

A Dashboard for Affective E-learning: Data Visualization for Monitoring Online Learner Emotions

Reza GhasemAghaei, Ali Arya, Robert Biddle
School of Computer Science
Carleton University
Canada
Reza.GhasemAghaei@carleton.ca

Abstract: In an ordinary classroom, teachers monitor their students' emotional reactions while learning, even if only by glancing at their faces while they work. In this way, teachers can gauge the effectiveness of their teaching strategies, determining whether students are bored, frustrated, or anxious. Teachers can see how emotions change over time, perhaps from positive, to challenged, and later triumphant. All this is difficult with educational software used online. In this paper we present software to address this gap. Our MADE Teacher's Dashboard is a web application that supports educators to inspect and reflect on the emotional states of students using web learning applications. We apply theories of emotion in learning, together with a software library to identify emotions using computer vision. The Dashboard features a novel visualization of the emotional state of learners through time over the process of a learning activity.

Introduction

Recently, more and more attention has been paid to emotions in the domain of Human-Computer Interaction (HCI) and education (Woolf, 2009). A student's emotions, such as sadness, happiness, and surprise, often significantly impact her or his behavior and performance in a learning environment. When you are a teacher in a traditional classroom, you can judge the emotional status of the students; but when your classroom is online, how do you know what the students are feeling? When there is a co-located environment, the teaching relationship can be managed in a way that is impossible in an online environment.

While learning online, students experience emotional reactions just as they do in an ordinary classroom. For example, difficult e-learning tasks can lead to failure and frustration, resulting in fear. Recognition of student emotions in such situations would help teachers. Eventually, students might learn to help themselves to develop more self-awareness and self-management (Woolf et al., 2009). It may be possible to create e-learning systems with affective intelligence to support this goal.

Our approach is more immediate, and rather than embedding affective adaptability in the system, we propose better supporting the teacher. Our suggestion is that the online educator should be able to monitor learning and emotion, and customize each student's learning tasks accordingly. While students work on the tasks, the system could show a graph of their emotions over time and display it with different visualizations showing proportions of emotions in specific time periods. In comparison to other research on learning dashboards, Muldner et al. (2015), our approach does not use artificial intelligence, but rather visual analytics for the teacher.

To support this approach, we developed the *MADE Teacher's Dashboard* to monitor emotion in e-learning. It is a visual analytics system developed to let the teacher see emotional states of the student. In earlier work we have articulated our MADE Framework (Multimodal Affect for Design and Evaluation) (GhasemAghaei et al., 2015). This features a number of techniques based on HCI practice, including processes for design (Affective Personas and Affective Essential Use Cases), and for evaluation (MADE Walkthrough and MADE Heuristics). In our studies of these techniques, we found that even with careful design and evaluation for affective education, there was still a need for teachers to monitor and manage the learning process, motivating our work on the MADE Teacher's Dashboard.

In this paper, we first review related work, and identify our design rationale. We next present our design process, from sketch to functional prototype system, and especially our innovation information visualization. We then discuss the issues that emerge, and plans for future work.

Related Work

Models of emotion

Mehrabian and Russell (1974) described what has become a common model of the practical dimensions of emotion. These consist of *positiveness* or *valence* (comparing states of pleasure e.g. happiness, with states of displeasure e.g., sadness), *arousal* (degree of excitement; states of low arousal e.g. quiet, with states of high arousal e.g. surprised), and *dominance* (degree of aggressiveness; state of low dominance e.g. in control, with states of high dominance e.g. controlled). These are associated with a person's affective reaction to a wide variety of stimuli, and are pervasive in organizing human judgment for a wide range of perceptual and symbolic stimuli. Of course, we acknowledge that affect and emotion are topics rich in depth and detail, and we expect more understanding to emerge from ongoing research. In our work on affect, we focus on the emotions that arise in the learning process.

