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Measuring Academic Emotions and Facial Expressions in Online Video-based Learning

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Abstract: This study proposes the new classification of analyzing academic emotions and facial expressions measured in online video-based learning contexts. To this end, we conducted a qualitative single-subject research on a learner to unpack the learner's academic emotions and facial expressions revealed during the online learning process. Drawn from the review of relevant literature, seven types of emotions were classified as positive or negative. The types of positive emotions captured are: 1) excitement, enjoyment, and pleasure 2) confidence, and 3) aspiration, enthusiasm and expectation. The types of negative emotions are: 1) fear and anxiety, 2) embarrassment and shame, 3) frustration and alienation, and 4) boredom. Recall interview and observation were also used to infer the facial expressions matched to each emotion type, which were measured through the movements of eyes, eyebrows, lip, and jaw. Overall, 3 to 4 facial expressions were revealed per emotion. Based on the results, we propose a new scheme to classify academic emotions in online video-based learning, and suggest some areas for future research on utilizing affective computing technology in academic emotions, and appropriating emotional support in online learning.

Keywords: Online learning, academic emotion, facial expression, affective computing

1. Introduction

Recently, research on emotion and affection in various learning situations has received increasing attention since learning experiences and emotions are understood as highly interweaved (Antonacopoulou & Gabriel, 2001; Norman, 2004; Rosiek, 2003). In online learning, learners have more burden to regulate and direct their learning pace because of the physical separation from teachers and peers. Previous studies have reported that online learners tend to experience more diverse but negative academic emotions (Astleitner, 2000; Marchand & Gutierrez, 2012; Moneta & Kekkonen-Moneta, 2007). Detecting learners' emotions in online learning environments, hence, can help design supporting mechanisms that help learners overcome emotional difficulties.

Research in the field of human-computer interaction has developed effective interaction methods utilizing the affordances of affective computing that detects, analyze and visualize human emotions in intelligent ways. In affective computing, facial emotion detection is one of the most important techniques in recognizing human emotion. Affective computing platforms (e.g., Affectiva, iMotions, and Air Class), can be used in online learning situations to automatically measure the type and degree of emotions, which can be the indicator of learner's engagement level (Park, Lee, & So, 2018). Despite such the potential of affective computing and difficulty that learners encounter in online learning, little research has been conducted for the utilization of affective technology to classify academic emotions in online learning situation thus far. While basic emotions such as anger, sadness, and disgust are easily detectable by the existing affective computing platforms, such emotions do not frequently happen in online learning contexts. Further, metacognitive feelings such as pride, interest, and shame cannot be easily measured by the existing affective computing technology (Ainley & Hidi, 2014), but are important to measure in learning contexts.

With this backdrop, the present study was motivated by the fact that the classification systems of emotions in the existing affective computing platforms are not suitable to detect and classify emotions in online learning contexts. This paper, therefore presents an in-depth analysis of the emotional experience that a learner encounters in online video-based learning to establish the basis for developing a new classification system of learner emotions relevant to online learning situations. In sum, this exploratory research aims to examine the following research questions:

RQ1. What types and degrees of emotions does a learner experience in an online video-based learning situation?
RQ2. How can emotions be inferred from the learner's facial expressions in an online video-based learning situation?

2. Theoretical Background

2.1 Emotions in Affective Computing

Emotions are the most direct and visual expressions of human's state of mind. Ekman and Friesen (2003) argue that facial expressions are universal regardless of racial differences and suggest a Facial Action Coding System (FACS) to describe facial changes through the anatomic analysis of muscles that cause facial changes. In FACS, each facial action unit can display the degree of emotion based on the maximum possible motion of facial muscles. Furthermore, Ekman and Friesen (2003) selected six basic expressions of emotions namely *anger*, *disgust*, *fear, happiness*, *sadness*, and *surprise* and argued that the six expressions are universal in many circumstances. Since then, many studies have focused on the detection of these basic emotions through facial expressions.

