Tracking Emotions through Facial Expressions in Online Education Systems Based on Transient Emotion Peak

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ABSTRACT
Two types of students' performance evaluation mechanisms are called formative and summative. To have good results at the summative evaluation, the students must have frequent constructive feedback throughout a course. It is not an easy task for a teacher to give frequent feedback. As a solution for that, online tests can be introduced with feedback. A constructive feedback should consist of three features, i.e. Appreciation, Advice and Evaluation. When incorporating the appreciation in a feedback in an online education system, the emotions can be analysed to appreciate the student' effort. The most feasible way to analyze the emotions is through the facial expressions in an online system. However, there should be a systematic way to track the emotions based on each question, while the students are answering. This research proposes a time interval based on the transient emotion peak considering the time taken to read a question as the stimulus activity to cause an emotional change, to capture the emotional changes. A series of photographs were captured by using a webcam for each question and analysed the emotions by using MS-emotion-API. At the end, a single photograph was selected based on this time, tracking the most different emotion out of the series. A video recording was taken simultaneously, and it was analysed by a psychiatrist and kept as the benchmark dataset. At the end, a cross validation test was done based on the output of API and the benchmark dataset and was noticed that this has given a good result.

Keywords: Constructive Feedback, Formative Feedback, Stimulus Activity, Student Evaluation, Transient Emotion Peak Time

1. Introduction

Two of the main types of students' performance evaluation mechanisms can be defined as formative and summative evaluations. In order to expect productive results from the students at the summative evaluation, the students must have had frequent constructive formative feedback throughout a course (Biggs & Tang, 2007).
A constructive feedback should at least consist of three features, i.e. Appreciation, Advice and Evaluation (Fisher, Sharp, & Richardson, 1998). Advice and evaluation factors can be

incorporated by taking into account the time taken by the students to answer the questions and based on the correctness of the answer respectively. When it comes to appreciation, it can be said that in an online environment, the emotion of the student can be analysed to appreciate the effort that the student has put in answering.
It was decided that one of the most feasible and convenient ways of analysing the emotions was through the facial expressions in an online system. However, there was a requirement to have systematic way to track the emotions based on each question, while the students have been engaged in answering. The other important thing was, it was decided to verify whether these emotions were affected by the body cues or not in an online education system.
This research proposes a time interval based on the transient emotion peak taking into account the time taken to read a question as the stimulus activity to cause an emotional change, to capture the emotional changes and it elaborates the methodology that was followed in analysing the impact on body cues in identifying the emotions through facial expressions.
The rest of the paper is structured as follows. First, a brief literature review on the related work in this area is presented. Next, the design and the implementation of this research are outlined. After that the evaluation of the presented object and finally, the paper will be winded up with a brief discussion.

2. Literature Review

2.1 Mechanisms used to evaluate the performance of the students

When it comes to students' performance evaluation, it can be defined like this way; student performance means their actions when the students are completing some tasks, roles or obligation. That is related to the word "students' performance" and now when it comes to the word "evaluation", it means the examination, judgment, appraisal and assignment a value of a particular performance. Hence the teachers have to evaluate the performance by giving examination papers or tests as well as they have to monitor students' behaviour and actions.
Usually there are two types of evaluations taking place in a learning environment i.e. formal and informal evaluation. Formal evaluation means a detailed review of the student's performance by means of an examination paper or assignment, according to a certain set of criteria defined in the curricula at the end of a term or semester. Informal evaluation means feedback and suggestions given by the instructor or the teacher frequently by observing the students.
But sometimes the evaluation criteria will not be fair because some of the factors that are affected to the learning methodology can be varied from student to student, for example a student's level of contribution to learn, his/her motivation, adaptability and supervision are subject to change, and they are not easy to observe.

2.2 Ways of Evaluating Online Learning Environments

Modern Learning Management Systems (LMS) uses questionnaires and tests/quizzes to evaluate the students after using SCORM (Shareable Content Object Reference Model) objects or games. Since the games are like sold products they are considered as difficult to adapt and most of the time the best way to evaluate the students' performance after playing the game is to give a test or get their ideas through a survey or a questionnaire in (Shen, Wang, & Shen, 2009).

