Measuring the impact of emotion awareness on e-learning situations

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Abstract—The adoption of emotion awareness features in learning environments, has been put on the focus of the research agenda towards students’ engagement and their authentic social interaction. In the current paper we provide a solution towards the provision of e-learning with emotion awareness features, which is based on self-reporting of emotions and affective response from the system. We also present research findings derived from two experiments with undergraduate students: in the University of Aegean (UoA) and the Open University of Catalonia (UoC). Finally, we set open questions for future research.

Keywords: Emotion awareness, assessment, measurement, detection, self-reporting, affective computing, affective feedback, sentiment analysis, CSCL

I. INTRODUCTION

Emotions have been acknowledged to play a vital role in learning [1]. Respectively, the enhancement of learning environments with emotion awareness features has been in the focus of the research agenda in Computer Supported Collaborative Learning (CSCL), during the last decade [2]. Emotion awareness is defined by the process of receiving emotion input, implicitly (motor-behavioural actions or bio-physiological signals) or explicitly (self-reporting of emotions), and affectively respond, manually (by human) or automatically.

In line with the above definition of emotion awareness, affective computing has been established as a new interdisciplinary field with input from psychology, cognitive science, neuroscience, sociology, education, and psychophysiology, building tools and technologies that can help learners become more aware of their emotions. However, we still lack in research studies that address the presence of emotions in e-learning or CSCL situations, while are far from adequate empirically proven strategies to respond affectively to individual or group detected emotions [3, 4].

In the current paper, we describe a system implementation towards the adoption of emotion awareness into e-learning environments. The proposed solution provides users with an easy-to-use interface to report their emotions, and based on fuzzy rules, it responds affectively, in order to ensure their engagement, to improve their performance, and to some extent to assure their “emotional safety”.

We begin our analysis by setting our theoretical background in section 2, identifying four fundamental requirements: what, how, when we want to measure, and why we wish to collect such valuable information. In section 3, we present our system’s design and implementation, and in section 4 the system’s validation that was accomplished by conducting two experiments with undergraduate students: in the University of Aegean (UoA) [5] and the Open University of Catalonia (UoC) [6]. Our research findings are outlined briefly in section 5, followed by our conclusions and future steps in section 6.

II. EMOTION AWARENESS

As it has been already mentioned, emotion awareness involves the following design requirements [7]:

\(a\) What we want to measure: It refers to emotion definition together with the models and theories that will be applied. There are two different approaches that appear in emotion research: the information processing and the interactionist [8]. The information processing approach treats emotion as an entity similar to information that is communicated from one person to another. The majority of emotion research studies adopts this approach and is further classified into two areas:

- Emotion labels:
  - Basic emotions that can be easily recognised universally [9, 10]
  - Eclectic emotions that apply into a specific context i.e. academic emotions [11]

- Emotion dimensions that project the user’s input into an emotional space, quantifying emotions by using variables such as [12]:
  - Arousal (deactivating/activating)
  - Valence (negative/positive)
  - Intensity (low–intense)
  - Duration (short–long)
o Frequency of its occurrence (seldom–frequent)
  o Time (retrospective like relief, actual like enjoyment, prospective like hope).

On the other hand, the interactionist approach sees emotion as constructed through interaction and expression [13]. It focuses on emotion as a social and cultural product, not as a measurable, biological fact. This approach skips the emotion recognition process: the translation of input and output signals to specific emotion information. Instead of picking emotion labels, users are encouraged to communicate their emotions i.e. by selecting a colour, a sound etc. Success of such a system is measured by whether users find the system’s responses useful for interpreting, reflecting on, and experiencing their emotions [13].

Schutz et al. [14] 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)
  - Affective tendencies (trait emotions like being depressed).

b) How we are going to measure it. Emotion measurement tools and techniques fall into three main categories [15]:
  - Psychological (1st person, subjective report using verbal or pictorial scales or questionnaires, etc.).
  - Physiological (use of sensors to capture biometric signals i.e. electromyogram-EMG, electrodermal activity-EDA, electrocardiogram-EKG or ECG, electrooculogram-EOG, blood volume pulse-BVP, etc.)
  - 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.).

