# Detect Students' Academic Emotions in Classroom: Measurement, Self-perception and Manifested Behaviors

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Abstract: The emotions students experience in the classroom are likely to influence their learning in school. For purposes of helping student improve their learning, this study seeks to further the development of the use of automated analysis of observed data to understand students' emotions and during their learning activities. This study looks at linking behavioral data about emotions with self-report data about emotions with the intent to determine if observed behaviors are able to predict student's emotions. The ICT-supported Learning Emotion Scale was used for 57 students to measure their learning emotion while learning in an ICT environment, meanwhile, classroom observations were conducted for 57 students for six weeks in 4 classrooms, paying close attention to student emotional behaviors and emotional changes. The results found that three key groups of behavioral indicators happened frequently. One of the key findings was that students who volunteered to answer questions in class were observed to have an observable "enjoy" emotion 84.79% of the time. The discussion highlighted that the bridge function of students' emotion engagement between classroom observation and questionnaire data.

Keywords: Emotional engagement; Learning analytics; Behavioral indicators; Observations and questionnaire

# 1. Introduction

It is an ideal of teachers in classroom that the learning status of the students can be fully understood, in one way or other, thus the classroom teaching can be more adaptive and effective. This is what learning analytics is trying to accomplish, to develop a new way of "measurement, collection, analysis, and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs" (LAK, 2011). While there are efforts of learning analytics focusing on different perspectives of learner behaviors and therefore in understanding learning status, students' academic emotions during classroom session, are remain relatively untouched, due to the challenges of detecting the emotion data from the live classrooms. The state of academic emotions opens a window in understanding studying, therefore, attract lots of research on this topic, among which the constructs of academic emotions, the ways of measuring academic emotions, and the scales used to measure academic emotions are the main topics in this area.

From the point of learning analytics, measuring and understanding academic emotions as a potential way to unfold learning, should be manifested as measurable behaviors, thus that they can be collected and analyzed together with other learner behaviors and learning context information for the purpose of learning analytics (LAK, 2011). Although there have already been quite a lot studies on academic emotions, most of the methods are using self-report to measure students' perceived emotions. The purpose of this study is therefore trying to propose a method to measure students' academic emotions with the manifestations of students' behaviors. By approximating students self-reported emotions status with their actual behaviors indicating their hidden emotions, this study aimed to provide a practical way for learning analytics in collecting important data of learner behaviors. Two steps were involved in carrying out this study, where first step was to adapt and verify a scale measuring students' academic' academic emotion with a self-report method; while the second step was to further verify the constructs and indicators of students' academic emotions, by approximating the self-reported emotions with their actual behaviors.

#### 2. Literature Review

Emotions are multifaceted phenomena involving affective, cognitive, physiological, motivational, and behavioral components (Damasio 2004). With the gradual recognition of emotions, emotions have gained a growing attention in education in recent years (Zembylas, 2007). Academic emotions refer to emotions related to students' academic learning processes, mainly including enjoyment, pride, hope, anger, shame, boredom, anxiety, and hopelessness (Pekrun et al., 2007). In the last decade, numbers of scholars have focused on understanding the role of affect, or moods and emotions in education (Efklides & Volet, 2005). Previous studies have showed the important effect of academic emotions in students' learning outcomes such as learning motivation, learning strategies, learning engagement, self-regulation, problem-solving, and academic achievement among others (Kim & Pekrun, 2014).

Emotional engagement is comprised of positive and negative affect in interactions with teachers, peers, schoolwork, and the school (Christenson & Reschly, 2012). Positive emotional engagement includes enjoyment, pride and hope, and negative emotional engagement includes anger, shame, anxiety, boredom (Pekrun et al., 2006). Previous studies have pointed out that emotions will indirectly affect students' academic achievement through engagement (Linnenbrink, 2007; Linnenbrink & Pintrich, 2004). González et al. (2015) also pointed out that behavior engagement is accompanied by emotions, such as enjoyment, enthusiasm, pride. While a large amount of research on student engagement during adolescence exists, with the ICT developed, there are some empty gaps during classes.