Emotion and learning

Bloom's taxonomy (Bloom, 1956) breaks learning objectives for students into three domains, being cognitive (mental skills, knowledge, e.g. rules of the road), affective (growth in feelings or emotional areas, attitude or self, e.g. teaching affective driving to teenagers in terms of driving safety) and psychomotor (manual or physical skills, e.g. physical skills in driving a car). The psychomotor domain includes physical movement, coordination, and use of the motor-skill areas. The cognitive domain includes many strategies for fostering a range of thinking skills. The affective domain is our focus, and while Bloom's work includes learning in the affective domain itself, our particular interesting is in the use of affective teaching strategies to support all kinds of learning.

We are particularly motivated the model of affective in education from Kort et al. (2001). This identifies four phases of emotion commonly cyclically involved in learning. This is based on the circumplex model of emotion, first developed by Russell, who proposed an emotion model based on the two dimensions of arousal and valence (see Figure 1). Kort et al. make connections between what emotional state the student is in and, from that, raises consideration of what help he/she needs. They proposed an affective model of interplay between emotions and learning; a four quadrant learning spiral model in which emotions change when the learner moves through the quadrants and up the spiral. It is well known that students' results can be improved with the right encouragement and support. Figure 1 shows this model, which attempts to merge the emotion and the cognitive dynamics of the learning process.

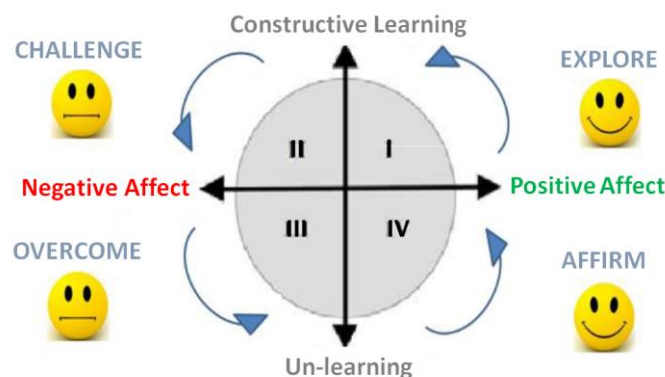


Figure 1: Kort et al.'s affective model of education.

To simplify: when students start the task: they are happy, then things go wrong and they are sad. Later, things start to pick up again and they happy again. We also see as related the *emotional flow state*

(Csikszentmihalyi, 1990), where the two main elements influencing flow are challenge and skill. Flow emerges when skills match the challenges of a learning situation. As regards to flow, an educational system requires conditions between activity and individual, and internal experience, and flow condition include: clear goals, immediate feedback, balanced between challenges and skills, easily controlled, merging of action and awareness, concentration on task at hand.

Emotion and educational software

Modeling student emotion has increasingly important for computational teaching systems. One limitation in these systems is they do not systematically examine the relationship(s) between student affective state and learning outcomes (Woolf et al., 2009), (Muldner et al., 2015). Theories and technologies are needed to understand and integrate the knowledge of student affect (e.g., surprised, happy or sad) into learning events for the educators. Woolf et al. (2009) identified emotion dimensions (valence and arousal) that, together with knowledge on-task engagement, can represent desirable or undesirable states related to student learning. These would also related to physical behaviours connected to emotion, indicating and corresponding to student affect. Their approaches to affect recognition include human observation, hardware sensors and machine learning techniques.

Basis for Design

Facial expression of emotions

Micro-expressions were first identified by Haggard and Isaacs (1966). They discovered the micro-momentary expressions while scanning motion picture films. Later, Ekman et al. (1972) found a selection of emotional labels that fit facial expressions to be universal including happy, sad, surprise, fear, disgust and anger. There has been interest in human ability to modify these gestures, including simulated expressions, neutralized expressions, and masked expressions. While we understand the importance of these possibilities in a range of applications, including teaching, we do not explore them further in our current work. Instead, we focus simply on the canonical forms of Ekman's categorisation of emotions based on analyses of facial expressions. Figure 2 shows examples of these six emotional facial expressions.



Figure 2: Basic facial expression phenotypes. 1: disgust; 2: fear; 3: joy; 4: surprise; 5: sadness; 6: anger. Posed images from Kanade et al. (2000). Copyright images used with permission.