(Steinwachs, 1992) had come up with a better solution to this pre and post tests conducted after LMS related activities. They had introduced an integration of games created with the <e-Adventure>, (Del Blanco et al., 2010) in educational gaming platform into LAMS. This allowed teachers to use the information gathered during a game-play session to conduct the student through different activities of the learning plan or simply to collect more information that can be used for further assessment and tracking purposes.

(Thomas, Labat, Muratet, & Yessad, 2012) had come up with another solution instead of the pre/post testing. They had come up with an automated tool so that a teacher can be able to monitor the actions performed by the student while learning. This was implemented using an "expert Petri Net" and a domain and game action ontology.

2.3 Ways of Forming and Effective/Constructive Feedback

A feedback for a particular situation should at least consists of following three kinds according to (Fisher et al., 1998).

- Appreciation: expression of gratitude or approval of another's effort. It is an expression of emotion, designed to meet an emotional need.
- Advice (or Coaching): suggestions about particular behaviour that should be repeated or changed. It focuses on the performance.
- Evaluation: ranking the subject's performance in relation to that of others or against an explicit or implicit set of standards.

In order to incorporate the appreciation to a feedback in an online education system, the emotions have to be automatically detected. Next section 2.4 describes the existing mechanisms that have been used in various research work to identify the emotional changes of the students in an online educational environment.

2.4 Existing Mechanisms to Evaluate the Performance and Emotional States of the Students Through Online Education Systems

(McQuiggan & Lester, 2006) had followed an approach which automatically constructs models of self-efficacy that can be used at runtime to inform pedagogical decisions of the students, since it was considered that the self-efficacious students were effective learners. In this research, they had allowed each student to enter the experimental area and to complete a survey and another survey after going through an online tutorial to indicate their Problem Solving Self Efficacy Scale.

(Sheldon, Malone, & Mc Bride, 2003) had come up with a component which helped to diagnose the students' performance in an intelligent tutoring system. They had taken into account physiological measures (skin conductance level, muscle tension, and heart rate) and these measurements were recorded to provide an objective evaluation of changes in the participants' affect in response to the feedback from their physiology at a state of rest in an Intelligent Tutoring System. Their conclusion was that the student performance was influenced by a function of his/her instructional interactions, affect, and personality.
(Baker, Navarro, & Van Der Hoek, 2005) had implemented a cognitive tutor called "The Help Tutor" and it had monitored the problem solving ability of the student step by step, provided feedback on their answers and given hints to solve the problem if the student has asked to do so. Then the tutor kept track of the knowledge growth of the student using Bayesian Algorithm and used that information to determine the amount of help a student may need on any given step. Their effort was different from other projects because it focused on a different meta-cognitive skill.
(Dragon et al., 2008) had come up with a model to detect whether the students were misusing an intelligent Tutoring System or not. Their model was successful at recognizing the students who played the game only and showed poor learning.
(Sandanayake, Madurapperuma, & Dias, 2011) had mentioned the methodology that they had followed to identify the physical behaviour that were linked with emotional states. In order to accomplish their target, they had used human observation and wireless sensors to detect emotions, learning and attitude.
(Shyamkumar et al., 2014) had come up with a system to identify the emotional status of the student by using biophysical signals when he/she is engaged in studies to improve the learning experience based on the evaluated emotions.
According to (Moridis & Economides, 2009)'s research they had come up with a student's mood model to analyse the effect of the recently correct or incorrect answers to the current question. They had come up with an equation to get the mood having two assumptions. The two assumptions are as follow.

- The students' goal influences the mood during the test towards the remaining questions.
- The students' mood influences by their success or failure in answering the previous question.

They had mentioned that this model was 80% successful in identifying the students' mood whether it was positive or negative.
(Goetz et al., 2008), (Barrow D., Mitrovic A., Ohlsson S., 2008) and (Fossati, 2008) had mentioned the importance of giving positive feedback in ITS because the positive feedback help the students in learning process while negative feedback can damage the students' confidence level and can cause many other cognitive destruction in learning process.
(Krithika & Lakshmi Priya, 2016) had conducted a research to identify the concentration level of the students' in an e-learning environment and in there they had characterized the levels into three levels as high, medium and low. They had analysed the head movements and the eyeball movements with the aid of a web camera.

