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Cognitive Emotions in E-Learning Processes and Their Potential Relationship with Students' Academic Adjustment

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In times of growing importance and emphasis on improving academic outcomes for young people, their academic selves/lives are increasingly becoming more central to their understanding of their own wellbeing. How they experience and perceive their academic successes or failures, can influence their perceived self-efficacy and eventual academic achievement. To this end, 'cognitive emotions', elicited to acquire or develop new skills/knowledges, can play a crucial role as they indicate the state or the "flow" of a student's emotions, when facing challenging tasks. Within innovative teaching models, measuring the affective components of learning have been mainly based on self-reports and scales which have neglected the real-time detection of emotions, through for example, recording or measuring facial expressions. The aim of the present study is to test the reliability of an ad hoc *software* trained to detect and classify cognitive emotions from facial expressions across two different environments, namely a video-lecture and a chat with teacher, and to explore cognitive emotions in relation to academic e-self-efficacy and academic adjustment. To pursue these goals, we used video-recordings of ten psychology students from an online university engaging in online learning tasks, and employed software to automatically detect eleven cognitive emotions. Preliminary results support and extend prior studies, illustrating how exploring cognitive emotions in real time can inform the development and success of academic e-learning interventions aimed at monitoring and promoting students' wellbeing.

Keywords: cognitive emotions, self-efficacy, academic adjustment, automatic detection of emotions, e-learning process

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Introduction

Scholars have already identified the importance of emotions to understand learning through face to face and distance educational settings (Artino, 2012; D'Errico, Paciello & Cerniglia, 2016; Feidakis, Daradoumis, Caballé, & Conesa, 2014; Parlangeli, Marchigiani, Guidi & Mesh, 2012). According to Scheffler (1991) such learning processes are not merely an aggregation of information, or fact-gathering exercises or the methodological application of procedures. Nor does learning operate in isolation of our emotions or emotional appraisals.

This paper is underpinned by a socio-cognitive approach (Castelfranchi & Miceli, 2009) and appraisal theories (Scherer, 2000) which define emotions as adaptive devices that either monitor the state of achievement, or serve to thwart individuals' goals. Thus, emotions can be constructed as multifaceted internal states, encompassing feelings and cognitive, physiological, expressive, and motivational aspects,that are triggered whenever an individual's goal is achieved/thwarted or likely to be (D'Errico & Poggi, 2016; Poggi, 2008).

Within traditional academic contexts, Pekrun and colleagues (2011) explored '*academic emotions*', demonstrating that positive emotions can predict creative thinking and reflecting, thereby fostering good academic outcomes, whereas negative emotions are more likely associated with lower grades. More specifically, positive emotions such as enjoyment, hope and pride have been positively associated with effort, self-regulation and more sophisticated learning strategies, whereas anger, frustration, shame, anxiety and boredom have been associated with lower performances and external regulation (Pekrun, Goetz, Frenzel, Barchfeld & Perry, 2011). *Achievement emotions* (Pekrun, 2006) when considered in relation to on-line situations, were suggested to be specific to that context.

Similarly, in the *e-learning* domain, previous studies (D'Errico, Paciello & Cerniglia, 2016) demonstrated that positive emotions across different e-learning activities were higher than negative emotions, particularly during synchronous activities with a teacher and also with peers. It was also found that experiencing positive emotions during exam preparation was strongly correlated with the behavioral and affective dimensions of engagement. Feeling positive during the different phases of e-learning processes helped students to enact constructive behaviors, achieve positive results, and to experience "affective relevance" in relation to acquired content. This emotional positivity during engagement, could also serve to increase students' sense of mastery during exam preparation. (D'Errico, Paciello & Cerniglia, 2016) further suggest however, that particular attention needs to be paid to the *negative* emotions reported during chat/interactions with teachers, as these could be an early warning sign of poor/flawed preparation and engagement on the part of the student.

In contrast to previous studies, which focused on the comparison between positive and negative emotions in e-learning contexts, the present work aimed to explore the role played by *cognitive* emotions. According to Scheffler (1991) cognitive emotions can be considered the ‘emotional filters through which we view the world, interpret its objects and evaluate its critical features. They involve seeing things as beneficial or harmful, promising or threatening, fulfilling or thwarting’ (p.45). In particular, cognitive emotions monitor incoming content and are elicited when acquiring or developing new skills/knowledges (Castelfranchi, 2000; O Regan 2003; Poggi, 2008). To this end, cognitive emotions could play a crucial role in understanding the learning process, as they can indicate the state of a student’s emotions, or the “flow”, when facing challenging new learning tasks (Bassi, Steca, Delle Fave & Caprara, 2007). Exploring cognitive emotions thus could be considered an opportunity for real-time evaluation of the emotional responses to the learning process.