Computer detection of facial expression of emotions

Based on the work above, understanding facial expressions can be an important behavioral way to study emotion, cognition, and social interaction. Bartlett et al. (1999) showed that computer vision can identify facial gestures. More recently, there has been work on software and algorithms for many practical applications in this area. For example, there are commercial products such as *Noldus FaceReader* (www.noldus.com/facereader), which can be used in research applications where tracking emotional state of participants is important. Saragih et al. (2009) introduced algorithms based on Constrained Local Models (CLM) for facial gesture recognition. Audun Mathias Øygard (2012) developed *Clmtrackr*, software based on the algorithms of Saragih et al., written in JavaScript and able to be used within web applications. *Clmtrackr* is open source and freely available, and supports tracking of facial features and detection of emotions in real time, identifying the six different emotions discussed above. This set of emotions emphasizes valence (pleasure/displeasure), and other dimensions (arousal and dominance) are less explicitly identified.

Unfolding the model of Kort et al.

As we discussed above, Kort et al.'s model (2001) suggests several phases of emotion in the learning process. In brief, first it starts with positive affect, then there are the challenge and overcome phases, which we have some negative affect, and finally the affirmation that has positive affect. We are interested to track the learner's progress over time. Hence, we want to "unfold" the model with time along the x-axis. Figure 3 shows our diagram. The valence of emotions progresses from positive (happy and surprised) through negative (sad and angry).

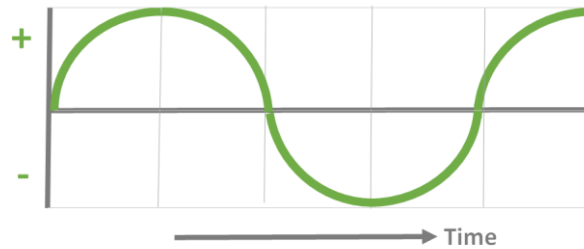


Figure 3: Model of the emotional state in learning.

MADE Teacher's Dashboard – Multi-Dimensional Emotion Analytics

Architecture

Figure 4 presents a schematic of the context for our current teacher's dashboard prototype. Technically, there are four main components to the data architecture: the teacher's dashboard, the student's screen, the web server, and the database.

In the figure, the educational software that the students use is shown on the right. We show several educational applications, corresponding to three case studies that we have conducted. This software is augmented with library code to access input from a camera, and identify emotional state as discussed earlier. The software runs from within a web browser, and communicates with a web server as shown in the center; this which stores emotional information in the database. Our teacher's dashboard is shown on the left side. Its also communicates with the web server which accesses the database. The information from the student application can then be displayed on the teacher's dashboard.

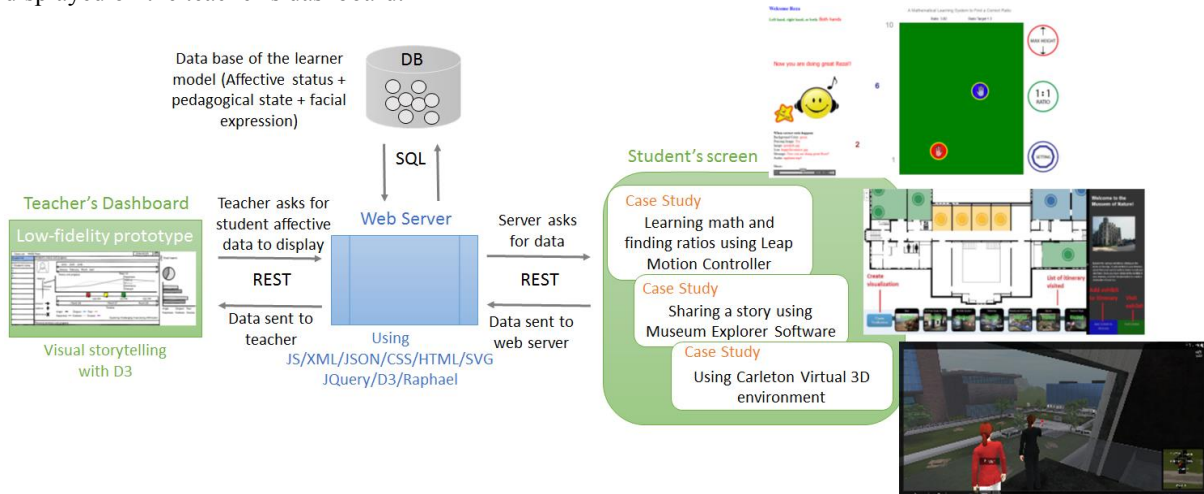


Figure 4: Architecture: overview of the MADE Teacher's Dashboard in context.