#### 3. Methodology

This study is part of a learning analytics project to measure students' emotion engagement through ICTsupported learning (iPads & PCs) in East China. A mixed-method design of both quantitative and qualitative techniques is employed, involving four classrooms in a Secondary school. Totally, we observed 57 students (31 female; age: M=12 years), who were a subset of students, four lectures in six weeks, including English, Chinese class.

The engagement only consists the emotion aspects in this article, Skinner once pointed out not the entire range of positive academic emotions are concluded in the emotional engagement (Meyer & Turner, 2002), but some energized emotional states, such as enjoyment, enthusiasm are included. However, when the students don't engage in the learning task, they may behavior disengagement. The on-task behaviors and off-task behaviors were divided active initiative, working, and passive, which three categories can distinguish the students learning behaviors between positive emotion and negative emotion. Furthermore, the observers need to note each behavior with emotions (enjoy, bored, and anxiety). For example, one student was putting his hand in the classroom, while his mood was enjoyment. The instrument was measured in Table 1 based on the literatures.

The questionnaires were used to investigate the secondary students' emotion toward ICT, which was developed from AEQ, and attempted to measure the students' emotions during class. Those items including enjoyment (4 items), anxiety (5 items), shame (9 items), boredom (11 items). The study validated the 29-item by confirmatory factor analysis, presented with a five-point Likert scale, ranging from strongly agree (5 points) to strongly agree to strongly disagree.

There were two observers and their starting times were aligned. Beginning with the first student, the observer recorded the occurrence of any of the behaviors and then systematically rotated through the team under study in 30-sec intervals (Horn et al., 1986), marked all student behaviors seen within that time and then moves on to observe the next student. Each student was observed for a period of thirty seconds and his/her behaviors and emotion will be recorded before moving to the next student. After one cycle of students (10-13 students), the observer returned to the first student and began another cycle. In all, the maximum of cycles, which were scheduled, was sixteen in one classroom. Reliability estimates are conservative when compared to real-time observations when two observers code simultaneously. An inter-rater reliability between observers reached to 0.794 before they started to

conduct coding for the three class sessions, and then reached an inter-rater reliability of 0.875, which is accepted to be a good figure for observation protocols.

	On-Task	Off-Task					
On-Task	B1 rising hands; B2 asking a question;	Off-Task	B14 Interrupt teacher; B15				
Active	B3 taking notes; B37 raising your hand	Active	others; B62 playing games				
Initiative	to answer questions by electronic tools;	Initiative	with iPad; B63 taking				
	B38 asking questions by electronic		photos with iPad;				
	tools; B39 taking notes by electronic		_				
	tools;						
On-Task	B5 question answering; B6 reading; B7						
Working	doing activities; B11 taking lessons;						
_	B12 listening to teachers' reviews; B17						
	discussing; B18 rolling play; B21						
	reading aloud; B41 listening to the						
	radio; B42 reading the e-textbooks; B43						
	doing activities by electronic tools; B44						
	APP;						
On-Task	B24 watching peers doing tasks; B46	Off-Task	B27 disturbing peers; B29				
Passive	listening to the teacher using electronic	Passive	sleeping; B30 whispering to				
	tools; B26 Ah, Ah; B47 comment from		each other; B31 looking				
	teachers by electronic tools; B48 do not		around; B33 laughing; B34				
	understand what teachers said		unwilling to participate in				
			the activities				

Table 1: the Emotional Engagement Observation Protocol (Sample)

Before completing the questionnaires, the research advised by the teacher who has been teaching participant students to inform the ability for students' respond. Then, respect students' willing and volunteer to finish the search online during class. It took about 20 minutes to complete the whole survey. The 29-item (1 = strongly disagree, 5 = strongly agree) ICT-LES (parts of AEQ; Pekrun et al., 2002) during class was used to measure students' levels of emotion scales. Barlett's Test of Sphericity and KMO Test were applied on the data sets of ICT-LES (enjoyment, anxiety, shame, and boredom). We obtained KMO, moreover, it was found that items which factor loadings were less than 0.5 cross-loaded were gradually omitted, resulting in the removal of 4 items about anxiety, and shame emotion. Furthermore, it is acceptable for reliability analysis (enjoyment ( $\alpha$ =0.912), anxiety ( $\alpha$ =0.944), shame ( $\alpha$ =0.967), and boredom ( $\alpha$ =0.979).

