in which an opinion or sentiment on a given matter is expressed. The system focuses on detecting opinions and sentiments of user text inputs in CSCL tasks (i.e. forums, wikis).

The system has been designed to support multiple languages; Spanish, Catalan and Greek are the basic. A lack of appropriate Spanish, Catalan and Greek sample

texts with manually tagged expressions of emotion, ruled out the development of models based on supervised learning. Since, we have been unable to find a suitable affective dictionary for opinion mining purposes, we created a new one for Spanish and Catalan languages. We have manually compiled a dictionary of lexical triggers of expressions of emotion, i.e. a list of lemmas based on verbs, nouns and adjectives commonly used when expressing opinions, such as *creo* ('I think' in Spanish), *mejor* ('better') or *entiendo* ('understand'). Precision and coverage are factors that must be taken into consideration in relation to manually compiling such a resource.

The method offers a very high level of precision, as the dictionary only contains words with a substantial element of opinion carefully chosen by a group of knowledge experts, after a thorough study of the messages interchanged by students in a Computer Science Master during two semesters. As the dictionary coverage is limited because its words have been compiled manually, we expanded the dictionary through the use of lexico-semantic knowledge, such as WordNet [Miller et al. 90], and multilingual linguistic resources, such as FreeLing [Carreras et al. 04].

The expansion of the dictionary terms is done following three steps:

1. Synonymy extension: the system uses each entry's lemma and grammatical category to generate a list of associated synonyms on the basis of WordNet. For example, in the case of the trigger *sentir#v*[5], which denotes the Spanish verb meaning 'to feel', there are 11 possible synonyms that can be used to extend the list of triggers as follows:
   entir#v | *saber#v* | *sentirse#v* | *considerar#v* | *encontrar#v* | *creer#v* | *deplorar#v* | *lamentar#v* | *experimentar#v* | *arrepentirse#v* | *percibir#v* | *notar#v*
2. Superordination extension: when necessary the system may use superordination relationships from Wordnet to enhance the coverage. Superordination allows for defining that one word has a generic meaning in relation to one or more words with a specific meaning. For example, the word *seat* is the superordinate of chair, armchair and stool. In the case of the trigger *sentir#v*, the following list of triggers may be automatically generated:
   considerar#v | *creer#v* | *pensar#v* | *juzgar#v* | *opinar#v* | *concluir#v* | *lamentarse#v* | *quejarse#v* | *declinar#v* | *rehusar#v* | *conseguir#v* | *obtener#v (etc.)*
3. Lema expansion: Once the dictionary terms have been expanded with synonymy and supordination, FreeLing will be used to enable the system to detect, not only the lemmas in our affective dictionary, but also every form of those lemmas appearing in messages. For example, the forms *siento*, *sientes*, *siente*, *sentimos*, *sentís*, *sienten*, *sentid*, *sentida*, *sentidas*, *sentimos*, *sentiremos*, *sentirá*, *sentirán*, *sentirás*, *sentiré*, *sentiréis*, *sentiré*, etc., are generated on the basis of the entry *sentir#v* in our affective dictionary. Similar resources to FreeLing will be used when implementing the prototype to deal with Greek language due to the fact that FreeLing only deals with English, Catalan, Spanish, Portuguese, Italian, Russian, Galician, Asturian and Welsh.

After the dictionary terms have been expanded, the expanded lists of terms will be searched within the students' messages in order to find out the opinions and

[5] The terms of the affective dictionary follow the format lemma#grammatical category.

sentiments the messages deal with. Then the opinions/sentiments detected are stored to be able to support automatic processes that take into account student opinions/sentiments and the words within the messages that denote opinions or emotions are tagged in order to facilitate the navigation thru messages driven by emotions.

At this stage of the prototype the system aims to detect the sentiments and opinions expressed and the fragments of text where they are expressed. In order to do so, a relation has been created between each of the dictionary words and the emotion they mainly represent. Then, each word in the affective dictionary is related to one and only one emotion, generating a set of disjoint keywords for each emotion. We say that an emotion is expressed in a given text if the text contains any of the keywords (or their expansion) related to the emotion. Since no strength has been defined for each triggering word, the strength of an emotion within a text is calculated as the number of words related with the emotion appearing in the text.

3.4 Affective feedback

We have developed an animated virtual agent assistant that employ dialogue moves and provide feedback to the user, by exploiting an online *Responsive Face*[6]. The agent uses speech synthesis and based on the user's input, responds in an empathetic way, according to a fuzzy table. The agent is displayed embedded in the emot-control block, using a JavaScript player to avoid frequent browser problems with embedded media.