2.5 Selecting Facial Expressions as the Best Option to Track the Emotions

According to the literature referred, the following conclusions were made related to the upliftment of the students who are engaged in online education systems. One of the main factors is that when monitoring the students' actual emotions/behaviour without letting them know that they are being monitored within a normal education environment .

Since emotion is an addressable factor when giving a feedback to a student, it should be tracked in a proper manner. According to some literature such as (Smythe, 2012)if the student is aware of tracking his/her emotion by using some electronic devices mounted on them it will get affected.

Moreover, according to section 2.4, the mechanisms that were used to measure the emotional level of the students by using physiological measurements are not feasible to use in everyday activities owing to the following reasons.

- There should be enough number of sensor devices to be fixed onto the students which may be financially infeasible.
- Wearing the sensor devices before a test is a time-wasting activity.
- There should be data receivers for the sensor devices so that they can cast the data.

Hence, it was decided to use facial expression analysis mechanism to track the emotions of the students even though it is an imponderable task.

Since the intention of this study was to analyse the facial expressions through a photograph, it was decided to use an application, which recognizes the emotions through facial expressions (VIRDEE-CHAPMAN, 2017).

Based on these results it was decided to use Microsoft Face API/ Emotion API in emotion recognition.

2.6 Transient Emotion Peak

The duration for each emotion cannot be a constant value always and it might get varied depending on each emotion and the situation. It seems that there was no strong correlation between the transient emotions strength with the duration (Frijda, 1988). Hence, tracking the emotion by a camera would be a complicated task and had to check when can see the transient emotion when answering the question with respect to this scenario.

It was found that an expression can be seen on a face after an occurrence of a stimulus after 2 seconds, but within the first 4 seconds (Ruiz-Belda, Fernández-Dols, & Barchard, 2003). Sometimes facial expressions can be seen within 100 milliseconds based on startling occurrences, but they were not recognized as emotions (Ekman, Paul & Simons., 1985). The other point was, for a natural spontaneous stimulus occurrence, the emotions may last for 0.5 seconds to 4 seconds on the face (Ekman, Friesen, & Ellsworth, 1972).

In this situation, the stimulus occurrences were defined as the reading of the question and the selecting of an answer. Hence the expressions were seen when reading the question for the first time or submitting the answer to the system.

3. Methodology and Implementation

This section is divided into two main sub sections i.e. the proposed methodology of tracking the transient emotion peak, checking whether the body cues were a major effect when analysing the emotion in an online education system. In order to collect data for the analysis, an online quiz was implemented.

3.1 Transient Emotion Tracker

The proposed way of analysing the emotion based on each question was the tracking of the transient emotion peak. As mentioned in the previous section, emotional changes can be triggered after a stimulus action and in this scenario that was taken as the reading the question and submitting of the answer. During that period the photographs were captured from the webcam and they were being sent to the Microsoft Emotion API.

In this situation, based on the time taken to read the question, the transient emotion peak time can be varied. Hence, the question reading time can be taken as the independent variable, while the transient emotion tracking time can be taken as the dependent variable.

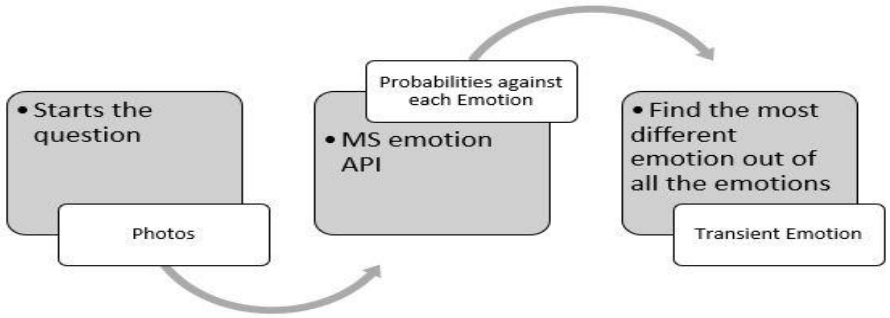
Hence, as the first step, the average time that takes to read each question was calculated. The questions were not lengthy questions and they were consisted of simple one or two-line sentences. Since the emotion changes can be seen from 2.5^{th} second- 8^{th} second according to the literature, it seemed it was sufficient to capture the images after the 2^{nd} second after the stimulus activity, but in order to check the reliability of this concept, the images were taken before that for every 1.1 seconds for 13 times.

