International Journal of Advanced Smart Convergence Vol.8 No.2 8-17 (2019)
http://dx.doi.org/10.7236/IJASC.2019.8.2.8

IJASC 19-2-2

Affective Computing in Education: Platform Analysis and Academic Emotion Classification

Hyo-Jeong So, Ji-Hyang Lee, Hyun-Jin Park

Department of Educational Technology, Ewha Womans University
hyojeongso@ewha.ac.kr, ljhyang@ewha.ac.kr, ba.gyunjin@ewha.ac.kr

Abstract

The main purpose of this study is to explore the potential of affective computing (AC) platforms in education through two phases of research: Phase I – platform analysis and Phase II – classification of academic emotions. In Phase I, the results indicate that the existing affective analysis platforms can be largely classified into four types according to the emotion detecting methods: (a) facial expression-based platforms, (b) biometric-based platforms, (c) text/verbal tone-based platforms, and (c) mixed methods platforms. In Phase II, we conducted an in-depth analysis of the emotional experience that a learner encounters in online video-based learning in order to establish the basis for a new classification system of online learner's emotions. Overall, positive emotions were shown more frequently and longer than negative emotions. We categorized positive emotions into three groups based on the facial expression data: (a) confidence; (b) excitement, enjoyment, and pleasure; and (c) aspiration, enthusiasm, and expectation. The same method was used to categorize negative emotions into four groups: (a) fear and anxiety, (b) embarrassment and shame, (c) frustration and alienation, and (d) boredom. Drawn from the results, we proposed a new classification scheme that can be used to measure and analyze how learners in online learning environments experience various positive and negative emotions with the indicators of facial expressions.

Keywords: *Affective Computing, Emotion, Affective Computing Platform, Classification*

1. Introduction

Affective computing(AC) is the computing area that relates to, arises from, or influences emotions [1]. In general, AC refers to an artificial intelligence-based system that can study, analyze and interpret human emotions. The need to study sentiment and emotion during learning processes has been emphasized for a long time. 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 [2-4]. Detecting learners' emotions in online learning environments, hence, can help learners overcome emotional difficulties. However, the current AC technology

Manuscript Received: Mar. 5, 2019 / Revised: Mar. 12, 2019 / Accepted: Mar. 16, 2019
Corresponding Author: hyojeongso@ewha.ac.kr
Tel: +82-2-3277-4124, Fax: +82-2-3277-2728
Department of Educational Technology, Ewha Womans University, Korea

has been mostly used in the commercial areas and little research is available to inform education applications of AC. Therefore, the main purpose of this study is to explore the potential of AC platforms in education through two phases of research: Phase I – platform analysis and Phase II – classification of academic emotions. Phase I research analyzes existing AC platforms that can be applied to the education field. Through the platform analysis, we identify the advantages and disadvantages of existing platforms. Phase II research focuses on an in-depth analysis of the emotional experience that a learner encounters in online video-based learning to establish the basis for a new classification system of online learner's emotions.

2. Theoretical Backgrounds

2.1 Emotions in Affective Computing

Emotions are the most direct visual expressions of people's state of mind. Ekman and Friesen[5] suggest a Facial Action Coding System (FACS) to describe common 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 motion of facial muscles. Ekman and Friesen[5] also selected six basic expressions of emotions namely anger, disgust, fear, happiness, sadness, and surprise, arguing that the six expressions are universal in many circumstances. Many of the existing algorithms and platforms of AC also detect and analyze emotions based on FACS. For instance, *Affectiva*, the most well-known AC platform, analyzes emotional data based on FACS, and calculates the degree of basic emotions by their machine learning system. As shown in Table 1, *Affectiva* detects emotions by 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. 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

2.2 Academic Emotions in Learning Process

Diverse and complex emotions occur during learning processes, affecting learners' perceptions and behaviors [6]. Table 2 shows the classification of learners' academic emotions experienced in traditional learning and online learning situations, derived from the previous studies. Pekrun, Goetz, Titz, and Perry [7] defined academic emotions as emotions directly linked to academic learning, classroom instruction, and achievement. There are nine types of academic emotions in 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, learning strategies, self-regulation, and the availability of cognitive resources [8]. While the classification scheme by Pekrun et al. [7] is useful to cover the basic range of emotions in academic situations, it is questionable whether this classification scheme can be directly applied to online learning situations where the nature of learning processes tends to be different from the traditional learning environment. In Table 2, the main emotions in online learning present that: (a) the positive emotions are excitement, enjoyment, pleasure, aspiration, enthusiasm, expectation, and confidence; (b) the negative emotions are fear, anxiety, embarrassment, shame, frustration, alienation, and boredom [9].