Depending on the emotion reported, the agent employs emotional scaffolds in an attempt to commence a dialogue with the student (Table 2) adopting a *parallel*, *reactive* or *task-based* strategy each time (refer to paragraph 2.5). In this phase, we provide feedback manually, developing affective sequences in an attempt to build a data set that will produce input for machine learning in the future. We opt to explore and validate sequences that have a positive impact both on students' task performance and affective state, adopting first a qualitative and then quantitative analysis.

Respondent's Emotion	**Agent's text response (1st iteration)**	**Agent's animated expression**
Inspired	Well done! You are doing great… What is this that inspires you?	Excitement (reactive)
Confused	Mmm! It is getting confusing... Can I help in something?	Compassion (parallel, task-based)
Bored	Maybe you need a break before continue to the next scene...	Thoughtful (parallel)
Indifferent	*(whistling indifferently)* Hey! I think that you are not with us... Why don't you try a bit more? Do you need help?	Humorous-annoyed (reactive, task-based)

Table 2: Affective Assistant's sample responses

[6] http://mrl.nyu.edu/~perlin/facedemo/

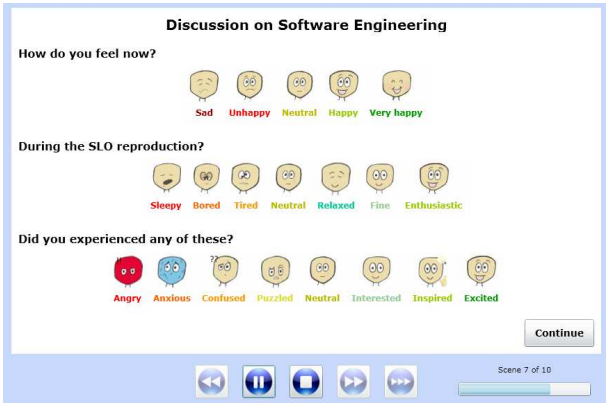

Figure 3: Emotion report interface using combinational questions [Feidakis et al. 12b]

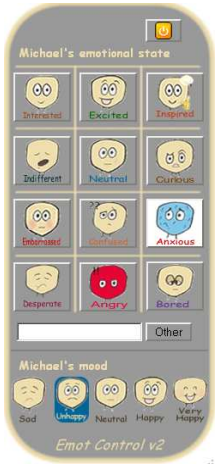

Figure 4: Emot-control v2 is a popup window, in resemblance to a TV remote control.

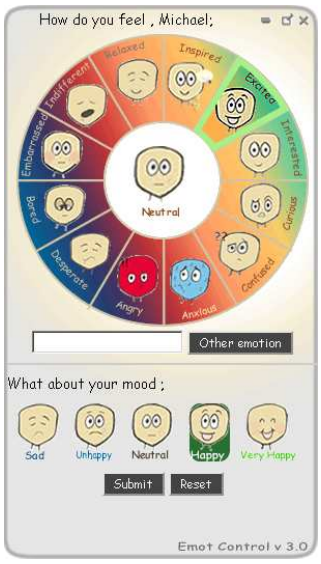

Figure 5: Emot-control v3.0 adopts the form of a spiked circle

Figure 6: Emot-control v4 has no text labels to overcome language barriers. Background colours change depending on mood selection

4 Research study

4.1 Description

In order to validate our *emot-control* system, we have conducted an experiment with 112 University students (adult male-female) in the Department of Cultural Technology and Communication, University of Aegean, Greece. The experiment took place in the context of a semester course, entitled "Intercultural Communication" for 3 months (Oct 16, 2012 – Jan 14, 2013). The participants worked in 28 groups of 4 members to carry out 4 online collaborative assignments (each one including a Wiki elaboration as well as forum and/or chat discussions). The first 3 assignments lasted 2 weeks and the fourth one four weeks. Moodle v2.3 served as the learning environment and *blended learning* as the learning method with weekly face-to-face meetings.

For the specific experiment, the emot-control was customised for Moodle to open as a popup window by clicking on a right-top button that was displayed in every course page. The participants were able to select one out of 13 emotional states (the state *embarrassed* was excluded*)* and one out of 5 moods, at any time they wanted, by simply clicking on an image-button at the top-right corner of each Moodle course page. Their selected affective state was displayed in the initial emot-control block, inside the specific button, with background depending on the selected mood [Figure 7]. Additionally, they could report an emotion other than the default ones or to expound their emotion selection by writing in a small text box. The participants could also monitor their group-members' emotions [Figure 8], while the tutor could monitor all emotional information per group, student, date and time, emotion and/or mood.