Many of the existing algorithms and platforms of affective computing also detect and analyze emotions based on FACS. For instance, Affectiva, the most well-known platform, analyzes emotional data based on FACS, and automatically calculates the degree of basic emotions (from zero to a hundred) by their machine learning system. In Affectiva, emotions are detected through 12 types of facial expressions; *smile, brow furrow, chin raised, lip press, mouth open, lip licking, eye enlarged, nose wrinkle, upper lip raised, inner brow raised, brow raised, and lip corner lowered.* Table 1 shows the matching between the facial expression and the emotions.

Table 1

Matching between Emotions and Facial Expressions in Affectiva

Emotion	Facial Expressions
Joy	Smile
Anger	Brow furrow, Chin raised, Lip press, Mouth open, Lip licking, Eye enlarged
Disgust	Nose wrinkle, Upper lip raised
Surprise	Inner brow raised, Brow raised, Mouth open
Fear	Inner brow raised, Brow raised, Brow furrow, Mouth open
Sadness	Inner brow raised, Brow furrow, Lip corner lowered

2.2 Academic Emotions in Learning Process

Diverse and complex emotions occur during learning processes, affecting learners' perceptions and behaviors (Yükselir, 2014). According to Pekrun, Goetz, Titz, and Perry (2002), learners' emotions during the learning process are highly related to their motivation, learning strategies, cognitive resources, self-regulation, and academic achievement. Facial expression in the learning process can predict the outcome of learning. Park, Jeong, Lee & Song (2006) analyzed the learners' facial expressions appeared in the e-learning situation. Learners' states were varied depending on their emotional changes. Learners' facial expression, measured by lip corner raised/lowered or the eye enlarged/diminished, could detect the emotional changes from pleasure to displeasure, and from arousal to sleep, which can be a clue to determine their interest and engagement that greatly affect learning outcomes. Furthermore, positive emotional experiences in learning can help learners better manage their task and time, which consequently affect their active participation (Kim & Kim 2011). Collectively, prior research suggests that emotion is a vital element that influences the quality of learning experiences, and should be considered in learning design.

Table 2 shows the classification of the learners' academic emotions experienced in traditional learning and online learning situations derived from the previous research studies. Pekrun et al. (2002) defined academic emotions as the emotions that are directly linked to academic learning, classroom instruction, and achievement. There are nine types of academic emotions occurring in the learning situations: *enjoyment, hope, pride, relief, anger, anxiety, hopelessness, shame, and boredom*. The criteria of valence are used to classify emotions as positive vs. negative on a bipolar dimension. Positive emotions include enjoyment, hope, pride, and relief, while the remaining emotions such as anger, anxiety, shame, hopelessness and boredom are categorized as negative emotions. The classification of positive/negative emotions is based upon their influence on motivation, the learning strategy, self-regulation, and availability of cognitive resources (Pekrun, 1992; Pekrun et al., 2002).

While the classification scheme outlined by Pekrun et al. (2002) is useful to cover the basic range of emotions that learners are likely to experience in academic situations, it is questionable whether this classification scheme can be directly applied to online learning situations where the nature of learning processes tend to be self-directed, isolated from instructors/peers, and driven by cognitive information. In Table 2, the main emotions in online learning are drawn from the study by Park (2015) who proposed the classification of academic emotions in online learning that: 1) the positive emotions are excitement, enjoyment, pleasure, aspiration, enthusiasm, expectation, and confidence; 2) the negative emotions are fear, anxiety, embarrassment, shame, frustration, alienation, and boredom. He excluded some emotions such as technophobia, and envy/jealousy because they are measured in the classroom environment where face-to-face communication is available.