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. Phase I Research: Affective Computing(AC) Platform Analysis

3.1 Purpose and Methods

The main purpose of Phase I research was to analyze AC platforms that have been actively used in various contexts for the last 5 years until June 2018. Overall, while a substantial number of research studies regarding the technological advancement of AC have been done, there are few studies on technology usage cases and applications. We conducted a primary search process using the online search method on Google to locate relevant platforms that utilize AC technology. The search process surfaced 31 AC platforms. The second-round search was conducted through collecting a wide range of literature published on the web, regarding case studies on the actual use of the selected platforms. Based on the above search process, we were able to identify platforms and classify them by the emotion detecting method, whether the platform perceives the emotion through facial, biometric, or text/verbal expression. The representative platforms were re-selected with the AC classification criteria derived from the second-round search. In total, seven platforms were selected according to (a) whether it has the potential to use or has been already used in education, (b) whether it is used for the research purpose rather than the commercial purpose, and (c) whether it offers free software (SDK/API) considering its easy application to educational fields in the future. We analyzed selected seven platforms by the category of AC, the technical characteristic (i.e., input method, input data, and output data), Internet access required, and fields of application.

3.2 Results

The results indicate that the existing affective analysis platforms can be largely classified into (a) *facial expression-based platforms*, (b) *biometric-based platforms,* (c) *text/verbal tone-based platforms,* and (d) *mixed methods platforms* according to the emotion detecting methods. Table 3 presents the comparison of seven AC platforms that we analyzed.

Table 3. Comparison of selected AC platforms

Platform	Detecting Category	Input Method	Input Data	Output Data	Free Software	Online/ Offline
Affectiva	Facial	Webcam, Video	Facial expression	Demographic data/ Chart and graph outlining the types and depth of emotion/ Emoji relevant to users' emotion	Y (Limited)	Both

Face Reader	Facial	Webcam	Facial expression, gaze direction, head orientation Action	Demographic data/ Chart and graph outlining the types and depth of emotion	Y (Limited)	Both
Air Class	Facial	Webcam	Facial expression	Chart and graph outlining Engagement score	N	Online
Empatica	Biometric	Wristband	Electrical changes across the surface of the skin, parasympathetic nervous system activation or vagal tone detected by heart rate variability	Chart and graph outlining users' biometric data including emotional state	Y (Limited)	Online/ Offline (Limited)
IBM Watson Tone Analyzer	Text/ Verbal	Speaking/ Writing	Text, words, phrase, sentence	Chart and graph outlining the types of emotion, the depth of emotion, users' social degree, and types of writing	Y	Both
Vokaturi	Text/ Verbal	Speaking	Live or recorded voice and speech	Five types of emotion	Y (Limited)	Both
iMotions	Mixed	Webcam, Eye-tracking glasses, EEG headsets, GSR/EMG/ECG devices, Video	Facial expression, eye-tracking EEG, ECG, GSR, EMG	Chart and graph outlining users' biometric data including emotional state, types of emotions including confusion &frustration	N	Both

1) Facial Expression-Based Platforms

Facial expression allows AC to detect what emotion is being expressed based on the position and the movement of eyebrows, lips, nose, mouth, and facial muscles. For instance, *Air Class* is a virtual training software program made only for the educational purpose in 2016. As *Air Class* is an education-specialized software program, the measured emotion is used to see learners' attention and engagement in the learning process. The information, which shows the degree of learners' attention and engagement (engagement score) is detected through facial expressions captured via a webcam. *Air Class* instantly analyzes and reflects the engagement score on the instructors' screen, allowing them to monitor learners' engagement, and flexibly deploy their teaching strategy in situ. *Air Class* needs an internet connection and does not offer free SDK/API.