Based on the emotion information submitted, an animated avatar, the *Affective Assistant,* provided user with affective feedback [Figure 7, Table 2], provoking sometimes the student to ask for additional help by tying his/her message in the respective text box. The student's message was stored in a helpdesk system that informed both the tutor and the support team by email. Within the day, the assistant provided the respective feedback to the student (tips, additional material, web links, etc).

The emot-control was also customised for the Moodle chat module, allowing for participants to express their emotions virtually, while they were chatting online. The user could also see the other participants' emotional state and mood [Figure 9]. Our objective was to monitor emotional sequences of users while chatting online as well as to measure the impact of emotion awareness (self and other emotions), in the chat.

In this experiment, the implicit emotion-detection mechanism was not validated, as we have been unable to find a suitable affective dictionary for opinion mining purposes for Greek language (the creation of a Greek affective lexicon is ongoing work).

4.2 Methodology

Our experiment was divided into a *control group* study which was carried out during the first two assignments. In this study, students were urged to use "emot-control", but we did not oblige them, so their participation in expressing their feelings was free and optional. Students could express their emotions any time, but no feedback (of any type) was given to them.

Moreover, in the first assignment, group members communicated via asynchronous communication. In the second assignment, we set up a chat for each group aiming at involving each group in a specific discussion/debate as a collaborative learning in-class activity. Again we did not "oblige" students to express their emotions during the debate. They could do it voluntarily, if they wanted, through the "emot-control".

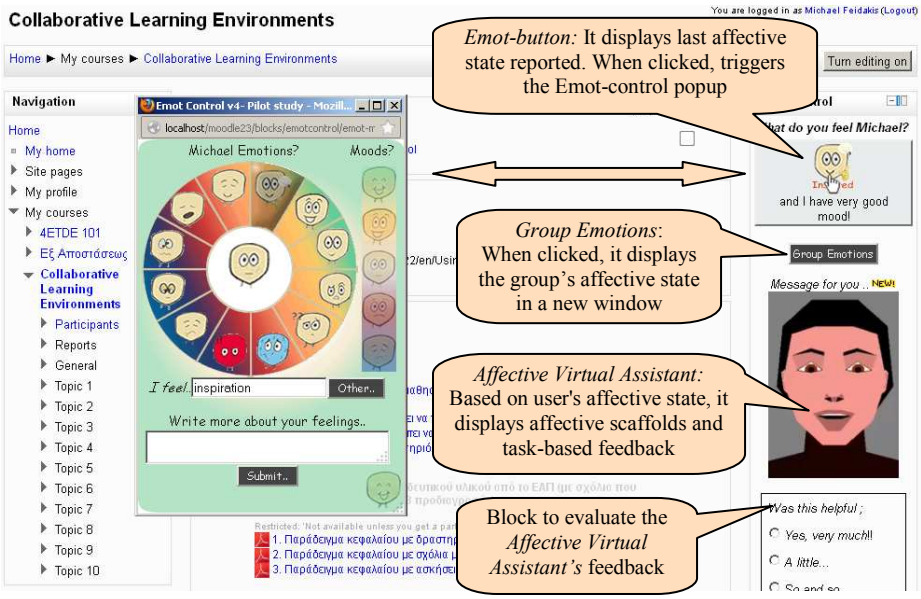

Figure 7: Screenshot displaying the emot-control block, emot-button and the affective virtual assistant in Moodle 2

Emotions of Group 149 members

ct09078 - Sevasti Koullia			
Date	Time	Emotion	Mood
13/03/2013	00:26:19	Tired	Moderate..
29/03/2013	00:26:30	Anxious	Bad..

ct09016 - Evangelia Vergaki			
Date	Time	Emotion	Mood
03/03/2013	17:51:45	Excited	Moderate..
06/03/2013	16:11:44	Interested	Moderate..
06/04/2013	20:30:49	Excited	Excellent!!

ct09154 - Antonios-Nektarios Stravatzakis			
Date	Time	Emotion	Mood
02/04/2013	03:22:24	Excited	Good!
03/03/2013	17:51:31	Excited	Good!
05/03/2013	13:22:23	Excited	Good!