Table 2

Classification of Academic Emotions

	Academic Emotions	
	Positive	**Negative**
Face-to-face learning	Enjoyment Hope Pride Relief	Anger Anxiety Hopelessness Shame Boredom
Online learning	Excitement Enjoyment Pleasure Aspiration Enthusiasm Expectation Confidence	Fear Anxiety Embarrassment Shame Frustration Alienation Boredom

3. Methods

3.1 Data Collection and Analysis

This study used a qualitative single-subject research design method to measure and categorize academic emotions and facial expressions in an online video-based learning situation. Since this is an exploratory study, we designed a single subject research study that allowed an in-depth investigation of data. The data was collected through the stimulated recall interview with the participant (a female graduate student). In the experiment, the participant watched a video clip (4mins 43sec) on the topic of 'Understanding Ballet' provided by one of the open online learning platforms in Korea. The video clip was selected based on the participant’s interest on the topic. Wlodkowski (1999) and Kim and Kim (2006) suggest that learners with prior knowledge show more academic interests during the learning process and consequently enjoy learning itself. Hence, we created the experimental condition where the learner with some prior knowledge could watch the online video clip in order to measure diverse types of emotions.

Data on academic emotions were extracted through the video recording and the recall interview. The video recording was done at the same time to collect data on changes in her facial expressions during the learning process. The participant had the stimulated recall interview conducted by two researchers for 20 minutes. To identify emotional experiences during the learning process, the interview questions included 1) the emotion revealed in the process of watching the video clip and 2) the potential cause of such emotions displayed. The recall interview data were analyzed by the concurrent data analysis method (Miles, Huberman & Saldana, 2014). Two coders, who are also the authors of this paper, used Nvivo 12 to analyze the video recording of the facial expressions. The coders categorized the group of academic emotions (Table 2) and facial expressions in online learning based on Park's research (2015). We reviewed the data repeatedly to analyze meaningful sentences and keywords, selected meaningful segments assigning primary codes, which were grouped based on the relational similarity and generated intermediate codes through further comparison, classification, and integration. The relationship across intermediate codes were reviewed considering the research problem, and consequently the parent codes were generated, categorized and conceptualized (Charmaz, 2014). During the process of coding and categorization, we created analytic memos reflecting whether the classification and integration of codes and the explanations for the relational similarity are appropriate. In case of inconsistency between the researchers during the coding process, they went through the process of explaining and discussing the reason until they reached an agreement.

The facial expressions for the determination of academic emotions were based on the interviews. In particular, eye enlargement and smile/laugh were the facial expressions that helped us infer academic emotions. Eye enlargement accounts for 18.86% of the total emotions occurred in the learning process and smile/laugh for 11.63%. The two expressions appeared almost at the same time or partially separated. The other types of emotions were categorized by cross-validating the content of the recall interview.

4. Results

Table 3 summarizes the overall results of the data analysis. In the online learning situation, the learner felt various types of positive and negative emotions that resulted in diverse emotional states and facial expressions. In subsequent sections, we present and discuss the key findings in (a) the positive emotions and (b) the negative emotions.

Table 3

Result of the Data Analysis

P/N*	Emotion	Facial Expressions	Coverage		Frequency
P	Excitement Enjoyment Pleasure	Eye enlarged	30.49%	18.86%	7
		Smile/Laugh		11.63%	
P	Confidence	Lip press	21.25%	12.34%	8
		Eye enlarged		10.52%	
		Lip corner raised		8.01%	
		Eye enlarged		0.07%	
P	Aspiration Enthusiasm Expectation	Chin raised	18.25%	11.63%	10
		Smile/Laugh		2.60%	
		Blink		2.69%	
		Brow raised		1.50%	
N	Fear Anxiety	Lip licking	12.17%	5.94%	4
		Eye enlarged		3.68%	
		Eye diminished		2.82%	
		Brow furrow		2.34%	
N	Shame Embarrassment	Blink	11.21%	8.69%	9
		Lip press		2.37%	
		Lip corner lowered		0.21%	
		Brow furrow		0.07%	
N	Frustration Alienation	Inner brow raised	9.17%	6.03%	3
		Brow furrow		3.07%	
		Lip corner lowered		0.07%	
N	Boredom	Eye diminished	8.21%	7.07%	3
		Blink slowly		1.14%	
Total			110.75%**	100%	52

* P = Positive emotion, N = Negative emotion **Since the facial expressions are overlapped, the total exceeds 100%.