So far, there is no evidence for which method is more suitable, to what context, and when is better to be applied. Physiological and behavioural tools can be used implicitly, without interrupting the user’s task, in order to provide more objective measurements. However, sensors are considered obtrusive or even invasive, out of the learning context, often raising the argument of how objective can be an emotion measurement from bio-physiological signals when the respondent knows that he/she is taking part on experiment. Additionally, sensors or cameras are expensive and require special expertise to run the equipment.

On the other hand, self-reporting tools are less expensive, less obtrusive, and more applicable to real educational settings. Their main drawback is that they are hardly applied in parallel with the user’s task without disrupt the task flow, resulting in high invasiveness. Additionally, they are usually subject to language barriers, although the use of pictorial scales is more language free and obtains brevity in response. Multimodal integration (combination of the three methods) seems the best option that can lead us to more precise results.

c) When we can measure it. The user’s affective state can be evaluated into three time points [16]:
  - 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 [17]. 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 [18]. Groups and roles in subsequent collaborative tasks can be based on the prospective assessment of their affective state.
  - In parallel with the task: The respondent’s affective state is monitored together with his/her learning performance.
  - 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).

d) Why we want to measure it. The last requirement corresponds to the utilization of our measurement; once we recognise the user’s emotional state, what we are going to do with this valuable information. Affective feedback design aims at sending appropriate affective or cognitive cues to the user, in response to their emotional state inspected, ensuring in that way their emotional safety and their engagement or persistence in the learning experience [19].

Affective feedback can be either 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 (change task sequence - supplementary to empathetic strategies) [20]. 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 [21, 22].

Unfortunately, there are few studies that exploit computer mediated affective feedback strategies and their impact on users’ task performance or affective state [7]. Furthermore, the number of tools and strategies to design expressive avatars in response to learner’s emotion detection is quite limited [7].
III. SYSTEM DESIGN AND IMPLEMENTATION

In previous section we have described emotion detection methods, which, unfortunately, are targeted at laboratory experiments, while their wide adoption in real education context is still very limited. Emotion recognition is susceptible to the same vulnerabilities of speech recognition; despite the advancements that have been attained in experimental settings, their utilization to cope with everyday needs is restricted by the lack of resources (cost of equipment, complexity of systems, etc.).

One possible solution is to employ available resources like the keyboard, mouse, the embedded pc camera or user’s text input. Most computers on a lab or portable devices are equipped with a camera that can be used for facial expression recognition. Zimmermann [23] has reported on an experiment where students’ emotions were inferred by analyzing their mouse and keyboard movements as they turn up from log files. In sentiment analysis, text is classified by its overall sentiment, for example determining whether a review is positive or negative. This new trend in emotion research involves the lexical analysis of the text in order to identify words that are predictive of the affective states of writers [24].

Self-reporting does not require extra cost or additional resources and can be easily customised to meet the requirements of a class experiment. It 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 [25]. Although, self-reporting is considered intrusive, 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. Additionally, emoticons and mannequins are student-friendly and are used quite often to add emotion information in posts.

For our experiments, we have designed and developed a usable interface for learners to report their emotions that is also able to provide affective feedback based on fuzzy rules. Emot-control is a cross-platform, open source, web tool, developed in PHP, JavaScript, MySQL and JQuery and can be easily customised to adapt to different VLEs [5]. Respondents are able to report their emotions by clicking on image-buttons located on a wheel, representing the different affective states usually appear in e-learning, as well as, their mood in an interactive way (the background colour changes based on the mood selection). The respective emotion labels appear in hints so that the tool can be easily translated in other languages. Additional text boxes have been provided for respondents to report other emotions than the default ones [Figure 1].

For the affective feedback mechanism we have embedded an animated, virtual assistant that employ expressive faces and synthesized speech to provide empathetic (parallel and reactive), as well as, task-based feedback based on a fuzzy table of responses [5, 6]. The affective assistant was displayed embedded in the emot-control block using a JavaScript player to avoid frequent browser problems with embedded media [Figure 2].

The implemented system corresponds to our emot-model [Figure 3]. We have followed the information processing and the interactionist approaches, based on the theories of the Learning Cycle [26], Flow [27], Circumplex of Affect [12] and Academic emotions [11], applying both basic emotion and emotion dimension strategies.

- Figure 1: The Emot-control for emotion reporting [5]
- Figure 2: The virtual affective assistant that provides affective feedback [5]
- Figure 3: Our emotion model deploys 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 to initialize 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) [5].