In support of this, Peters (1981) suggested that cognitive emotions are ‘strictly connected with the demands of consistency, order, clarity and relevance’ (Peters, 1981, 143). In this sense cognitive emotions firstly orient toward *content*: with students evaluating it as useful or applicable and therefore responding as interested, happy or disappointed, or evaluating what is presented as innovative, and new, eliciting curiosity, or surprise or conversely: boredom. Secondly, cognitive emotions can also be considered in relation to *moral or aesthetic values,* reflecting enthusiasm, disappointment or simply interest. Yob (1997) summarized these perspectives by underlining how cognitive emotions reflect an individual’s ‘*critical appraisal of the learning environment’* (p 46).

The relationship between content delivery, and students’ cognitive style was explored by Riding and Cheema, (1991) who noted that students can be differentially affected by the presentation of content or the formal features of the learning experience: for example, a student who focuses on words or on images, will respond differently to students who focus analytically or divergently on concepts (Tamblin & Ward, 2006). This relationship between cognitive emotions and learning style would seem even more relevant in a modern learning context such as distance/e-learning that employs a variety of different content oriented formats (video, chat, forum) so students can engage both synchronously and asynchronously.

Finally, recognition of cognitive factors that characterize each learner's beliefs, expectations and goals (Miceli & Castelfranchi 2014) are of importance as they underpin how individuals approach learning and content delivery. The learner’s mental state can thus be described in terms of the appraisal process which compares incoming information with beliefs and prior knowledge. It is this appraisal which contributes to excitement at learning something new; or frustration and confusion at not understanding something. Seen in this light, cognitive emotions are a very important part of the appraisal of and response to the learning process. Exploring the role of cognitive emotions in e-leaning contexts, and considering their associations with dimensions of self-efficacy and academic adjustment will contribute to further understanding of online learning contexts and how to improve delivery of content to support student outcomes.

Self-efficacy, emotions and academic adjustment

Academic self-efficacy is one of most well-recognized constructs in learning and has been found to be associated with positive emotions (Liu et al. 2017), performance (Richardson, Abraham, & Bond, 2012) and well-being in educational settings (Chemers, Hu, & Garcia, 2001). Self-efficacy, a construct rooted in social cognitive theory, refers to “people's beliefs in their capability to exercise some measure of control over their own functioning and over environmental events’ (Bandura, 2001, p.10). In education, academic self-efficacy refers specifically to students’ beliefs so that they can plan, control, and direct their learning activities in order to master academic subjects and achieve their educational goals. It operates through cognitive and metacognitive strategies such as (a) planning for learning actions, (b) self-assessment of learning activities, and (c) self-reflection and acts to modulate learning actions and self-motivation when difficult tasks require more effort. In other words, this dimension reflects students’ confidence in their ability to regulate the different aspects of their learning and it is crucial especially when educational tasks become more challenging.

The educational literature has also widely attested the importance of perceived self-efficacy for successful academic adjustment in terms of performance and well-being. Indeed, self-efficacy not only promotes academic outcomes (Richardson, Abraham, & Bond, 2012); career success (Abele & Spurk, 2009); academic selection (Britner & Pajares, 2006); persistence in the chosen major (Gore, 2006); but also promotes quality of students’ experiences (Newby-Fraser & Schlebusch, 1997); high academic resilience to stressors and difficulties (Chemers, Hu & Garcia, 2001); and hinders stress and burnout (Zajacova, Lynch, &

Espenshade, 2005). Moreover, recent studies showed that the more students perceived themselves to be able when performing learning tasks, the more they felt positive emotions related to the so-called "flow" of the experience: and the more they were likely to achieve academic goals (Bassi et al. 2007; Zhen et al., 2017).

The links between self-efficacy, positive emotions, and quality of academic experience resonate with theory of "flow" (Csikszentmihakyi, 1990): which suggests that optimal experience occurs when (1) individual resources are invested in realistic goals, and (2) concurrently, personal skills match the external opportunities for realizing a set of goal-oriented actions. Optimal experiences during self-regulating learning processes reflect a motivational state in which perception of personal control fits with the challenging tasks (Rheinberg, Vollmeyer, & Rollett, 2000). Even if the task is perceived as difficult, students with high self-efficacy transform obstacles and difficulties into opportunities to improve competence and to develop skills. Moreover, the perceived likelihood of future success fosters positive learning-related emotions, and hinders negative feelings, permitting students to stay focused on academic tasks (Putwain, Sander & Larkin, 2013).

In sum, the literature underlines the role of academic self-efficacy in the appraisal of learning-related situations as threats or challenges; which in turn activate arousal of different academic emotions, such as fear/anxiety or enjoyment. Indeed students who perceive themselves as able to exercise personal control over learning activities, and attribute positive academic outcomes to controllable efforts, show positive emotions such as enjoyment and pride(Goetz, Frenzel, Hall, & Pekrun, 2008) (By contrast, students who perceived themselves as not able to manage their learning activities and academic outcomes, showed negative emotions such as anxiety and boredom (King & Gaerlan, 2014). These emotions are also related to academic well-being, which could be considered a self-reactive response to a self-regulatory process in which students monitor and evaluate if and how internal resources are adequate in the face of external, academic requests. In particular, positive emotions are strictly connected with well-being (Low, King & Caleon, 2016) since, as suggested by Fredrikson (2009), they attest that learners who feel supported and able to improve their skills, can face the further stages and challenges of their academic path**.**