2) Biometric-Based Platforms

Emotions can be detected by biometric information left on a human body. The most notable AC platform in biometrics is *Empatica*, which developed one of the first devices in the world detecting users' physiological data sensed from the wrist in 2011. Their device comes in two types with different purposes. One named Embrace is optimized to manage convulsive seizures, and the other one, named E4 is for research requiring physiological signals in real-time. While both can be used for research purposes, E4 is more appropriate to encompass all research areas that require biometric data. Although Embrace and E4 indicate emotions, they are more suited for healthcare and human behavior analysis settings, due to the focus on users' physiological conditions in daily life.

3) Text/Verbal Tone-Based Platforms

Emotions can be detected by tones of a speech or texts based on what word is selected and how strong it is expressed. For instance, *Tone Analyzer*, which is one of the services enabled by IBM Watson, can detect tones, degree of sociality, and types of emotion including fear, anger, joy, sadness, analytical, confident, and tentative by either analyzing text, word, phrase, and sentence in documents or converting speech to text for analyzing the tone of the dialogue. While output data revealed differently across the type of developers, the platform shows charts and graphs outlining emotional data. *Tone Analyzer* provides a spell and grammar check function, which increases the accuracy of the detection. It can be also effectively applied in educational settings by analyzing learners' written feedback to see if they are frustrated or satisfied. API/SDKs are available for developers and the platform can work both online and offline according to how it is built.

4) Mixed Emotion Detecting Platforms

There is also a rare type of platforms which see emotions through multiple detection techniques combined. As an example*, iMotion* enables scalable biometric and human behavior research in various areas. *iMotion* perceives affective data through a webcam, eye-tracking device, EEG headset, and GSR/EMG/ECG devices, and even a recorded video to combine all biometric information resulting in concrete and accurate data. While it is possible to request a free demo, the company does not offer free software to the public. *iMotion* can be used in both online and offline situations when it is not necessary to use immediate facial expressions from a webcam and is fine with a recorded video instead.

4. Phase II Research: Academic Emotion Classification

4.1 Purpose and Methods

The main purpose of Phase II Research was 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 with a female graduate student that allowed an in-depth investigation of emotional data. In the experiment, the participant watched a video clip (4 mins 43 sec) on the topic of 'Understanding Ballet' on an open online learning platform. Data on academic emotions were extracted through video recording on the participant's facial expression during the learning process and the recall interview with 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 [10]. 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 framework [9]. 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.

4.2 Results

As summarized in Table 4, the learner in the online learning situation felt both positive and negative emotions that resulted in diverse emotional states and facial expressions. Below, we explain each group of academic emotions.

Table 4. Emotions and facial expressions during online learning

P/N*	Emotion	Facial Expressions	Coverage		Frequency
P	Confidence	Lip press	30.94%	12.34%	8
		Eye enlarged		10.52%	
		Lip corner raised		8.01%	
		Eye enlarged		0.07%	
P	Excitement Enjoyment	Eye enlarged	30.49%	18.86%	7

	Pleasure	Smile/Laugh		11.63%	
P	Aspiration Enthusiasm Expectation	Chin raised	18.42%	11.63%	10
		Smile/Laugh		2.60%	
		Blink		2.69%	
		Brow raised		1.50%	
N	Fear Anxiety	Lip licking	14.78%	5.94%	4
		Eye enlarged		3.68%	
		Eye diminished		2.82%	
		Brow furrow		2.34%	
N	Shame Embarrassment	Blink	11.34%	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		123.35%**	100%	52

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

4.2.1 Positive Emotions

Overall, we found that positive emotions were shown more frequently and longer than negative emotions. Based on the degree of similarity in the facial expression data, we categorized positive emotions into three groups: (a) confidence; (b) excitement, enjoyment, and pleasure; and (c) aspiration, enthusiasm, and expectation. As shown in Fig. 1, the first group (confidence) covers 30.94% of the total emotions. The second group (excitement, enjoyment & pleasure) was 30.49%, whereas the third group (aspiration, enthusiasm & expectation) was 18.25%. The first group of positive emotions consists of the following facial expressions: chin raised (12.34%), lip pressed (10.52%), eye enlarged (8.01%), and lip corner raised (0.07%). The second group of positive emotions includes the following facial expressions: eye enlarged (18.86%) and smile/laugh (11.63%). The third group of positive emotions includes the following facial expressions: smile/laugh (11.63%), blink (2.69%), eye enlarged (2.60%), and brow raised (1.50%). This group of emotions shows more diverse facial expressions than the second emotion group. The combined facial expressions, such as eyebrows lifted while the eyes are enlarged with blinking, appeared simultaneously or sometimes separately.