As an example and test for our architecture and the MADE Dashboard, we used our MADE Ratio software (GhasemAghaei et al., 2016), which is web-based software for learning about mathematical ratios, designed using Affective Personas and Affective Essential Use Cases. To adapt the software to our architecture, we used the Clmtrackr software library; this accessed the webcam, and in real-time analyzed the image of the

user's face, rating the intensity (on a scale from 0.001 to 1.000) of 6 emotions (happiness, sadness, surprise, disgust, and anger). These ratings were calculated every second, and for efficiency these were uploaded to our database in bulk once every minute. (This is also much more efficient than uploading video images.) We also modified the MADE Ratio software to upload details for every significant event that occurred as the software was used. Every time the user began a new task, succeeded or failed, etc., an event was entered into the database. This enabled exploration by the teacher of correlations between cognitive learning events and emotional states.

Low-fidelity prototype

To design the teacher's dashboard, we followed standard practice in HCI. We first identified the user tasks, then developed "low-fidelity" sketches, and then walked through how they would be used to perform the tasks. We used an iterative approach, with our findings from the walkthroughs being used to change or refine the sketches. We used the Balsamic Mockups software (<https://balsamiq.com/>) to develop the sketches. Figure 5 shows one of the later sketch prototypes. On the top we show the learning activity (e.g. MADE Ratio), on the left we show a list of students and their characteristics, and in the main window we imagined a graph with time on the horizontal, and the emotion dimensions graphed on top. On the right we imagined summary graphs of the emotion distributions.

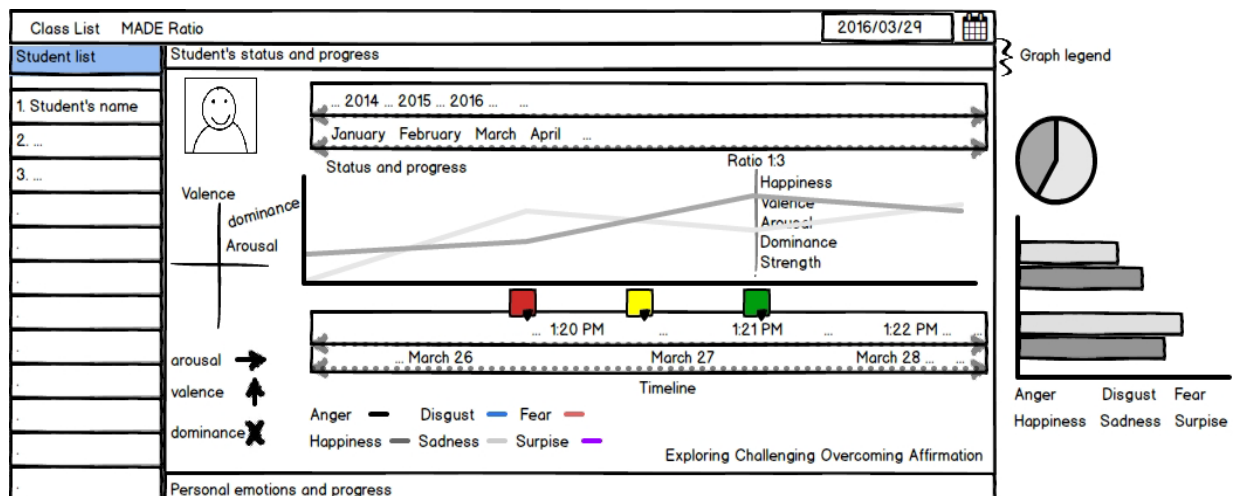


Figure 5: MADE Dashboard low-fidelity prototype.