The case of E-Learning Settings

In the specific case of e-learning settings, academic self-efficacy has been operationalized as a perceived capability to strategically use digital tools to learn and carry out study activities, relevant to the peculiarities of distance learning contexts (Di Mele, D'Errico, Cerniglia, Cersosimo & Paciello, 2015). With respect to

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performance, academic e-efficacy promotes academic engagement (D’Errico, Paciello & Cerniglia, 2016) and achievement (Di Mele et al., 2015). Moreover, D'Errico et al. (2016) found that academic self-efficacy was positively associated with the experience of positive emotions during e-learning activities, and negatively associated with negative emotions. The more students felt positive emotions during e-learning activities, the more they perceived themselves as able to interact constructively with other students and teachers through the learning platform, and the more they engaged affectively and behaviorally during learning activities. By contrast, the more negative emotions experienced during e-learning activities, the less students perceived themselves as able to use learning tools and to regulate their learning, and the less they were organized, motivated to learn and able to do well on the tests they take.

Most of the aforementioned studies have used self-report measures however, and have not considered the actual, expressed emotions of learners ‘in the moment’ when engaged in learning tasks. Moreover, scholars interested in eLearning settings, have mainly explored the role of basic emotions, or comparison between positive and negative emotions. To date, no studies, to the best of our knowledge, have examined *cognitive emotions in e-learning contexts in relation to personal beliefs, academic well-being and performance.*

Cognitive emotions detection in E-Learning settings

Facial expressions are one of the most common non-verbal channels that humans use to convey internal mental states and emotions. Although there exists a wide range of emotions, research on emotion recognition from facial expressions has focused on six basic, universally recognized expressions: happiness, sadness, fear, disgust, surprise, and anger (Ekman, 1992). However, in many domains, basic emotions are not sufficient nor they do not allow for a deep understanding of the user’s mental state. E-learning is one of these domains as the learning tasks do not require these basic emotional responses, rather they require more cognitive expressions of emotions in relation to the learning task such as: *attention, interest, surprise, curiosity, concentration, enthusiasm, disappointment, boredom, confusion, annoyance, and frustration*.

Many systems propose to use facial expression analysis for continuously and unobtrusively monitoring learners’ behavior during e-learning and to interpret this into emotional states, however, they focus mainly on primary emotion recognition. This pilot study seeks to explore cognitive emotions generated during online learning experiences, through facial expression recognition.

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Outline of the present study

The exploratory, pilot study reported here, builds upon previous work by the current authors (D'Errico, Paciello & Cerniglia 2016; Di Mele et al, 2015) and was undertaken at the Italian Distance University with a purposive and convenience sample of students from the Psychology Faculty. It employed an innovative "in-the-moment" facial expression recognition (FER) methodology to detect and classify the following cognitive emotions direct from facial expressions of participants whilst engaged in e-learning activities: *attention, interest, surprise, curiosity, concentration, enthusiasm, disappointment, boredom, confusion, annoyance, and frustration*. This study is directed by two goals, to:

1. Test the reliability of dedicated facial expression recognition (FER) software to ascertain cognitive emotions across two different, commonplace e-learning activities/situations: viz, viewing pre-recorded video lectures and participating in an online chat with a teacher/tutor.

2. Explore cognitive emotions in relation to: (a) e-efficacy in technology-mediated learning situations (Di Mele et al., 2015); (b) academic well-being (i.e. satisfaction, persistence, interdependence and gratitude; see Renshaw, Long & Cook, 2014) and (c) achievement (i.e. exams).

Method

Sample and design

A case study approach, which included a 'within subjects' design was employed, whereby the same group of students (n=10) participated in 2 different learning tasks (teacher chat and video-lecture), and included three control variables: age; wellbeing; and task e-efficacy. Ten (10) female, Online University students, enrolled in the first year of a course in psychology, aged between 20 and 64 voluntarily agreed to participate in this exploratory, pilot study. On the basis of the literature on emerging adulthood (Arnett, 2000) students were grouped according to two categories: emerging adult (aged under 30 years, n=5) and adult students, (over 31 years, n=5).

Procedure

Before the end of the course, students were invited to read information about the general purposes of the study, and sign an informed consent. Participants then completed online questionnaires providing socio-demographic data and information concerning their e-self-efficacy, and subjective well-being. Following this, they participated in two online learning tasks and associated educational activities from the Social Psychology field: led by the same female teacher. Whilst doing these two activities, they were video-recorded using a webcam, ensuring their face was foregrounded. The recorded learning activities consisted of: (1) a chat session with the teacher, in which students synchronically discussed the content of the lesson (Social Psychology), writing their possible questions, comments and queries online; and (2) a video-lecture, which refers to an asynchronous activity which could be viewed at any time. The videos of the students engaging in the two tasks were then uploaded to a shared drive with individually created acronyms/pseudonyms to guarantee anonymity (e.g. the first three letters of the surname and date). These 20 student videos were then collated in a shared drive along with the 50 minute video-lecture and the 50 minute chat with the teacher, achieving about 17 hours of total recordings.