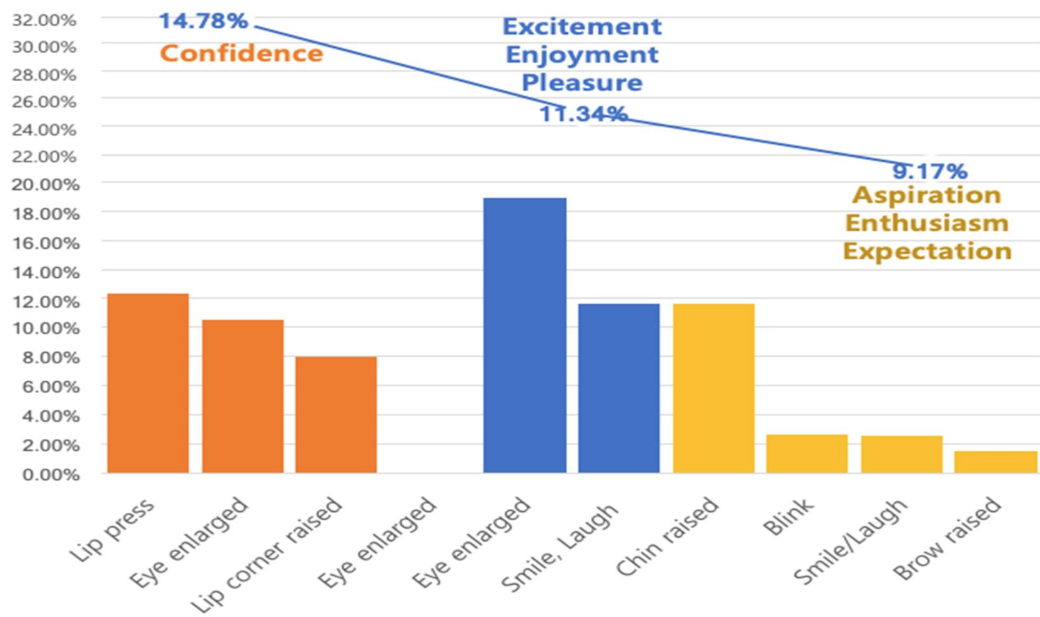

Figure 1. Facial expressions in positive emotions

4.2.2 Negative Emotions

Negative emotions show lower frequencies and retentions, but more various types than positive emotions. The negative emotions take 43.50% of the total academic emotions. As shown in Fig. 2, the negative emotions are categorized into four groups based on the collected facial expression data: (a) fear and anxiety, (b) embarrassment and shame, (c) frustration and alienation, and (d) boredom. Fear and anxiety (14.78%) were the most observed emotions, followed by embarrassment and shame (11.34%), frustration and alienation (9.17%), and boredom (8.21%). The first group (fear and anxiety) was the most expressed when the participant faced unfamiliar concepts to learn. The facial expressions that appeared when fear and anxiety occurred were coded as follows: lips licking (5.94%), eye enlarged (3.68%), eye diminished (2.82%), and brow furrow (2.34%). The second group (embarrassment and shame) came out when recalling previous experiences or facing misconception and wrong actions. The facial expressions caused by 'embarrassment and shame' include: blink (8.69%), lip press (2.37%), lip corner lowered (0.21%), and brow furrow (0.07%). 'Blink' appeared most of the time in embarrassment and shame with other remaining facial expressions simultaneously. The third group (frustration and alienation) can be detected by: inner brow raised (6.03%), brow furrow (3.07%), and lip corner lowered (0.07%). Frustration is reported when learners face the interruption of ongoing tasks or goal blocking. Alienation occurs when learners go through low levels of effort, inattention, poor task persistence, class cutting, and high rates of problems caused by other disciplines. The fourth group (boredom) did not appear frequently compared to other groups. The facial expressions revealed in boredom include eye diminished (7.07%) and blink slowly (1.14%). We suspect that boredom was hardly found due to the participant's interest in the topic.