4.1 Positive Emotions

Overall, we found that positive emotions were shown more frequently and longer than negative emotions. Positive emotions take a high proportion (about 70%) of the total online academic emotions appeared. Some types of emotions appeared to have same facial expressions. Based on the degree of similarity in the facial expression data, we categorized positive emotions into three groups: 1) excitement, enjoyment, and pleasure; 2) confidence; 3) aspiration, enthusiasm, and expectation. As shown in Figure 1, the first group (excitement, enjoyment & pleasure) covers 30.49% of the total emotions. The second group (confidence) was 21.25%, whereas the third group (aspiration, enthusiasm & expectation) was 18.25%.

The first group of positive emotions (excitement, enjoyment, and pleasure) includes the following facial expressions: a) eye enlarged (18.86%) and b) smile/laugh (11.63%). We speculate that the high proportion of the first emotion group (excitement, enjoyment, and pleasure) was due to the learning content that was related to the participant's interest and the level of prior knowledge about the subject. This speculation was confirmed in the recall interview. When watching the explanation of the ballet movements in the video clip, the participant recalled her previous ballet experiences, which stimulated to recall the positive experiences in her emotion. The following is an excerpt from the interview that the participant described how she felted excited during the learning process:

- "*I thought ballet is very interesting and it helped me a lot with improving my physical condition*". (excitement)

The second group of positive emotions (confidence) consists of the following facial expressions: a) chin raised (12.34%), b) lip pressed (10.52%), c) eye enlarged (8.01%), and d) lip corner raised (0.07%). Basically, confidence is an emotion driven by the familiarity from the past experiences, not by the pleasure of current learning experiences. While other positive emotions come out of the pleasure of learning itself or the desire and expectation for future learning, the 'confidence' emotion appears when the learner's level of prior knowledge is high enough to make her/him feel competent. An example is as follows:

- "*I was being confident because I learned it from my last class*". (confidence)

The third group of positive emotions (aspiration, enthusiasm, and expectation) includes the following facial expressions: a) smile/laugh (11.63%), b) blink (2.69%), c) eye enlarged (2.60%), and d) brow raised (1.50%) This group of emotions shows more diverse facial expressions than the first emotion group. The combined facial expressions, such as eyebrows lifted while the eyes are enlarged with blinking, appeared simultaneously or sometimes separately. In addition, smile, coded when a facial expression that the lip corner is raised, appeared repeatedly throughout this group of emotions. An example from the interview for the third group is:

- "*I thought the move is really beautiful, so I must learn how to do it in the future session*". (expectation)

Similar to the first emotion group, emotions of aspiration, enthusiasm, and expectation are based on the prior experiences, and the facial expressions of positive emotions are generated by the mixture of the current learning experience with the past memory about the learning subject, and expectation for future learning.

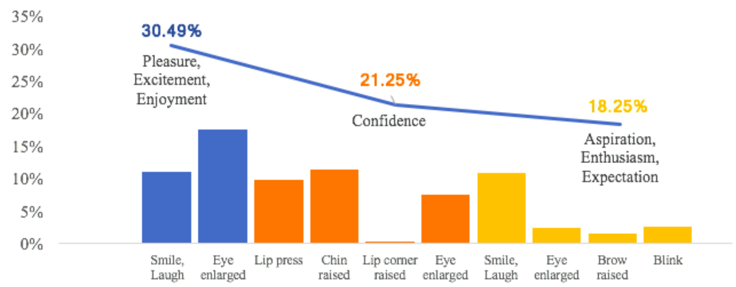

Figure 1. Facial Expressions in Positive Emotions

4.2 Negative Emotions

In this study, negative emotions show lower frequencies and retentions, but more various types than positive emotions. The negative emotions take 40.76% of the total academic emotions. The negative emotions are categorized into four groups based on the collected facial expression data: 1) fear and anxiety, 2) embarrassment and shame, 3) frustration and alienation, and 4) boredom. As shown in

Figure 2, fear and anxiety (12.17%) were the most observed emotions, followed by embarrassment and shame (11.21%), frustration and alienation (9.17%), and boredom (8.21%).