# 4. Results and Discussion

# 4.1 Descriptive Statistics for the Emotion Engagement and Behavior Engagement

According to the result of ICT-supported emotion engagement scales, the mean value of each emotion engagement is enjoyment (M=3.79, SD=1.01), anxiety (M=3.22, SD=0.70), shame (M=3.07, SD=0.44) and boredom (M=3.37, SD=1.21). It points out that students show more positive emotion engagement in the ICT-supported learning environment. Students also have less negative emotion engagement when they learn with the support of ICT, like boredom, anxiety, but less likely to appear the emotion of shame.

According to the behavioral data, the percentage of on-task behavior averaged across all observations (80.7%) was within the range of previously reported estimates of on-task behavior in K-9 school students (90%-50%). Conversely, the frequency of off-task active initiative behaviors accounted for 19.3% of the total behaviors. Specifically, the frequency of on-task passive was 52.4%, the frequency of on-task working was 8.8%, and the frequency of on-task active initiative was 19.5%. In the present study, the two most common types of on-task passive behavior observed included: listening to teachers saying (B11), question answering (B5), and praising (B13). The two most common types of off-task active initiative behavior included: interrupting the teacher with a nonacademic issue (B14),

and unwilling to participate in the activities (B35). The most common type of on-task active initiative behavior contained putting up hands to answer questions (B1).

#### 4.2 Detecting Behavioral Sequences Patterns

In order to investigate changes and influence in the students' behaviors, the behaviors sequences patterns were performed with observations nested within classroom using Observation Scale. In this study, we used classroom observation protocol to get students behavioral sequences in the ICT-supported learning environment. Then we use the GSEQ 5.1 software to analysis students' behaviors. The study shows the analysis results of the students' behaviors sequences after adjusted residuals (in Figure 1). The connectivity of sequence has statistical significance (p < 0.05) if the Z-value of a sequence is greater than 1.96 (Bakeman & Gottman, 1997). The greater the value, the more significant the relationship between the two behaviors, and the more likely to promote the generation of the next behavior. Therefore, we can get those significant behavioral sequences, such as B1 $\rightarrow$ B33, B1 $\rightarrow$ B30, B1 $\rightarrow$ B31, B35 $\rightarrow$ B16, B35 $\rightarrow$ B17, B33 $\rightarrow$ B1, B5 $\rightarrow$ B33, B5 $\rightarrow$ B32, B5 $\rightarrow$ B17, B12 $\rightarrow$ B30, B13 $\rightarrow$ B15, B15 $\rightarrow$ B35, B16 $\rightarrow$ B13, B24 $\rightarrow$ B24, B24 $\rightarrow$ 23, B21 $\rightarrow$ B35, B21 $\rightarrow$ B12, B21 $\rightarrow$ B22, B23 $\rightarrow$ B7, and B22 $\rightarrow$ B1.