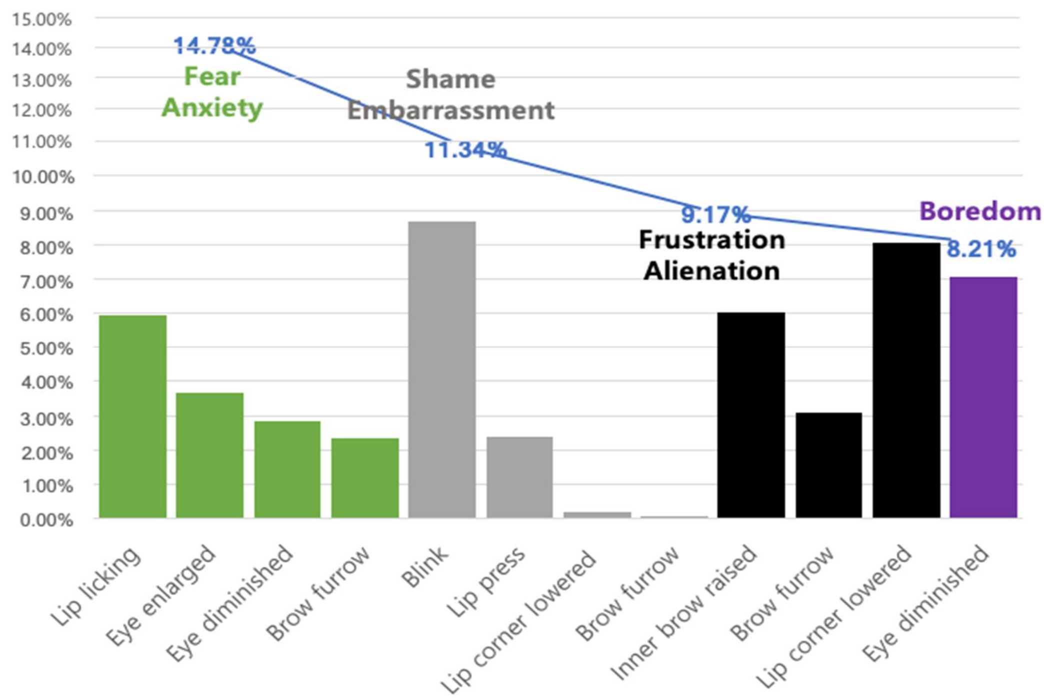

Figure 2. Facial expressions in negative emotions

4.2.3 Proposed Classification Scheme

Table 5 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 [5] and the academic emotions by Pekrun et al. [7] for the ease of comparison. The proposed classification scheme can be used to measure and analyze how learners in online learning environments experience various positive and negative emotions with the indicators of facial expressions.

Table 5. Classification scheme of academic emotions in online video-based learning