The first group of negative emotions (fear and anxiety) was the most expressed when the participant faced unfamiliar concepts to learn. Considering that the positive emotions of the participant took a higher portion in the total emotional experience than the negative emotions, it can be inferred that the participant was quite confident about the whole learning process. She did not expect a concept that she would not understand to appear in the learning process, and consequently she expressed the negative emotions when facing unfamiliar concepts. This was also seen in the interview:

- "*I was thinking Ballet is still amazing after all the lessons I took. I still have a lot to go*". (anxiety)

In general, learners experience fear and anxiety when confronting new learning situations that cause cognitive load (Conrad, 2002). The facial expressions that appeared when fear and anxiety occurred were coded as follows: a) lips licking (5.94%), b) eye enlarged (3.68%), c) eye diminished (2.82%), and d) brow furrow (2.34%). 'Lip licking' is mainly expressed together with 'eye diminished'. Lip licking is the motion from the nervousness when the participant encountered unfamiliar concepts. 'Eye enlarged' mostly appeared with 'brow furrow'. These expressions of emotion appeared almost at the same time as a compound facial expression or partially revealed as each facial expression for fear and anxiety.

The second group of negative emotions (embarrassment and shame) came out of the recollection of the previous experience or the misconception and wrong action. The interview revealed such emotions as:

- "*I got embarrassed because it reminded me of the mistake I had made while I was watching a ballet performance*". (embarrassment)

The facial expressions caused by 'embarrassment and shame' can be categorized as follows: a) blink (8.69%), b) lip press (2.37%), c) lip corner lowered (0.21%), and d) brow furrow (0.07%). 'Blink' appeared most of the time in embarrassment and shame with other remaining facial expressions simultaneously.

The third group of negative emotions (frustration and alienation) can be classified by the following facial expressions: a) inner brow raised (6.03%), b) brow furrow (3.07%), and c) lip corner lowered (0.07%). When learning about concepts that learners first encounter, it can be expressed with 'fear and anxiety'. When learners realize misconceptions, 'embarrassment and shame' can happen. Frustration is reported when learners face the interruption of ongoing tasks or goal blocking (Rothbart, Ahadi, Hershey, & Fisher, 2001). Alienation is developed when learners go through low levels of effort, inattention, poor task persistence, class cutting, and high rates of problems caused by other disciplines (Ekstrom, Goertz, Pollack, & Rock, 1989). In this study, frustration and alienation less appeared than other negative emotions.

- "*I thought I am unable to do that move…*" (frustration)

The fourth group of negative emotions (boredom) did not appear frequently compared to other groups. The facial expressions revealed in boredom are: a) eye diminished (7.07%), and b) blink slowly (1.14%).We suspect that boredom was hardly found due to the participant's interest toward the topic. Nevertheless, the participant expressed boredom when she felt the instructor was conveying irrelevant information or when she was learning about basic concepts that she already knew:

- "*It was a waste of time...I just wanted to skip that part. What on earth does it have to do with it Asada Mao?*" (boredom)