Figure 8: Monitor of group member's emotions

An *experimental group* study was designed in the third and fourth assignments. The most important aspects that make this study different are the following:

1. We let the students know that if they express their emotions this will provide them with very useful feedback that will reward them with options to overcome learning difficulties and thus improve their learning experience.
2. We provided the students with affective feedback of different type:
    a. Direct emotional scaffolds, parallel or reactive empathetic (see Table 2).
    b. Task-based feedback, aiming at student mood by offering assistance related to the task, i.e. helping a frustrated student with the task, e.g., by offering her an easier task to do, or giving her a hint, or asking her to explain her problem and helping her to solve it.
3. Group discussions (forums or chats) are directly supported by the "emot-control", since the application is coupled within the chat/forum, so students can easily use it to express their emotions during the debate (and possibly get immediate feedback).
4. In addition, the emot-control system provided the functionality of group emotion awareness so that each group member could be aware of the emotions of their peers at any time.

At the end of the two experiments, we carried out a comparative study to see the possible advantages gained by the experimental group vs. the control group as regards certain indicators, such as students' behavior, usefulness and individual/group performance. Additional measurements were taken through a questionnaire considering the look-and-feel of the emot-control, its usage, usability and expressiveness.

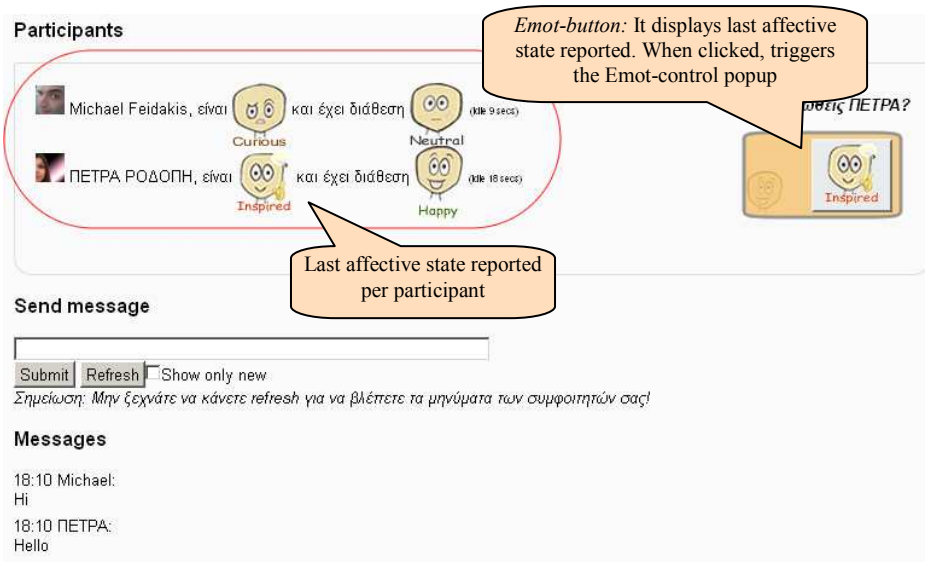

Figure 9: Emot-control in Moodle chat

4.3 Discussion of results

Regarding *usage*, the emot-control was popular as 62 out of 92 (67,4%) active students chose to use emot-control submitting up to 713 emotion reports, regardless of the study. So, in both studies students were willing to participate and express their emotions, since the emot-control provided an easy way for them to do it. Similarly, the emot-control scored very high in *usability* (52% responded "Very usable" and 30% "usable") and high in *expressiveness* (when students were asked whether emot-control expressed their emotions, 36.5% responded "always" and 50% "very often").

At the end of the *control group* study we obtained the following results as regards students' behavior, usefulness and individual/group task performance:

- Members of groups 7, 17 and 27 showed a negative behavior and task performance. In fact they worked very poorly, whereas their emotions reported values such "Desperate", "Anxious" and "Angry". They found no real usefulness in the emot-control.
- Two groups (10 and 21) lost two members each, so they had to be merged in one group (10) for the next phase of the experiment. Here, the four members who abandoned their groups showed a negative behavior and performance, and just one of these members reported a "Desperate" emotion. Their abandonment indicated that the emot-control was not useful for them.
- In group 18, one member (MA1), expressed "Anger" and her willingness to leave her group after the end of the first assignment. Her behavior was very negative towards the rest of her group members. This situation also influenced her performance in the task negatively. However, the emot-control proved to be useful in her case, since instead of dropping out of the course, she preferred to move to another group (9) which had lost one of its members.

In general the results we obtained from the *control group* study showed that when students' behavior was very negative, it did not change easily; instead, it conducted to insufficient performance and in several cases to course drop out. The emot-control did not prove to be useful for the most of the cases.