Facial Expression Recognition Process

This FER system was developed to be able to recognize the cognitive emotions that typically arise during the learning process: *enthusiasm, interest, surprise, curiosity, concentration, attention, disappointment, boredom, perplexity, worried, frustration*. Following the approach used for primary emotions recognition, as described in Del Coco et al., (2015), the same process was implemented (See Figure 1) in this study: whereby a pipeline from the raw image to the classification was outlined and enabled. A classifier was trained using a different dataset as a means of determining independent accuracy and consistency of detection and classification.

The current study performed facial expression recognition on a single video frame using the whole face approach. It directly tries to extract a representation of the emotions considering the whole face as the region of interest. The set of descriptors used to recognize human emotion traits is based on the Histogram of Oriented Gradients (HOG) (Dalal & Triggs, 2005). The system takes a single video frame, and performs a preliminary face detection (Viola & Jones, 2004), then applies the HOG descriptors for the features extraction step, and finally classifies the facial expression by Multi Support Vector Machines (MSVM) (Cortes & Vapnik, 1995). For each video frame, a facial expression classification is performed. The pipeline is illustrated in Figure 1.

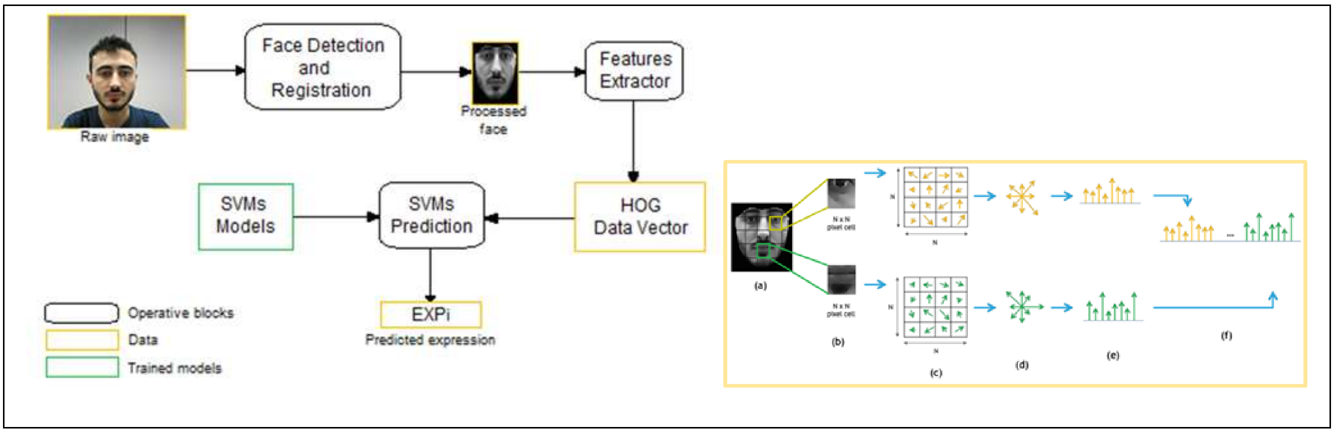


Figure 1. Pipeline of the proposed system.

In the first step a video frame is acquired then the face is detected and the features are extracted. Finally a Multi SVM classification is performed. In detail, the feature vectors extracted by the HOG descriptor are given as input to Multi Support Vector Machines classifier. A SVM is a discriminative classifier defined by a separating hyperplane. Given labelled training data, the algorithm outputs an optimal hyperplane which categorizes new examples. This approach is suitable only for a 2-class problem whereas FER is a multiclass problem. To classify more than two classes, a “one-against-one” approach is used**.** The multi class classification is returned by a voting system among all the classifiers. In particular, the multi C-support vector classification (multi C-SVC) learning task implemented in the LIBSVM library (Chang & Lin, 2011) was used in the following experiments with a Radial Basis Function (RBF) kernel (penalty parameter C = 1000 and γ = 0.5).

Measures

To measure the subjective adjustment of the students, an adapted version of the College Student Subjective Wellbeing Questionnaire (CSSWQ, Renshaw Long and Cook., 2014) was employed, where responses were collected using a 5 point Likert scale (0 =not at all; 5= extremely). This is a 26-item self-report rating scale for measuring four classes of college-specific wellbeing behavior: academic persistence (6 items; α. =70), academic satisfaction (7 items; α.=92), school connectedness (7 items; α.=90), and college gratitude (6 items; α.=95). Examples of items are: "I'm happy to study at this University" (satisfaction); "academic obstacles do not make me give up," (persistence); "I know that I can count on my classmates' support" (interdependence) and "I am grateful to the staff of this university for the received help" (gratitude).