After calculating the value for independent variable, the transient emotion peak time can be calculated Hence, an emotion can be seen at the 2.5^{th} second after the occurrence of a stimulus in the best case or in the worse- case, it can be seen at the 8^{th} second according to the literature (Ruiz-Belda et al., 2003), (Ekman et al., 1972).

3.2 Selection of the Photograph Against the Changed Emotion

The design of the selection of the emotion against each question can be depicted by Figure *1*.

Figure 1 Transient Emotion Identification



Through the MS Emotion API, the output was given as a probability value against each and every emotion and a set of values for one instance, are listed in the Table 1.

Table 1 Ms Emotion API Output

Anger	0.00006
Contempt	0.00087
Disgust	0.00028
Fear	0
Happiness	0.88729
Neutral	0.11144
Sadness	0.00002
Surprise	0.00004

Then by comparing all the values received from the API for the series of photographs, the most different value (outlier) which was considered as the emotion that can be noted after the stimulus action was selected following the method described in Figure 2.

After tracking the image according to above mentioned equation, the emotions against each question were stored into a file. In addition to the webcam, a video camera was used to record the behaviour of the students while they were answering the questions (The video was recorded with an angle so that the video analyser can see the mouse clicks to have an idea when the student was moving from question to question). This video tape was analysed by a psychiatrist and for each question a student was given a ground truth emotion. The emotions correspond to the images at the transient emotion peak were compared with the benchmark data (report produced by the psychiatrist based on the video).

The goal was to cross validate the accuracy of identifying matching pairs of emotions (from the API and the psychiatrist) during the proposed time interval. For this, a confusion matrix was used.