As concerns the *experimental group* study, during the third assignment, where affective feedback was used, several member problems were managed successfully. The *affective assistant* interfered in 7 cases where students reported *frustration* and managed to provide task-based assistance by exploiting up to 3 dialogue moves. In 2 cases, she encouraged *tired* respondents not to abandon but better take a break, take a nap and come back later, offering to play a humorous lullaby. Other interferences included playing a relaxing song for a student that reported "angry" for long time (the specific student thanked the *assistant* for the nice song) or directing "bored" and "sad" students in a nice, music, online game. According to students' responses in the questionnaire, the *affective assistant* managed to give the impression that "*someone was caring about me"* and became familiar to the students who started a dialogue with her.

In five specific cases we noticed a conflict in groups 9 and 25, disagreements in group 10 and unequal contributions in groups 2 and 6. Affective feedback managed to relax anxious members, make them reflect upon the current group situation and take positive decisions. For instance, active members of the groups 9, 25 and 10 expressed

their wish to move to other groups in order to relieve the heavy situation created in their original groups, in which behaviour was very negative. Besides, active members of groups 2 and 6 also wanted to move to other groups in order to improve task performance that was in danger because of malfunctioning in their original groups. This strategy proved to be very useful for these members, since we noticed a radical change of their behaviour and a substantially better performance in their new groups during the fourth assignment.

In general, the results we obtained from the *experimental group* study showed that negative students' behaviors and performances were positively influenced by an appropriate affective feedback, which resulted very useful in all cases, especially in extreme cases where serious decisions had to be taken for group change. Finally most of the students reported that the group emotion awareness was a very useful functionality since many members had the chance and the initiative to intervene in their groups when they noticed bad feelings of their peers. This helped improve both group and individual performance and behavior.

5 Conclusions and Future Work

In the current paper, we have described a system's implementation that is able to fortify current VLEs with emotion awareness features (capture user's emotions and respond affectively). To this end, first, we have reviewed prominent theories and models of emotion with respect to learning, together with emotion detection techniques and affective feedback strategies. Then, we have described in detail and analysed our emot-control, a cross-platform, web tool that provides students with a friendly, easy-to-use, and above all, joyful way to report their emotions.

Based on user input, the emot-control also provides affective feedback, employing a virtual expressive avatar. We have also described how this tool can be combined with sentiment analysis to provide both implicit (analyse text input) and explicit emotion recognition. Finally, we presented some preliminary findings from our experiment with university students, validating our emot-control self-reporting interface in real education context –the implicit mechanism was not validated in the current experiment due to the lack of the Greek Affective lexicon.

The main result of this research is the integration of our emot-control system into Moodle, which constitutes a significant step towards the embodiment of emotion awareness in VLEs. From our questionnaire responses, students seem to acknowledge a system that "cares" about what they feel. Although, self-reporting lacks in objectiveness and task-relevance, it is an easy and available solution towards the broader adoption of emotion awareness into VLEs. There is a need to develop rich-expressive multimedia interfaces that evaluate student's affective state towards the qualitative and quantitative analysis of emotion data.

This paper also entails the need for available tools that are able to easily produce expressive avatars that can be exploited to provide feedback to students, enriched with parallel or reactive empathetic, affective scaffolds that motivate learners as well as preserve their emotional safety.

Our next step is to package the emot-control for Moodle and make it available for broader experimentation, contributing in its improvement. Future plans also include running more experiments and collecting more emotional data to feed more thorough

statistical analysis, which might reveal interesting patterns and affective sequences, meaningful for both academic performance and emotional well-being. We have already customised emot-control for Virtualized Collaborative Sessions (VCS) for an experiment in the Open University of Catalonia that is already on foot. Furthermore, we opt to run experiments in junior high schools.

It is also in our plans to exploit *expressive avatars* in order to provide VLE users with affective feedback, especially in cases where negative states such as confusion, frustration or boredom are detected. We have already started to work on an *Affective Assistant* that employs empathetic expressions and phrases, enriching task-based feedback with affective scaffolds. Future needs indicate the enhancement of agent's behaviour with more complex and "humanised" actions.

Finally, we plan to implement an automatic opinion mining system in Greek in order to couple the input from the self-report of emotions (subjective and conscious process) with results from sentiment analysis (objective and unconscious process). This integration allows us to evaluate the quality of the teaching and learning resources by analyzing students' emotions and opinions and draw conclusions about affective sequences that lead to fruitful collaborations. According to the limitations of the automatic sentiment analysis process the improvements to be done to the proposed system is to extend the system to be able to deal with the Greek language, which will require to create the Greek affective dictionary from scratch. Texts of students in past editions of the subject may be used to detect the triggers (words) of the opinions to deal with.

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