To measure perceived self-efficacy in learning within technological contexts, specific items derived from an *e-task self-efficacy scale within e-learning settings* was utilized (Di Mele et al., 2015), assessed on a 5 point Likert scale (0 = not at all; 5 = completely able). Specifically, three items referring to e-learning tasks were considered transferrable to the e-learning activities for the detection of cognitive emotions (α.=70). The three items selected are: "I feel able to review documents or hyperlinks useful for my learning on the site "; "I feel able to study an argument from materials attached to the video-lectures"; and "I feel able to search additional information useful for my study"-on the internet.

To automatically detect and measure cognitive emotions, a Facial Expression Recognition (FER) system was used (See description of process above). The software, proposed by computer scientists from University of Bari, is composed of three modules: Face Detection; Feature Extraction; and Facial Expression Classification (Palestra et al., 2015) leveraging face symmetry and combining actions derived from geometric features. All video recordings provided by the students were submitted and automatically analysed by the system.

Results

Determining the Cognitive Emotions

Initial examination of the data (videos) confirmed that students rarely displayed one of the basic emotions whilst engaged in e-learning activities. In order to trial and test the performance of the proposed approach for the recognition of cognitive emotions, images conveying emotions beyond the basic six, were integrated from three different datasets: i) "EU-Emotion Stimulus Set (EESS)" (O'Reilly et al., 2016), from the University of Cambridge (UK); ii) "The Cambridge Mindreading (CAM) Face-Voice Battery" (Golan, Baron-Cohen & Hill, 2006); and iii) "The Cambridge Mindreading Face-Voice Battery for Children (CAM-C)" (Golan, Sina-Gavrilov & Baron-Cohen, 2015). E-learning sessions were analyzed using a dedicated software for primary emotion recognition and indicated accuracy of 95% (Palestra et al., 2015). Subsequently, 11 cognitive emotions were selected: *enthusiasm, interest, surprise, curiosity, concentration, attention, disappointment, boredom, perplexity, worried, frustration.*

The output of this selection is a set of 4184 images depicting emotions whose distribution is as follows: enthusiasm (n=498), interest (n=340), surprise (n=295), curiosity (n=453), concentration (n=495), attention (n=374), disappointment (n=370), boredom (n=270), perplexity (n=369), worried (n=461), frustration (n=259). See Figure 2 for examples of images for these emotions.

Figure 2. Examples of expressions in the dataset.

Facial Expression Recognition Accuracy

The confusion matrix concerning the accuracy of the recognition of 11 emotions is shown in Table I. From the matrix (See Table 1) four commonly used evaluation metrics were calculated to evaluate the performance of the classifier: the AVG Accuracy, the Precision, the Recall and the F-Measure. The following formulas define each of the metrics, where Q can be any emotion that we are trying to recognize:

(a) AVG Accuracy= No. of correctly recognized emotions of all types/No. of all the emotions

(b) Precision= No. of correctly recognized emotions labeled as Q/ No. of all the emotions recognized as Q

(c) Recall= No. of correctly recognized emotions labeled as Q/ No. of all the emotions labeled as Q

(d) F-Measure=2*((Precision + Recall)/(Precision*Recall))

All emotions could be recognized to a very high degree of accuracy. The following significance results were obtained: AVG accuracy= 92%, TP Rate=0.918, FP Rate=0.08, Precision=0.919, Recall=0.918, F-Measure=0.918, MCC=0.910, ROC Area=0,933, PRC Area=0,867 indicating these are very encouraging validation results.

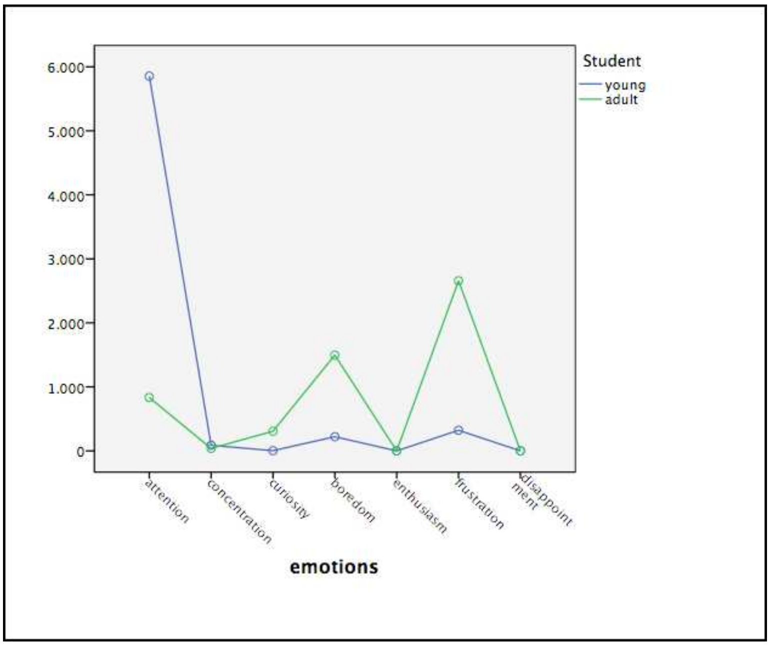
Table I. Confusion matrix for each emotion.

