Emotional engagement assessment: self-reports versus facial expressions

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Abstract: Current research utilizes self-reports and facial expression recognition analysis to provide a more continuous and objective insight into how students' emotional engagement unfolds and impacts learning. Analysis of nursing students learning with virtual reality simulation revealed that only the facial expression data channel, compared to self-reports, was sensitive to fluctuations in engagement which varied throughout the different learning session phases. In addition, findings show that learning achievements were negatively associated with facial expressions of anger and positively associated with positive self-reported emotions. Hence, this study demonstrates that the methodology of using multimodal data channels which encompass different types of measures, can provide insights into a more holistic understanding of engagement in learning and learning achievement.

Introduction

Engagement is a multidimensional construct that refers to an individual's active involvement in a learning activity (Christenson et al., 2012). This study explores only the emotional aspect of engagement. The *emotional engagement* focuses on states that are related to students' emotional involvement during learning activities (Christenson et al., 2012). Positive emotions include enthusiasm, interest and enjoyment while learning (Renninger & Bachrach, 2015). Whereas, negative emotional components include boredom, sadness, and frustration in the classroom (Skinner et al., 2008). Theories of motivation, including the self-determination theory, and the control-value theory (CVT) of academic emotions (Deci & Ryan, 1985; Pekrun & Linnenbrink-Garcia, 2012), emphasize the role that both positive and negative emotions have on students' involvement in learning activities, and underscore how affective dynamics sustain or disrupt learners' engagement to impact learning performance. The CVT predicts that positive activating emotions (e.g., curiosity and enjoyment) positively influence learning outcomes, whereas the inverse is true for negative-deactivating emotions (e.g., boredom) (Pekrun & Perry, 2014). Given the importance of emotional engagement, it is therefore crucial to capture how emotional engagement unfolds and what initiates and diminishes emotional experiences with the long-term goal of helping leaners to re-engage. So far, the most predominate measures of emotional engagement were self-reports and observations (D'Mello et al., 2017). This study suggests evaluate the additive value of the multimodal approach, using both, subjective self-reports and objective facial expression recognition analysis.

Facial expression recognition is a fully automated measure which it is based on artificial neural networks that can match varying sets of action unit activities to different discrete emotions (Ekman & Rosenberg, 1997). Facial expression analysis allows identification of changes in facial movements at very short time intervals, and can therefore provide an unobtrusive detailed view of students' emotions transitioning throughout a learning session (Dindar et al., 2020). Importantly, it has been suggested that self-report measures mainly reveal emotions a person has become consciously aware of, whereas an automatic facial expression analysis captures fast changing emotions in the implicit dimension of the subconscious (van Bommel et al., 2020). As such, incorporating the traditional measures of engagement, such as self-reports, with fully automated measures of engagement, can capture the grain size of engagement dynamics and provide both objective microlevel and subjective macrolevel perspectives (D'Mello et al., 2017).

Research questions

(1) How do students' emotional engagement unfold while they learn, as revealed by their self-reports and by facial expression analysis; and (2) What is the synergistic effect of this emotional engagement, as measured by the multimodal data streams of self-reports and facial expressions, on the students' learning achievements?

Methods

Participants

In total, 65 freshmen nursing students at an Israeli university volunteered to participate in the study. Due to technological issues of data collection (e.g., calibration errors), data of four participants was excluded, resulting in a final sample size of 61. Most participants were female (n=44), and the mean age was 23±5.1 years.

The study was conducted following the approval of the university's ethics committee (#0001776-2).

Research design and procedure

This study is part of a more extensive study (Dubovi, 2022). This was a prospective study with a pre-test – post-test design. The students' demographics and prior content knowledge were assessed via a pre-test paper-and-pencil survey. Each participant was then asked to sit in front of a computer and a calibration of their facial expression tracking was performed. Following this, participants were offered to learn with a desktop virtual reality simulation. The VR simulation incorporated the architecture of a 3D hospital (Dubovi et al., 2017). Playing the role of a nurse-avatar, participants were asked medication administration procedures. Emotional engagement characteristics were captured during the entire learning experience using facial expressions recognition algorithm. In addition, students were asked on three occasions by the VR simulation to complete the Positive and Negative Affect Scale (PANAS) questionnaire (Watson et al., 1988): Time 1, before the intro phase; Time 2, after the intro phase; and Time 3, after the last phase of the summing-up video. After the learning session, participants completed a paper-and-pencil content knowledge post-test. The iMotions 9.0 Biometric Research Platform (https://imotions.com) was used to setup the experimental design and to collect the data.