Figure 2 Finding the emotional change at the transient emotion peak

```
Store all the probabilities against each emotion into a matrix A [13] [8];
For each column i= 1:8
        meanProb(i)=mean(emotionProbability);       % Calculate the mean value
        deviationOfProb(i)=(emotionProbability)- mean(emotionProbability);
% Reduce the mean value from each data point;
        Store all the values in another matrix B [13] [8];
        Store the indices, which show the maximum Variance for each column;
        If the maximum variance of a column is 0 store the index as 0;
        Vector C ();
End

Take Vector C
Omit the columns, which has zero; % Omit the emotions that are not dominant
Get the index, which shows the maximum occurrences in Vector C;
If there are, no maximum occurrences get index which has the highest value
against it.
The photograph, which has the above index shows the transient emotion
peak.
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3.3 The Effect of Body Cues in Emotion Analysis

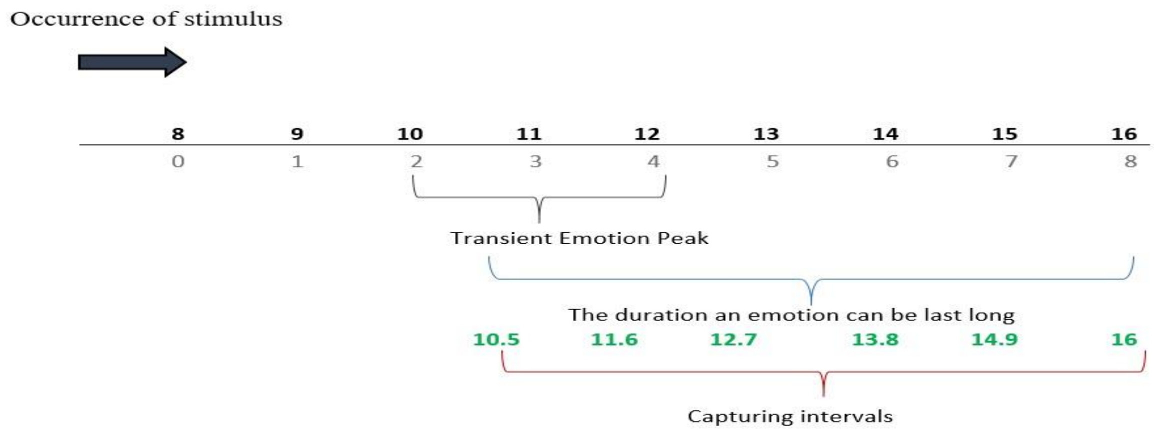
By using the data taken from the system while the students were answering the questions, the data sheet was filled. To analyse whether the body cue was used in expressing the emotions when answering to the questions on the quiz, the feedback taken from the psychiatrist was used. Next it was calculated the probability of occurring a mismatch in an emotion when it was given that it had been affected by a body cue.

4. Results

The first step was to find the value for the independent variable, i.e. the time taken to read a question. It was concluded that to read a single question in the quiz, it was taken 8 seconds and the occurrence of stimulus must happen after this 8 seconds duration.

The Figure 3 shows, that the emotion changes can be seen from 2.5th second- 8th second according to the literature (Ekman et al., 1972)and (Ruiz-Belda et al., 2003). Even though, it seemed it was sufficient to capture the images from the 8th second (to reading a question it takes 8 seconds) after reading the question, in order to check the reliability of this concept, the images were taken from the 5^{th} second for every 1.1 seconds for 13 times. Best case, the first emotion was expected to be triggered from the 6^{th} image which was taken at the 10.5^{th} second or else the emotion was expected to be tracked in one of the other images taken as the 7^{th} – 11^{th} photograph.

Figure 3Transient Emotion Peaks Vs Duration of the Online Quiz



Using the details of the 13 photographs, the most prominent emotion was identified by using the method described in Equation 1(Figure 2). Apart from the data gathered through the system, the rest of the data columns were filled with the data provided by the psychiatrist, i.e. the emotion defined by the psychiatrist (as the bench mark data), whether the both emotions were matched or not and whether the body cues were used in each analysis or not.

4.1 Data Analysis

A cross validation analysis was conducted to check the reliability of the proposed time interval in tracking the emotion by generating a confusion matrix and the results obtained from the data is as shown below in the Table 2.

Table 2 Confusion Matrix for Cross Validation

Within the expected time interval	Emotion Matching	
	YES	NO
YES	202	80
NO	14	34
Sensitivity	93.52%	
Specificity	70.83%	
Accuracy	71.52%	
Misclassification Rate	28.48%	

Assuming that, it would predict the emotion correctly when the capturing time was in the defined interval, the above confusion matrix was filled. According to that the accuracy is 71.52% and the sensitivity rate was 93.52% while the specificity rate was 70.83%.

Out of the 33 students 9 students were wearing spectacles and there were 9*10 records from them. 26 records out of the 90 records reported emotion mismatches while 7 out of the 26 records had time mismatches.

4.2 The Effect of Body Cues

Out of all the 330 records, only 24 instances found where body cue was used in predicting the emotion and 19 out of 24 were affected by the body cue. The probability of using the body cue in this study was 0.072 and the probability of noticing an emotion mismatch when it was given that the instance had been affected by a body cue was 0.057.

5. Evaluation

The accuracy of this module was depending on the independent variable, i.e. the estimated time to read a question. Hence it has to be mentioned here that it is better to estimate that time properly and if a quiz contains questions with different lengths, for each question the time which starts to take photographs should be adjusted.