a	b	c	d	e	f	g	H	i	j	k	classified as
472	4	6	1	0	0	0	5	1	4	5	**a = happiness**
1	313	5	1	2	1	2	7	1	2	5	**b = interest**
3	3	260	0	1	6	4	6	1	3	8	**c = surprise**
0	1	1	437	7	2	0	0	2	1	2	**d = curiosity**
1	4	1	9	462	5	2	1	5	4	1	**e = concentration**
0	2	2	3	9	330	4	4	10	1	9	**f = attention**
2	3	6	0	0	4	338	3	1	8	5	**g = disappointment**
4	10	6	1	0	1	4	235	1	3	5	**h = bored**
1	2	1	2	7	7	0	1	346	0	2	**i = perplexity**
8	1	6	1	1	1	3	4	0	432	4	**j = disgust**
6	6	2	0	1	6	4	11	4	2	217	**k = frustration**

Relation between cognitive emotions, self-efficacy and academic adjustment across different e-learning contexts

Emotional profiles across e-learning settings. As shown in Figure 3, preliminary descriptive results of the two groups, emerging adult/adult students suggest that among the real emotions expressed during the video-lectures, *attention (M=3345)* was the most frequent cognitive emotion, followed by *frustration* (M=1490) and *boredom (859).* This result is quite predictable, since in video-lectures the focalization/attention phase takes a central role. But it is noticeable that younger adult students were much more attentive than adult students. Adults during the video-lectures however, expressed more frustration and boredom than did the younger adults.

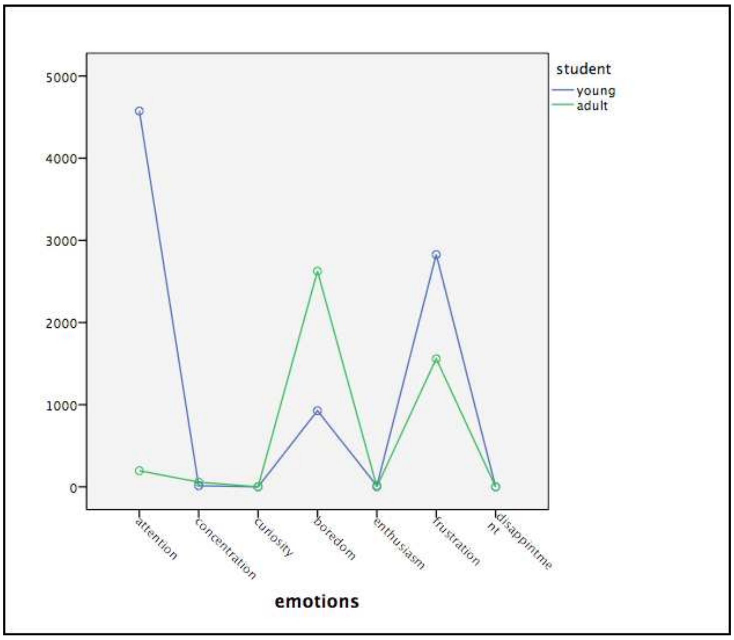
From a cognitive point of view *frustration* can be seen as a state of discordance, of discrepancy between new and old beliefs and thus presumably, video-lectures could be considered the contexts where adults check, compare and reflect on prior knowledge. For similar reasons, they have also expressed boredom. By way of contrast, young adult students were highly attentive to begin with, which might indicate their ease with visual learning approaches. These issues will be considered in follow up studies.



Note: Y-axis = Frequency of each emotion on x-axis

Figure 3. Emotional Profiles in video-lectures*Age

In the teacher/tutor chat scenario (see figure 4) the descriptive results indicated the main emotional expressions detected were again: *attention (M=2885)*, *frustration* (M=2192) and *boredom (1776).* In this learning experience, young adult students expressed not only more attention but also more frustration than adult students. Adults in the chat scenario expressed mainly boredom, demonstrating possibly less interest for the discussions with teachers.