Functional prototype

Figure 6 shows the main screen of our functional prototype. This was based on our low-fidelity sketch, but is fully implemented and works within the architecture we outlined above. On the left side of the dashboard we have the student list; the instructor is able to see the details of a specific learner on the graph and can zoom-in. For the selected activity and learner, it shows six different emotions shown by colored lines as they vary over time. Emotions associated with positive valence (e.g. happy) are shown above the axis (0 to +1), and emotions associated with negative valence (e.g. sad) are shown below the axis (0 to -1).

Below the main graph is a visual analytics "brush", which allows the user to select and zoom in on a specific time period. Vertical lines with "balloons" show specific learning events, allowing the teacher to related cognitive and emotional states. When the teacher hovers their cursor on the balloon, a tooltip with descriptive text is shown. On the right side of the dashboard we have the analytics, showing user proportions of emotions in specific time periods (which can be selected by moving the brush).

For visual metaphors we are using two visual representations to summarize the emotion analysis results: the *emotion brush* allowing emotion selection of specific time period, and the *emotion pie chart* showing user proportions of emotions in specific time periods.

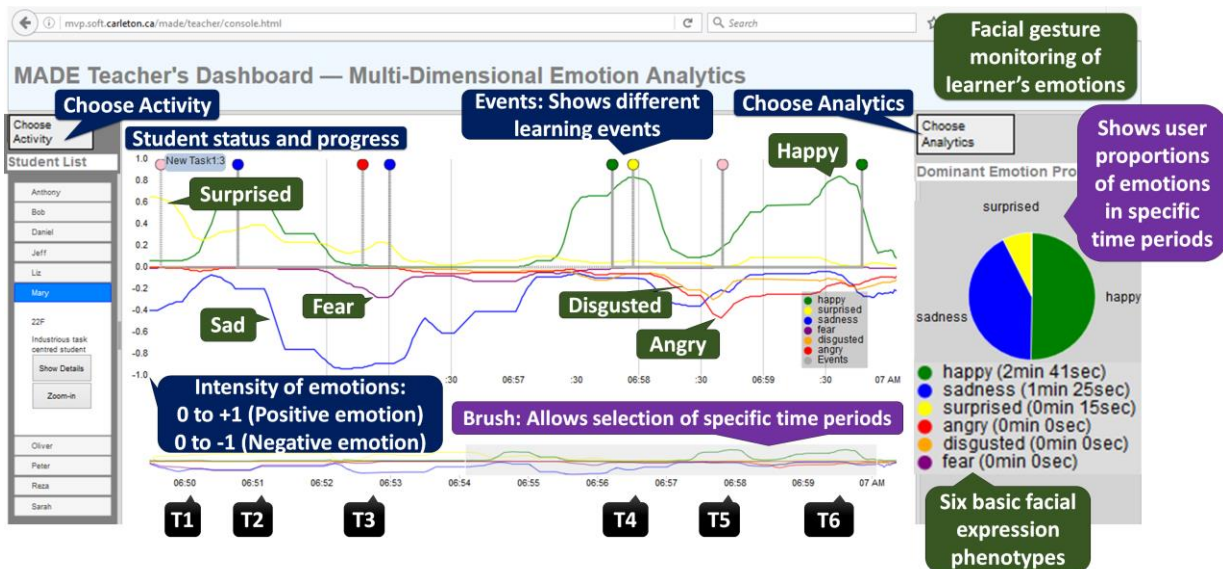


Figure 6: The MADE Teacher's Dashboard functional prototype.

Implementation technology

The time series visualizations for emotional data were developed using Data-Driven Documents (D3) (<https://d3js.org/>), a JavaScript library for producing dynamic, interactive data visualization for the web (bears a resemblance to lower-level graphics libraries such as Processing and Raphael) with HTML5 for page content, JavaScript for interaction, SVG for vector graphics, Cascading Style Sheets (CSS) for aesthetics, and the jQueryUI JavaScript library for screen layout. The student software and the teacher software communicate with the web server using the *ReST* (*Representation State Transfer*) protocol. The web server communicates with the database using *SQL*. Vision based emotion detection is done using the *CImtrackr* JavaScript library.