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	-	-	-	-	-

5. Discussion and Conclusion

The need to study the role of various types and states of emotions in human learning processes has long been emphasized. The role of emotions, which was perceived as secondary in the human cognitive process, has recently gained a renowned interest with the importance of socio-emotional learning. Now, the process of learning is considered not as a mere act of motivation or cognition alone, but a collective process in which various emotional responses are intertwined. While Affective Computing (AC) has several potentials discussed in the Phase I research, some challenges of integrating AC in education exist. Firstly, AC platforms are mainly used in commercial contexts. Thus, there has been only limited applications of AC to learning contexts. The intuitiveness of affective data is another challenging area. As AC platforms are still limited in presenting or visualizing emotional data, learners tend to have difficulties intuitively understanding and interpreting data output. How to visualize affective data for learners' intuitive interpretation is the promising area for future research. The last challenge is associated with detecting and analyzing the flow of emotional changes and co-occurring multiple emotional statuses. Human emotions are highly vulnerable to the surrounding situations, including the place, time, other people, content, and tools. So far, many research studies on AC have been conducted in lab settings, hence limiting their applications in real situations with diverse factors involved. Further, human emotion is seldom a single state, but rather a complex composite of multiple emotional states (e.g., surprise and sad) [11]. Such complexity of co-occurring multiple emotional states should be considered in the education use of AC, since learning processes are not linear, but complex, iterative with several states of emotion emerging, evolving and disappearing. As open online learning has become one of the main instructional approaches, there should be serious considerations on how to provide appropriate emotional feedback to learners who are physically and psychologically dispersed in various locations. Therefore, we conducted the Phase II study and the classification of academic emotions derived from this study can be used as a methodological framework for designing emotional support in online learning programs. The result of Phase II research 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 the Phase II study should be noted. First, the generalizability of the findings should be limited due to the single-subject design. It is necessary to perform the repetitive measurement of dependent variables with more subjects under various conditions. Next, individual differences in the level of prior knowledge and interest in 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 AC in learning contexts.

Acknowledgment

This work was supported by the Ministry of Education of the Republic of Korea and the National Research Foundation of Korea (NRF-2018S1A5A8030048). Portions of this research were presented at the ICoME 2018 (Cheongju) and ICCE 2018 (Manila) conferences.

References

[1] Picard, R. W., *Affective Computing. Perceptual Computing Section Technical Report No. 321*, Cambridge, Massachusetts, M.I.T. Media Lab, 1995.
DOI: https://affect.media.mit.edu/pdfs/95.picard.pdf

[2] Astleitner, H. (2000). "Designing emotionally sound instruction: The FEASP-approach.", *Instructional Science,* Vol. 28, No. 3, pp. 169-198, 2000.
DOI: https://doi.org/10.1023/A:1003893915778

[3] Marchand, G. C. and Gutierrez, A. P., "The role of emotion in the learning process: Comparisons between online and face-to-face learning settings.", *The Internet and Higher Education,* Vol. 15, No. 3, pp. 150-160, 2012.
DOI: https://doi.org/10.1016/j.iheduc.2011.10.001

[4] Moneta, G. B. and Kekkonen-Moneta, S. S., "Affective learning in online multimedia and lecture versions of an introductory computing course.", *Educational Psychology, Vol. 27*, No. 1, pp. 51-74, 2007.
DOI: https://doi.org/10.1080/01443410601061413

[5] Ekman, P, and W. V. Friesen., *Unmasking the face: A guide to recognizing emotions from facial clues*. Ishk, 2003.

[6] Yükselir, C., "An analysis of the perceptions on academic emotions and emotional experiences in English language teaching.", *International Journal of English Language Education*, Vol. 2, No. 2, pp. 269-278, 2014.
DOI: http://dx.doi.org/10.5296/ijele.v2i2.6617

[7] Pekrun, R., Goetz, T., Titz, W. and Perry, R. P., "Academic emotions in students' self-regulated learning and achievement: A program of qualitative and quantitative research.", *Educational Psychologist*, Vol. 37, No. 2, pp. 91-105, 2002.
DOI: https://doi.org/10.1207/S15326985EP3702_4

[8] Pekrun, R., "The impact of emotions on learning and achievement: Towards a theory of cognitive/motivational mediators." *Applied Psychology*, Vol. 41, No. 4, pp. 359-376, 1992.
DOI: https://doi.org/10.1111/j.1464-0597.1992.tb00712.x

[9] Park, T. J., *A study on developing the design principles of an emotionally affordable e-learning environment*, Ph.D. Dissertation. Seoul National University, Seoul, Korea, 2015.

[10] Miles, M. B., Huberman, A. M., and Saldaña, J., *Qualitative data analysis: A methods sourcebook. 3rd.,* Sage, 2014.

[11] Harley, J. M., François, B., and Roger, A., "Measuring learners' co-occurring emotional responses during their interaction with a pedagogical agent in MetaTutor." in *Proc. International Conference on Intelligent Tutoring Systems on Springer, Berlin, Heidelberg*, pp. 40-45, 2012.
DOI: https://link.springer.com/chapter/10.1007/978-3-642-30950-2_5