	<b>B1</b> .1	B35.,	<b>B33</b> .,	<b>B5</b> .1	<b>B7</b> .1	B32.1	<b>B30</b> .,	<b>B12</b> .1	<b>B13</b> .1	B15.1	<b>B16</b> .,	<b>B17</b> .1	B24.1	B21.1	B23.,	B22.,	<b>B31</b> .1
<b>B1</b> .1	-0.01.1	-0.68.1	2.13.1	0.19.1	-0.43.1	-0.43.1	2.13.1	-0.43.1	-0.3.,	0.23.1	-0.43.1	-0.92.1	-1.38.	0.19.1	0.74.,	-0.3.1	2.13
B35.,	-0.68.1	-0.3.1	-0.19.1	-0.64.1	-0.19.1	-0.19.1	-0.19.1	-0.19.1	-0.13.	0.31.,	<mark>5.22</mark> .,	2.18.	0.45.,	-0.43.	-0.33.1	-0.13.,	-0.19.
B33.,	2.13	-0.19.1	-0.12.1	-0.4.1	-0.12.,	-0.12.1	-0.12.1	-0.12.	-0.08.1	1.39.,	-0.12.1	-0.26.1	-0.56.1	-0.27.1	-0.21.1	-0.08.1	-0.12.
<b>B5</b> .,	-1.48.	-0.65.1	<mark>2.25</mark> .,	0.33.,	-0.41.,	<mark>4.92</mark> .,	-0.41.	-0.41.,	-0.29.1	1.67.,	-0.41.	<mark>2.93</mark>	-1.26.	0.28.1	-0.71.,	-0.29.1	-0.41.,
<b>B7</b> .,	-0.43.	-0.19.1	-0.12.,	-0.4.,	-0.12.,	-0.12.,	-0.12.1	-0.12.,	-0.08.	1.39.,	-0.12.1	-0.26.	1.54.,	-0.27.1	-0.21.,	-0.08.1	-0.12.
B32.,	-0.43.	-0.19.1	-0.12.1	-0.4.1	-0.12.1	-0.12.1	-0.12.,	-0.12.	-0.08.1	1.39.,	-0.12.1	-0.26.1	-0.56.1	-0.27.1	-0.21.	-0.08.1	-0.12.
<b>B30</b> .1	-0.43.	-0.19.1	-0.12.1	-0.4.1	-0.12.1	-0.12.1	-0.12.1	-0.12.1	-0.08.1	-0.6.1	-0.12.1	-0.26.1	-0.56.1	-0.27.1	-0.21.1	-0.08.1	-0.12.1
B12.1	-0.43.1	-0.19.1	-0.12.1	-0.4.1	-0.12.1	-0.12.1	<mark>8.4</mark> .1	-0.12.1	-0.08.1	-0.6.1	-0.12.1	-0.26.1	-0.56.1	-0.27.1	-0.21.1	-0.08.1	-0.12.1
<b>B13</b> .1	-0.3.1	-0.13.,	-0.08.1	-0.28.1	-0.08.1	-0.08.1	-0.08.1	-0.08.1	-0.06.1	2.38.1	-0.08.1	-0.18.1	-0.39.1	-0.19.1	-0.15.1	-0.06.1	-0.08.1
B15.1	0.03.,	2.65.	-0.63.1	0.34.1	-0.63.,	-0.63.1	-0.63.1	-0.63.	-0.44.1	-0.48.1	-0.63.1	-1.35.1	-0.59.1	0.31.,	0.02.1	-0.44.1	-0.63.
B16.1	-0.43.	-0.19.1	-0.12.1	-0.4.1	-0.12.1	-0.12.1	-0.12.1	-0.12.,	11.94 <sub>.1</sub>	1.39.1	-0.12.1	-0.26.1	-0.56.1	-0.27.1	-0.21.1	-0.08.1	-0.12.1
<b>B17</b> .1	-0.92.1	-0.41.,	-0.26.1	0.44.1	-0.26.1	-0.26.1	-0.26.1	-0.26.1	-0.18.	-0.33.1	-0.26.1	-0.55.1	1.8.1	-0.58.1	-0.45.,	-0.18.,	-0.26.1
B24.1	-1.22.1	-0.83.,	-0.52.1	-0.35.,	1.67.,	-0.52.1	-0.52.1	-0.52.,	-0.37.,	-1.59.1	-0.52.1	-1.12.1	<mark>3.49</mark> .1	1.8.	2.92.a	-0.37.,	-0.52.1
B21.1	1.35.,	2.03.1	-0.27.1	1.56.,	-0.27.1	-0.27.1	-0.27.1	3.59.a	-0.19.1	-0.45.1	-0.27.1	-0.58.1	-1.26.	-0.61.,	-0.47.1	<mark>5.26</mark>	-0.27.1
B23.1	-0.75.1	-0.33.,	-0.21.1	-0.7.1	<mark>4.74</mark>	-0.21.1	-0.21.1	-0.21.,	-0.15.,	0.11.1	-0.21.1	-0.45.1	1.46.1	-0.47.,	-0.36.1	-0.15.,	-0.21.
B22.1	3.31.a	-0.13.,	-0.08.1	-0.28.1	-0.08.1	-0.08.1	-0.08.1	-0.08.1	-0.06.1	-0.42.1	-0.08.1	-0.18.1	-0.39.1	-0.19.1	-0.15.1	-0.06.1	-0.08.1
<b>B31</b> .1	-0.43.,	-0.19.1	-0.12.,	-0.4.,	-0.12.1	-0.12.1	-0.12.,	-0.12.1	-0.08.1	1.39.,	-0.12.1	-0.26.1	-0.56.1	-0.27.1	-0.21.1	-0.08.1	-0.12.1