Usage walkthrough

To illustrate how the teacher's dashboard can help, we now present a step-by-step walkthrough of how it might be used. We start with the teaching strategy; what the instructors' expectations might have been, and how the dashboard can help them understand what is actually happening in the e-learning software.

Consider a teacher using our MADE Ratio software, which helps learners explore mathematical ratio by tracking learner hand positions. In that software, the teacher might select tasks for the student, such as finding ratios of simple 1:3, or ones that might appear more difficult to understand, e.g. 3:9 or 2:5. The teacher can also select affective strategies for each student. For example, a teacher might know that a student, Mary, likes frequent feedback with audio elements, such as praising text messages, Justin Bieber music, and applause. The teacher can set these to accompany appropriate learning events that occur in use of the MADE Ratio software.

Imagine that the teacher has chosen those tasks, and those affective feedback settings. The teacher can then monitor or review what happened using the teacher's dashboard, as illustrated in Figure 6. We can now follow the events shown on the timeline from left to right over a 10 minute period marked T1 through T6 on our figure.

- T1: First, Mary is given an easy task (pink balloon, finding ratio 1:3). Initially, she is surprised (yellow line).
- T2: Mary becomes happy (green line), and we can see her hands are being successfully tracked (blue balloon). After that, she becomes less happy, and increasingly sad (blue line), and we see her hands stop being tracked (red balloon).
- T3: Mary's hands start being tracked again (blue balloon), and she continues to work with the system, initially with neutral emotions, but eventually becoming happier (green line).
- T4: Mary succeeds at the task (green balloon), and is happy, then receives positive feedback (yellow balloon), and becomes happier still (green line). Her happiness then diminishes.

- T5: A new task is then assigned (pink balloon, finding ratio 3:9). Initially she is a bit angry at the challenge (red line), but she engages, the anger goes away, and her happiness increases (green line).
- T6: Mary completes task (green balloon). She is happy (green line), although then the happiness dissipates.

If you were the teacher, you would know the tasks, and know about Mary. You might be aware of the model of Kort et al., and expect emotions to vary during the course of a learning activity: exploring, challenging, overcoming and affirmation. In our example, much that happens reflects an ideal state. Figure 7 shows how emotions rise, fall, or stay constant in each time period. However, between T2 and T3, or between T3 and T4, perhaps more could have been done. You do not want the learner to give up; you want her to be on-task and active, engaging and involving her. For example, perhaps there could be another affective intervention here, where it could be saying: “you should keep trying” or “you are almost there”. Alternatively, you could take a meta-cognitive strategy, and suggest that Mary might take a different approach, or review earlier learning materials before returning to the tasks. More generally, you might adopt the concept of Flow from Csikszentmihalyi (1990), and consider whether Mary is either too bored or too frustrated, or whether she is in the desirable Flow channel.

Emotions / Time	T1-T2	T2-T3	T3-T4	T4-T5	T5-T6
Happiness	→	→	→	→	→
Surprise	→	→	→	→	→
Sadness	→	→	→	→	→
Anger	→	→	→	→	→
Fear	→	→	→	→	→
Disgust	→	→	→	→	→

Figure 7: Mary’s emotions during the task.

Conclusions and Future Work

In an ordinary classroom environment, it is easy for teachers to monitor the emotional state of students as they work, and teachers can provide affective support accordingly. In an online environment, this is all much more difficult. In this paper we presented our work to address this challenge. It involved augmentation of learner software with computer vision software to identify learner emotions, and presents this emotion data, together with cognitive learning software events, in a visual form with an affective e-learning teacher’s dashboard. Our principal contributions are the use of web-based emotion tracking for education software, and the visualization techniques displayed on the teacher’s dashboard.

Our prototype system is working as described, but we wish to explore several additions to the teacher’s dashboard. In addition to the time distribution shown by the pie chart, we will explore a bar graph, and a Kiviat graph, to see which is most suitable. We would also like to allow Self-Assessment Manikin (SAM) emotion queries, the most popular visual self-report measure, (Bradley and Lang, 1980), in the education software. We could then display those results on the teacher’s dashboard as an alternative to the results from the camera-based data. SAM can be used to also report dimensions such as arousal, and dominance.