Note: Y-axis = Frequency of each emotion on x-axis

Figure 4. Emotional Profiles in chat with tutor*Age

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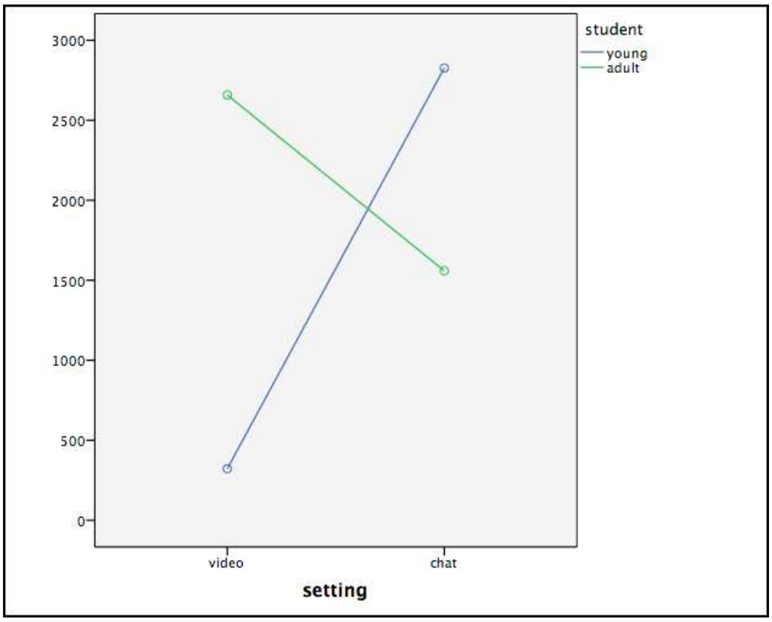
These descriptive results seem to suggest support for young adult learners preferring visual learning styles (video-lecture) as they were detected as being more bored and frustrated during the teacher/tutor chat scenario: respectively (bored M = 927, SD = 181; frustrated M = 2827, SD = 1220), than the video-lecture setting (M = 221, SD = 386 ; M = 322, SD 122. In addition, these descriptive results further suggest that the levels of frustration are different between age and online contexts (video vs. chat with tutor): while young adult students expressed more frustration in the chat with tutor scenario, it was the reverse for the adult students for the video-lecture (Fig.5). Given the small sample and exploratory and descriptive nature of this study, caution is advised in interpreting these data: however, younger students appeared more engaged, and less bored and frustrated learning from visual approaches such as video-lectures. Future studies will examine these indicators with a larger cohort.



Note: Y-axis = Frequency of each emotion on x-axis

Figure 5. Frustration*e-learning environments

Cognitive emotions, self-efficacy and academic adjustment across e-learning settings. A *single case study* approach was employed to explore insights concerning the potential role of self-efficacy. Preliminary descriptive statistics of the total pilot sample (n=10) and younger *versus* older students are reported as indicative baseline levels of study variables (table 2).

Table II. Descriptive analyses of participants by age groups

	Total sample		Younger students		Older students	
	Mean	S.D	Mean	S.D	Mean	S.D
Exams N	12.4	4.4	14.4	4.7	10.4	3.4
Exam Average	27.0	1.4	27.4	1.7	26.6	1.1
SAT	4.26	.74	4.20	.64	4.31	.90
PER	4.30	.43	4.30	.46	4.30	.45
INT	4.17	.75	4.06	.65	4.29	.90
GRA	4.53	.78	4.57	.35	4.50	1.12
e-Task	4.33	.63	4.33	.53	4.33	.78

Note: SAT = satisfaction; PER= persistence; INT= interdependence; GRA = gratitude; e-Task= task self- efficacy

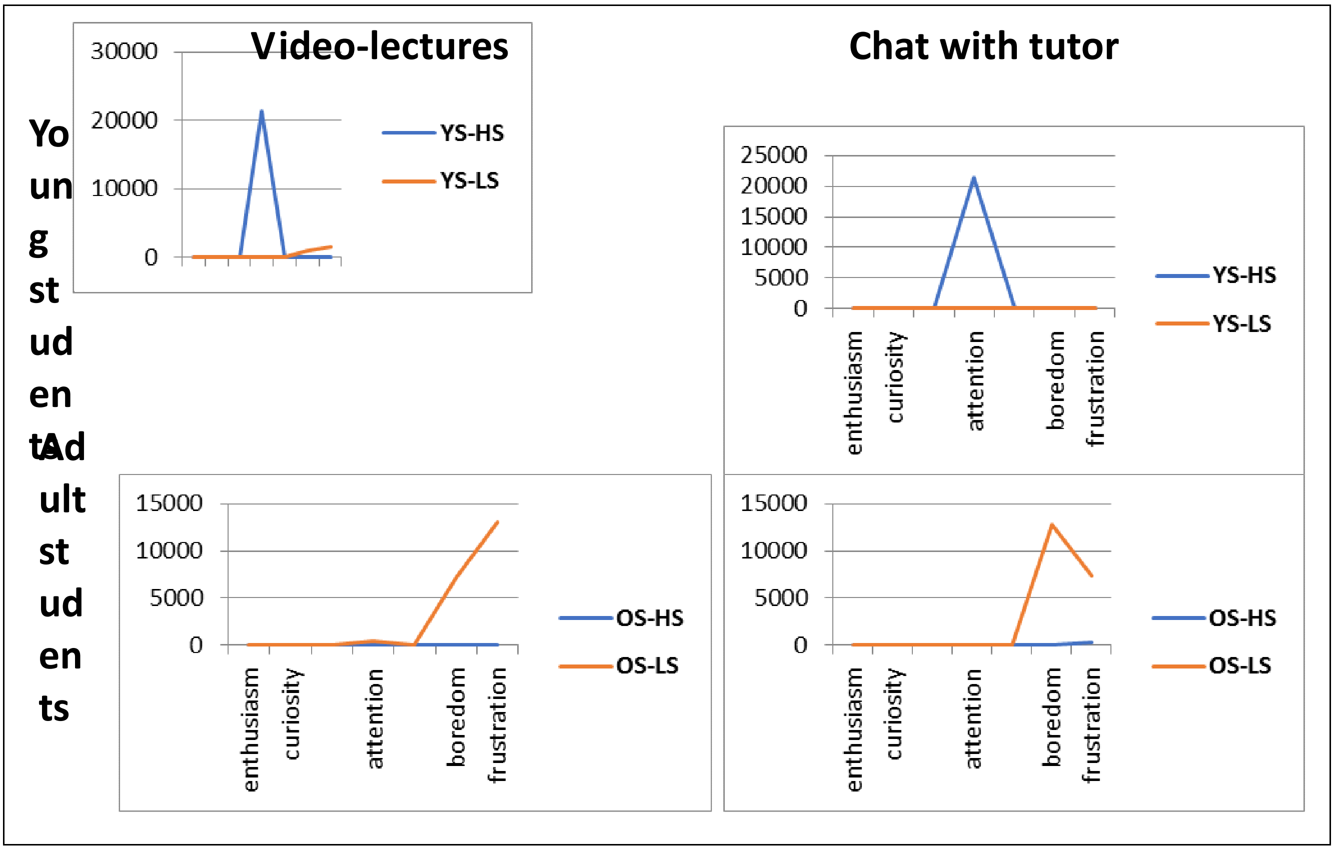
A purposive and convenience sub-sample of two younger and two older students, with opposite levels of self-efficacy (high and low) were selected. Preliminary examination of the data revealed it was possible to observe correspondence between different levels of academic adjustment (well-being and performance) and e-task self-efficacy levels (See Table 3). In order to visually inspect the emotional patterns separately for younger and older students who had opposite levels of self-efficacy, data were analyzed by plotting each student's emotion scores across e-learning activities. With regard to academic adjustment, as shown in Table 3, students with high levels of self-efficacy showed a more positive presentation than students with low levels of self-efficacy, in both the younger and older cases.