After analysing the whole data set, by using the cross-validation methodology, it can be claimed that if this methodology was used it is capable of capturing the emotion with an accuracy of 71.52%. The sensitivity value implies that if the image (prominent emotion) was detected within the defined (proposed) time interval it is capable of capturing the correct emotion with an accuracy of 93.52%. The specificity value indicates that, when the image (prominent emotion) was detected out of the defined time period, there is a chance of 70.83% of having a misclassification.
Even though it was found that this methodology can be used in tracking the appropriate emotion out of the series of emotions, when analysing the videos, it was realized that it is better to analyse the features such as eye ball tracking since that shows the concentration level of the student. Hence it can be said that this could be more enhanced analysing the concentration level as in (Krithika & Lakshmi Priya, 2016) rather than focusing only on the emotions.

5.1 Evaluation of the Effect of Body Cue

According to the results it can be clearly seen that the body cues could not make a considerable effect on the emotion recognition in an online system. When analysing the videos, it was noticed that the body cues were rarely occurred during the online test and those body cues were not strong body cues as mentioned in (Aviezer, Trope, & Todorov, 2012). During a sport activity the subjects engage with physical activities and they seem to use their whole body in responding to everything but in contrast in an online education system, the subjects use their brain power to think than using the physical strength, hence this could be the reason in noticing less number of body cues in this study.

6. Conclusion

After analysing the data set statistically it is proven that, the transient emotion peak can be tracked productively following the suggested algorithm described in
Figure 1. Even though most of the emotions that were tracked by using the algorithm had matched with the benchmark data set, when synthesizing an effective feedback to the student based on the emotion, it is better to group them as positive, negative and neutral. In order to have such an approach it is better to have an enhanced way to track the facial features along with the eye movements to classify the expressions of the students. By looking at the iris and the eye movements, it can be analysed whether the student is concentrating on the question, panicked or not. Hence, it is suggested to use the transient emotion tracking time to track the specific emotions that can be seen in an online education system rather than focusing on all the emotions. In (Krithika & Lakshmi Priya, 2016), the eye movements and the head movements had been taken into account in analysing the concentration based on a video lecture and it would be a good way of analysing the emotion changes in an online education system. (Krithika & Lakshmi Priya, 2016) did not need to track the transient emotion peak time to time since they had analysed the behaviour of the students at a lecture. However, for an online test, it is better to have the transient emotion peak tracker to analyse the emotion type (as positive/negative/neutral emotion) so that it can be used to form a feedback according to that. Since it is a technical and a systematic way to track the transient emotion, it can be able to give a better result and a student can receive an effective feedback from the system based on the emotion, correctness and the timing comprising the all three key features that a feedback should have.
Since the teachers also can receive feedback based on the overall students' performance, the teachers can modify the course content accordingly so that the students can perform better in their final formal evaluations.
When it comes to the effect of the body cues in online education system, it has to be mentioned that the body cues do not seem to affect as when it is compared to the other fields like sports. Hence, it can be said that when synthesizing a feedback for an online test, it is sufficient to analyse the facial expression to get an idea about the emotion/ concentration level of the student without trying to incorporate the information about the body cues.

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7. References

1. Aviezer, H., Trope, Y., & Todorov, A. (2012). Body Cues , Not Facial Expressions , Discriminate Between Intense. Science, 338(November 2012), 1225–1230. Retrieved from https://www.semanticscholar.org/paper/Aviezer-Positive-and-Negative-Emotions-Body-Cues-%2C-Rana-Kakuda/6101d0fd6f00679d56b60c12d4f97377ebc29cf6