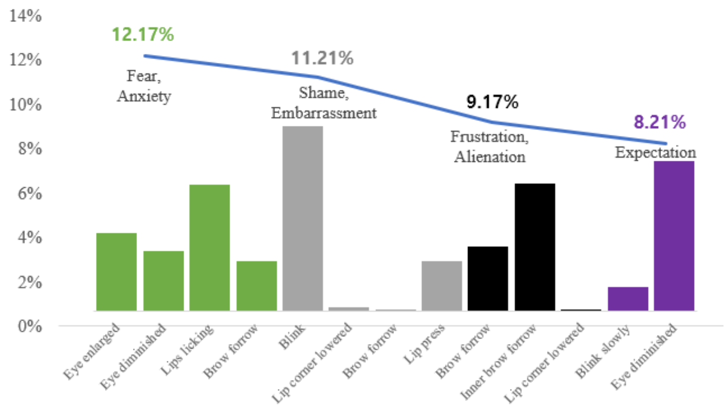

Figure 2. Facial Expressions in Negative Emotions

Table 4 present the classification scheme of academic emotions and corresponding facial expressions, drawn from the results of this study. We present the proposed scheme along with the basic emotions by Ekman and Friesen (2003) and the academic emotions by Pekrun et al (2002) for the ease of comparison. The proposed classification scheme can be used to measure and analyze how leaners in online learning environments experience various positive and negative emotions with the indicators of facial expressions.

Table 4.

Proposed classification scheme of emotions

Emotions				Facial Expressions						
Basic	**P/N***	**Academic**	**Online Learning**							
Joy	P	Enjoyment	Excitement Enjoyment Pleasure	Smile	Eye enlarged	-	-	-	-	-
		Hope	Aspiration Enthusiasm Expectation	Mouth open	Eye enlarged	Smile	Brow raised	-	-	-
		Pride	Confidence	Lip press	Lip corner raised	Smile	Chin raised	-	-	-
Anger	N	Anger	-	Eye enlarged	Lips licking	Mouth open	Lip press	Chin raised	Brow furrow	Lip protrude
Disgust	-	-	-	-	-	-	-	-	-	-
Surprise	-	-	-	-	-	-	-	-	-	-
Fear	N	Anxiety	Fear, Anxiety	Lip licking	Lip biting	Eye diminished	Blink	-	-	-
		Shame	Embarrassment Shame	Lip corner lowered	Mouth open	-	-	-	-	-
Sadness		Hopelessness	Frustration Alienation	Brow furrow	Inner brow raised	-	-	-	-	-
-		Boredom	Boredom	Blink slowly	Mouth open	-	-	-	-	-

* P = Positive, N = Negative

5. Discussion and Conclusion

In this study, we investigated the characteristics of academic emotions in an online video-based learning context through the analysis of facial expressions. As open online learning has become one of the main instructional approaches, concomitantly, there should be serious considerations on how to provide appropriate emotional feedback to learners who are physically and psychologically dispersed in various locations. In this section, we discuss some implications and areas for future research. The classification of academic emotions derived from this study can be used as a methodological framework for designing emotional support in online learning programs. In particular, this study proposes the structure matrix (Table 4) of academic emotions in online learning situations, which can be used as a checklist when integrating diverse components of emotional design. Next, the results of this study can inform the development of affective computing platforms that can better detect, measure, and analyze academic emotions in online learning situations. While recent development on affective computing is promising in automatically detecting and analyzing human emotions, the existing platforms tend to limit their analysis to the basic emotion types and cannot capture diverse and subtle types of academic emotions discussed in this study. Lastly, the result of this study may inform the design of a recommendation system for the appropriate learning material and contents by understanding the learner 's facial expressions in real-time. It can provide more personalized learning mechanisms considering individual characteristic and interests and eventually support meaningful learning experiences.

Some limitations of this study should be noted. First, the generalizability of the findings should be limited due to the single-subject design. It is necessary to perform repetitive measurement of dependent variables with more subjects under various conditions. Next, individual differences in the level of prior knowledge and interest toward learning topics, which interact highly with emotional states during learning processes, should be considered when interpreting the results. Future research can be conducted with learners with various levels of prior knowledge and academic interest. Despite the limitations, we believe that this exploratory study makes contributions to broaden the measurement of academic emotions in online learning situations, and can be used as a basic data for future applications of affective computing and artificial intelligence in learning contexts.

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