Data Collection Instruments

Facial expression recognition

The Affectiva Affdex algorithm provided by iMotions 9.0 (https://imotions.com) was used to obtain in real-time the 7 basic emotion likelihoods for joy, anger, surprise, contempt, fear, sadness, and disgust at a 30 Hz frequency. The algorithm uses the Facial Action Coding System to identify and categorize facial expressions based on specific facial 'action units' and was shown to be reliable (Ekman & Rosenberg, 1997; Kulke et al., 2020). The metrics can be thought of in terms of probability; as the emotion or facial expression occurs and intensifies, the score rises from 0 (no expression) to 100 (expression fully present). Then a thresholding for time and for absolute amplitude probability was carried out based on the iMotions guidelines (https://imotions.com/blog/facial-expression-analysis/) to extract emotion percentage metrics. Facial expressions were collected for the overall learning experience.

Positive and Negative Affect Scale (PANAS) questionnaire

The PANAS is a list of 20 adjectives used to describe 10 positive emotions and 10 negative emotions (Watson et al., 1988). The positive affect captures the feelings of being attentive, active, alert, excited, enthusiastic, determined, inspired, proud, interested, and strong. Negative affect includes the feelings of being hostile, irritable, ashamed, guilty, distressed, upset, scared, afraid, jittery, and nervous. The order of questions in the questionnaire was mixed between positive and negative affect scores. Respondents are required to indicate the extent to which they feel these emotions "at this moment" on a 5-point scale. Cronbach alpha yielded a good internal consistency score of .86 for the global positive affect and 0.82 for the global negative affect.

Content knowledge test

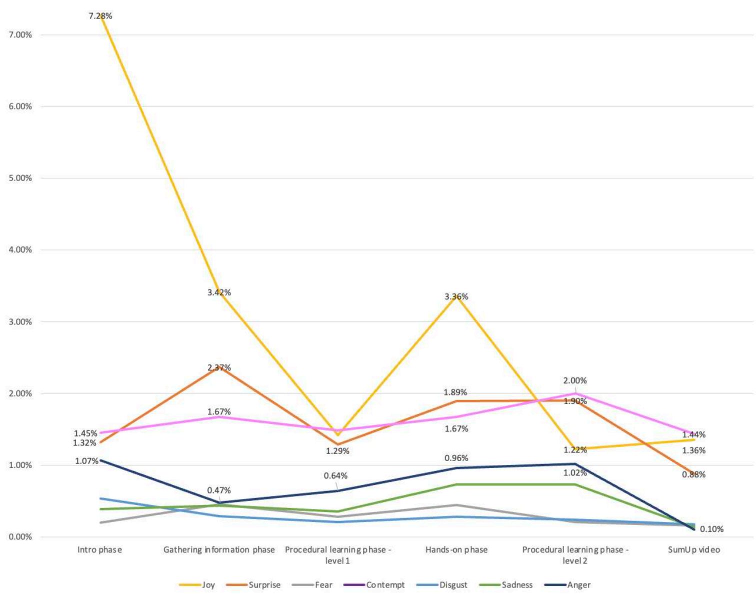
The Medication Administration Test (MAT) assessed the nursing students' understanding and practical applications of the medication administration guidelines. The test was validated in a previous study (Dubovi et al., 2017). The test consists of 13 multiple-choice items. Analysis of the MAT using Cronbach alpha yielded a good internal consistency score of .74.