There are also many research questions to be explored. In future, we need to conduct user studies having some instructors to find if the system is easy to use or not, and if it is understandable and engaging. Also, we have to check the reliability of data to see how well it detects the right emotions. If we have the same kind of data for many learners, we have to analyze how to improve the educational experience. Will the learners accept this approach, and allow their emotions being tracked in this way?

Acknowledgments

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References

- Bloom, B.S., Engelhart, M.D., Furst, E.J., Hill, W.H., & Krathwohl, D.R. (Eds.) (1956). *Taxonomy of Educational Objectives – The Classification of Educational Goals – Handbook 1: Cognitive Domain*. London, WI: Longmans, Green & Co. Ltd.
- Bartlett, M. S., Hager, J. C., Ekman, P., & Sejnowski, T. J. (1999). *Measuring facial expressions by computer image analysis*. *Psychophysiology*, 36(02), (pp.253-263).
- Bradley, M. M., & Lang, P. J. (1994). *Measuring emotion: the self-assessment manikin and the semantic differential*. *Journal of behavior therapy and experimental psychiatry*, 25(1), (pp.49-59).
- Csikszentmihalyi, M. (1990). *Flow, The Psychology of Optimal Experience*, New York, NY: Harper Perennial.
- Ekman, P., Friesen, W.V. and Ellsworth, P. (1972). *Emotion in the Human Face: Guidelines for Research and an Integration of Findings*, New York: Pergamon Press.
- GhasemAghaei, R., Arya, A., & Biddle, R. (2015). *The MADE framework: Multimodal software for affective education*, In Ed-Media: World Conference on Educational Multimedia, Hypermedia, and Telecommunications, Montreal, Canada, Association for the Advancement of Computing in Education.
- GhasemAghaei, R., Arya, A., & Biddle, R. (2016). *MADE Ratio: Affective Multimodal Software for Mathematical Concepts*, Proceedings of the 18th International Conference on Human-Computer Interaction International, HCII'16, Toronto, Canada, Springer.
- Haggard, E. A. & Isaacs, K. S. (1966). *Micromomentary facial expressions as indicators of ego mechanisms in psychotherapy*. In L. A. Gottschalk & A. H. Auerbach (Eds.), *Methods of Research in Psychotherapy* (pp.154-165). New York: Appleton-Century-Crofts.
- Kanade, T., Cohn J. F., & Tian Y. (2000). *Comprehensive database for facial expression analysis*. Proc Fourth IEEE International Conference on Automatic Face Gesture Recognition, Grenoble, France. (pp.46-53).
- Kort, B., Reilly, R., & Picard, R. W. (2001). *An Affective Model of Interplay between Emotions and Learning: Reengineering Educational Pedagogy-Building a Learning Companion*, ICALT '01.
- Mehrabian, A. & Russell, J. A. (1974). *An approach to environmental psychology*. Cambridge, MA: MIT.
- Muldner K., Wixon, M., Rai, D., Burleson, W., Woolf, B., & Arroyo, I. (2015). *Exploring the Impact of a Learning Dashboard on Student Affect*. In *Artificial Intelligence in Education* (pp.307-317). Springer.
- Øygard A. M. (2012). *Fitting faces: An explanation of Clmtrackr*. <http://auduno.com/post/61888277175/fitting-faces>, accessed on 2016-04-22.
- Saragih, J., Lucey, S., & Cohn, J. (2009). *Face Alignment through Subspace Constrained Mean-Shifts*, IEEE International Conference on Computer Vision, ICCV.
- Woolf, B. (2009). *Building Intelligent Interactive Tutors: Student-Centered Strategies for Revolutionizing E-learning*, San Francisco, CA: Elsevier Inc., Morgan Kauffman.
- Woolf, B., Burleson, W., Arroyo, I., Dragon, T., Cooper, D., & Picard, R. (2009). *Affect-aware tutors: recognising and responding to student affect*. *International Journal of Learning Technology*, 4(3-4), (pp.129-164).