Our main objective is to evaluate the proposed model into CSCL tasks and search for possible affective
sequences and patterns of students’ emotions and mood, through time (i.e. per day, per time, per task phases).

Figure 3: The applied emotion model [5]

IV. SYSTEM VALIDATION

We have validated our system by conducting two experiments with university undergraduate students [Table 1]. The participants took part in learning tasks that allowed emotion reporting and respective affective feedback in parallel, in an attempt to enhance motivation and engagement during the learning process.

| Table 1: UoA and UoC Experiments: Comparative Table |
| University | University of the Aegean (UoA) | Open University of Catalonia (UoC) |
| Department | Cultural Technology and Communication University of Aegean, Greece | Department of Computer Science, Multimedia and Telecommunications Open University of Catalonia, Spain |
| Participants | 112 (adult male-female) | 55 (adult male-female) |
| Age | 20 (on average) | 32 (on average) |
| Duration | 3 months | 2 weeks |
| Course | Intercultural Communication | Organization Management |
| Learning Method | Blended learning (weekly face-to-face meetings) | Virtual learning |
| Platform | Moodle Version 2.3 | Virtualized Collaborative Session (VCS) [28] |
| Methodology | The participants worked in 28 groups of 4 members to carry out 4 online collaborative assignments (each one including a Wiki) | The participants worked individually on an activity consisted in filling a test with questions on Software projects management, after watching an interactive CC-LR material embedded in the VCS prototype from their on-line classroom of the UOC. |

| Emotion Report | Emot-control was customised for Moodle to open as a popup window by clicking a right-top button that was displayed in every course page [Figure 4] |
| Emotion Monitor | Group emotion awareness: The participants could monitor their group-members’ emotions [Figure 6] The tutor could monitor all emotional information per group, student, date and time, emotion and/or mood. |
| Affective Feedback | a. Parallel or reactive empathetic | a. Parallel or reactive empathetic |
| | b. Task-based | b. Task-based |

The affective assistant employed emotional scaffolds in an attempt to commence a dialogue with the student.

Only the tutor could monitor all emotional information per student, date and time, emotion and/or mood.

Figure 4: Screenshot from the UoA interface (Moodle 2)

Figure 5: Screenshot from the UoC interface (VCS)
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.

VI. CONCLUSIONS AND FUTURE STEPS

In the current paper we have presented a solution towards the provision of e-learning environments with emotion awareness features, which is based on self-reporting of emotions and affective response from the system. We have presented an epistemic analysis of emotion awareness that is built on four questions namely what, how, when we want to measure and why to do this. We have also presented preliminary findings and conclusions from two experiments that we conducted with university students, validating our solution in real education context.

In both experiments, students were willing to report on their emotions, since they found a usable way to do it. Although, self-reporting lacks in objectiveness and task-relevance, it is an easy and available solution towards the broader adoption of emotion awareness in e-learning environments.

However, the affective feedback mechanism did not appear to have a positive impact on students’ performance. On the contrary, the older the students were, the more negative attitude they had towards the affective assistant. Definitively, the students’ profile as well the learning scenario mode (virtual or blended learning) seemed to be important factors to consider in the interpretation of our results.

This problem is attributed to our forth requirement; ‘why to report on emotions’, and has to do with the feedback process. The connection of affective feedback to learning benefits is a grand challenge that prompts for further experimentation. The provision of other than the task options like a relaxing song, a nice video, an amusing game did produce some positive impact on the learner’s mood in general, but not on learner’s mood for learning. In UoA, the appearance of group emotions appeared to improve social interaction. However, we are far from a satisfactory proof of positive impact, and additional efforts should be made.

Our future steps include a detailed analysis of students’ behaviour from the data we have collected so far. More deep statistical analysis on our data may reveal interesting patterns that lead to increased engagement or performance. We also opt to couple these data with patterns that may be inferred from sentiment analysis on the chat posts that produced in the UoA experiments.

Considering affective feedback, we plan to add alternative paths in the learning sequence, based not only on the task performance, but also on the emotion reporting, in an attempt to provide more personalized and adaptive learning. We have also highlighted the need to develop
tools that easily produce expressive avatars in order to provide feedback to students, enriched with affective scaffolds that motivate learners as well as look after their emotional safety. Finally, our future steps include experimentation in junior high schools, to draw conclusion on emotions awareness in an extensive range in age.

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REFERENCES