Figure 1. Adjusted residuals table (Z-scores) of students' behavioral sequences

According to those significant behavioral sequences, we can draw students' behavior prediction trajectory diagram in the classroom learning. It indicates that when one student raising his hands and answer questions, there are three possibilities for the next actions: students are likely to laugh at him, or whisper with others, or look at other people's reaction as group 1 of key behavioral indicators (seeing the Figure 2). When a student is named to answer questions, other students may be doing little tricks, or discuss his answer, or ridicule him, as group 2 of key behavioral indicators in the Figure 2.

The paper shows that if students have the passive on-task behavior, then, it will lead to students in the off-task state, and eventually lead to students do not participate in classroom activities as group 3 of key behavioral indicators (in Figure 2). Students who read aloud with the teacher will also lead students to not participate in classroom activities. It finds that when a student was looking at someone else's task, he may have an On-Task action, which in turn causes him to finish classroom learning activity as group 4 of key behavioral indicators (in Figure 2).



Figure 2. the key groups of behavioral transition

# 4.3 Evaluation the Key Groups of Behavior Indictors by HMM

At the core of this approach is a hidden Markov model methodology that builds students' behavior models from data collected by observations. A hidden Markov model (HMM) is a tool for representing probability distributions over sequences of observations. In HMM, the state is not directly visible, but the output, dependent on the state, is visible (Blunsom, 2004). In this study, based MATLAB coding, the HMM consists of hidden states that are not directly visible, and is governed by three sets of parameters: initial probability (behaviors state by observation), the transition probabilities (emotion state by observation) between states, and output probability matrix. The behaviors patterns (the output probability) associated with each state (Jeong, & Biswas, 2008). The transition probability associated with a link between two states indicates the likelihood of the behavior transitioning from the current state to the emotion state. For example, the HMM model states students rising hands would demonstrate a 92.7% likelihood of transitioning to enjoyment emotion. Likelihoods less than 10% were not represented, and there were 8 sequences in Table 2 below.

No.	<b>Behavior state</b>	<b>Emotion state</b>	transition probability
1	B21	E1	79.1%
2	B1	E1	92.7%
3	B11	E1	67.8%
4	B5	E1	82.1%
5	B17	E3	39.3%
6	B15	E1	79.6%
7	B3	E1	91.8%
8	B23	E1	76%

Table 2: the output probability

The study contains the relations between emotion self-report and the emotional observations, organized into behavioral observations through HMM. In the finding, total activity level, duration of anxiety emotion and boredom, has been affected by negative emotions, and has effect on the internal relations. The highly behaviors showed that if one student answering the question with enjoyment emotion, then he would return to on-task active initiative state (B5 $\rightarrow$ B17, Z-score = 2.93) in Figure 3, however, he would turn to off-task state with passive emotion having a 17.9% stationary probability. Another example key behaviors conducted that one student was off-task state, and he returned on the on-task state (B15 $\rightarrow$ B13, Z-score = 2.38) if the possibility of 79.6% was being enjoying. There was probability one student being on on-task working state turn to do activities passively with enjoyment emotion with the possibility of 76%.



# 5. Conclusion and Limitations

The study conducted three groups of key behavioral indictors by a practical way for learning analytics. On the one hand, the paper verified the impact of interest between the emotions engagement by self-report and emotional observations. On the other hand, through the association with the behavior analysis, it can predict students' behavior outcomes. The findings can help teachers concerned about the key behaviors of students, and adjust the learning strategy to be on the better emotional. In the future, the study will collect more observation data in different schools.

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