Results

Emotional engagement throughout the overall learning experience was captured via facial expressions extraction and PANAS self-reports. The Kruskal-Wallis H test of facial expressions revealed that participants experienced significantly more joy 4.0±3.6% than other emotions, such as surprise 1.7±2.6%, fear 0.3±0.9%, contempt 1.5±2.5%, disgust 0.3±0.6%, sadness 0.4±1.2%, and anger 0.8±1.6%; ($\chi2(6) = 314.710$, $p < .001$). Furthermore, a linear mixed effects model (LMM) for repeated measures showed a significant interaction between the type of expressed emotions and the VR simulation phase ($F (30, 420.699) = 7.545$, $p<0.001$). Post-hoc analysis showed significantly more joyful expressions for the intro phase ($p < 0.001$) and for hands-on phase ($p < 0.001$; Figure 1). In addition, facial expressions of anger and surprise were expressed significantly less during the final sum-up video phase ($p < 0.005$).

While facial expression analysis captured the fluctuation of the students' implicit and fast changing emotions, the PANAS self-report detected the students' explicit emotions at three different time-points. Similarly to the facial expression analysis, the PANAS analysis revealed that students experienced significantly higher levels of positive emotions than negative emotions ($F(1, 3658)=6882.5$, $p<0.001$; 3.8 ± 1.1 vs. 1.3 ± 0.7, Table 1). The most predominant emotions while interacting with VR were interest (4.5 ± 0.4), attentiveness (4.5 ± 0.5) and alertness (4.3 ± 0.5). A non-significant change in emotions was demonstrated by an LMM for repeated measures throughout the three times that the PANAS was administered ($F(38, 2239.068) = 0.964$, $p=0.533$).

Figure 1
Changes in students' emotions according to the VR simulation sequence phase.



The MAT content knowledge post-test scores were significantly higher than the pre-test scores (paired $t=-6.422$, $p<0.001$; 90 ± 9 vs. 78 ± 16). To further understand the impact of emotional engagement on the students' knowledge gain, a bivariate intercorrelation analysis was performed (Table 1). The analysis revealed a significant negative correlation among anger facial expressions and post-tests scores ($r=-0.323$, $p < 0.1$; Table 1); as well as positive correlation of PANAS positive self-report emotions to post-tests scores ($r=0.294$, $p < 0.1$; Table 1).

Table 1

*Bivariate intercorrelations between MAT content knowledge post-test with emotional engagement (*N*=61)*

Variable	1	2	3	4	5	6	7	8	9	10
1. Content post-test knowledge	--									
Facial expressions										
2. Joy	-.116	--								
3. Surprise	-.048	.008	--							
4. Fear	.135	-.031	**.294***	--						
5. Contempt	.017	**.265***	.090	-.048	--					
6. Disgust	.088	.090	.080	-.027	**.545****	--				
7. Sadness	-.122	-.025	.084	-.075	-.057	.048	--			
8. Anger	**-.323***	-.119	-.095	-.033	-.018	.119	.114	--		
PANAS self-report (Positive/Negative)										
9. Positive	**.294***	-.003	-.106	.106	0.190	**-.267***	-.06	-.104	--	
10. Negative	-.111	.106	-.055	-.054	.026	-.111	.081	-.085	-.044	--

$^*p < .05$; $^{**}p < .01$

Discussion

The main goal of this study was to identify the synergistic impact of the multimodal metrics on the students' learning achievements. The facial expression continuum revealed that joy (i.e., enjoyment) was the most predominant emotion that was expressed by students. It became evident that the frequency of the joy expression changed across the different VR learning phases. Although facial expressions of joy were the most frequent emotions expressed by students, there was no significant impact of joy on post-test learning achievements. In contrast, although facial expressions of anger were expressed at a relatively low frequency with no significant changes across the different phases of the learning session, they did show a significant association with post-test learning achievements. Interestingly, the subjective perception of their emotional experience, a PANAS self-report, demonstrated the significant impact of self-reported positive emotions on learning achievements. This study demonstrates that it is crucial to integrate both automated objective channels with subjective methodologies to provide a more holistic and comprehensive perspective on complex learning processes and learning outcomes.

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