2. Baker, A., Navarro, E. O., & Van Der Hoek, A. (2005). An experimental card game for teaching software engineering processes. Journal of Systems and Software, 75(1–2), 3–16.

3. Barrow D., Mitrovic A., Ohlsson S., G. M. (2008). Assessing the Impact of Positive Feedback in Constraint-Based Tutors. SIntelligent Tutoring Systems. ITS 2008, 5091, 250.

4. Biggs, J., & Tang, C. (2007). Teaching for quality learning at university Maidenhead. Berkshire, UK: McGraw-Hill Education.

5. Conati, C. (2002). Probabilistic assessment of user's emotions in educational games. Applied Artificial Intelligence, 16(7–8), 555–575.

6. Del Blanco, A., Torrente, J., Marchiori, E. J., Mart\'\inez-Ortiz, I., Moreno-Ger, P., & Fernández-Manjón, B. (2010). Easing Assessment of Game-based Learning with< e-Adventure> and LAMS. In Proceedings of the second ACM international workshop on Multimedia technologies for distance leaning (pp. 25–30).

7. Dragon, T., Arroyo, I., Woolf, B. P., Burleson, W., El Kaliouby, R., & Eydgahi, H. (2008). Viewing student affect and learning through classroom observation and physical sensors. In International Conference on Intelligent Tutoring Systems (pp. 29–39).

8. Ekman, Paul, W. V. F., & Simons., R. C. (1985). Is the startle reaction an emotion? Journal of Personality and Social Psychology, 49(5), 1461.

9. Ekman, P., Friesen, W. V., & Ellsworth, P. (1972). What emotion categories or dimensions can observers judge from facial behaviour? In Emotion in the Human Face (pp. 39–55). https://doi.org/https://doi.org/10.1016/B978-0-08-016643-8.50025-2

10. Fisher, R., Sharp, A., & Richardson, J. (1998). Getting it done: how to lead when you're not in charge. HarperBusiness New York.

11. Fossati, D. (2008). The Role of Feedback in Intelligent Tutoring System. HLT Student Research Workshop, (Companion, 31–36. https://doi.org/10.2478/acss-2013-0011

12. Frijda, N. H. (1988). The laws of emotion. American Psychologist, 43(5), 349–358.

13. Goetz, C. G., Tilley, B. C., Shaftman, S. R., Stebbins, G. T., Fahn, S., Martinez-Martin, P., … Zweig, R. M. (2008). Movement Disorder Society-Sponsored Revision of the Unified Parkinson's Disease Rating Scale (MDS-UPDRS): Scale presentation and clinimetric testing results. Movement Disorders, 23(15), 2129–2170. https://doi.org/10.1002/mds.22340

14. Krithika, L. B., & Lakshmi Priya, G. G. (2016). Student Emotion Recognition System (SERS) for e-learning Improvement Based on Learner Concentration Metric. Procedia Computer Science, 85(Cms), 767–776. https://doi.org/10.1016/j.procs.2016.05.264

15. McQuiggan, S. W., & Lester, J. C. (2006). Diagnosing self-efficacy in intelligent tutoring systems: an empirical study. In International Conference on Intelligent Tutoring Systems (pp. 565–574).

16. Moridis, C. N., & Economides, A. A. (2009). Mood recognition during online self-assessment tests. IEEE Transactions on Learning Technologies, 2(1), 50–61.

17. Ruiz-Belda, M. A., Fernández-Dols, J. M., & Barchard, K. (2003). Spontaneous facial expressions of happy bowlers and soccer fans. Cognition and Emotion, 17(2), 315–326. https://doi.org/10.1080/02699930302288

18. Sandanayake, T. C., Madurapperuma, A. P., & Dias, D. (2011). Affective E learning model for Recognising learner emotions. International Journal of Information and Education Technology, 1(4), 315.

19. Sheldon, E., Malone, L., & Mc Bride, D. (2003). Objective Measurement of Student Affect to Optimize Automated Instruction. In Proceedings of Workshop on Modelling User Attributes and Affect (pp. 1–4).

20. Shen, L., Wang, M., & Shen, R. (2009). Affective e-learning: Using �emotional� data to improve learning in pervasive learning environment. Journal of Educational Technology & Society, 12(2), 176–189.

21. Shyamkumar, P., Rai, P., Oh, S., Ramasamy, M., Harbaugh, R., & Varadan, V. (2014). Wearable Wireless Cardiovascular Monitoring Using Textile-Based Nanosensor and Nanomaterial Systems. Electronics, 3(3), 504–520. https://doi.org/10.3390/electronics3030504

22. Smythe, M. (2012). Toward a framework for evaluating blended learning. Future Challenges, Sustainable Futures. Proceedings Ascilite Wellington, 854–858.

23. Steinwachs, B. (1992). How to facilitate a debriefing. Simulation & Gaming, 23(2), 186–195.

24. Thomas, P., Labat, J.-M., Muratet, M., & Yessad, A. (2012). How to evaluate competencies in game-based learning systems automatically? In International Conference on Intelligent Tutoring Systems (pp. 168–173).

25. VIRDEE-CHAPMAN, B. (2017). Face Recognition: Kairos vs Microsoft vs Google vs Amazon vs OpenCV. Retrieved February 5, 2017, from https://www.kairos.com/blog/face-recognition-kairos-vs-microsoft-vs-google-vs-amazon-vs-opencv