Table III. Academic profiles across younger and older students with opposite levels of self-efficacy

Students		Exams		Well-being				Self-efficacy
	age	Number	Mean	SAT	PER	INT	GRA	e-Task
YS-HS	25	14	29	4.29	4.83	4.71	4.83	4.67
YS-LS	21	9	25	3.29	3.67	3.29	4	3.67
OS-HS	63	14	28	4.86	4	4.57	5	5
OS-LS	64	9	25	4.71	4.5	4.71	5	3.67

Note: SAT = satisfaction; PER= persistence; INT= interdependence; GRA = gratitude. YS-HS= younger students with high self-efficacy; YS-LS = younger students with low self-efficacy; OS-HS= older adult students with high self-efficacy; OS-LS= older adult students with low self-efficacy

The plotting of the emotional profiles across e-learning activities (figure 6), indicated that self-efficacy can play a different role for younger and older students. Indeed while the young adult students with high self-efficacy had a high level of attention during both video-lecture and chat with tutor, this was not the case for the older student with high self-efficacy. Moreover, while the older student with low self-efficacy had a high level of boredom and frustration during both e-learning activities, the younger adult students did not show these kinds of emotions. These results support those noted above.



Note: YS-HS= younger students with high self-efficacy; YS-LS = younger students with low self-efficacy; OS-HS= older adult students with high self-efficacy; OS-LS= older adult students with low self-efficacy

Figure 6. Frequencies of cognitive emotions. Single cases study (age*self-efficacy)

Discussion

Overall, these preliminary and largely descriptive results suggest that when students interact within an e-learning academic context, they can experience different cognitive emotions and it is likely that these emotions are related to: the type of activities they are doing (video-lesson or chat); the phase of life they are in (younger adult/older adult); and beliefs of their self-efficacy with respect to the use of e-learning technologies.

The variety of emotional states when considering cognitive emotions is most interesting. The most expressed cognitive emotions ranged from those closely related to cognitive effort (e.g. attention, concentration); to those related to a moment of difficulty in the learning process (e.g. frustration and boredom); to those related to motivational and cognitive investment (e.g. curiosity, enthusiasm).

Another important preliminary result is the difference evident between the cognitive emotions experienced by younger adult and adult students during the activities with teacher/tutor interactions (chat) and video activities. Young adult students expressed more attention during video lessons and chats while adults showed more states of frustration and boredom. However, when considering the single case examination, differentiating for opposite levels of self-efficacy, the emotional paths suggested that for younger adult students, self-efficacy was associated with positive cognitive emotions related to learning processes (i.e. attention) and high levels of academic adjustment, in terms of both well-being and performance. This was different in the case of older adult students: lower levels of self-efficacy were associated with negative cognitive emotions (i.e. frustration and boredom) and low levels of academic indicators. These findings suggest that younger students' self-efficacy could be recognized as reflecting their individual ease with using technology and preference for visual learning, thus promoting successful academic pathways, which is in line with previous literature (Di Mele et al. 2015). By contrast, for older students, weak self-efficacy beliefs could be an index of personal difficulty associated with negative emotional states incurred during these learning processes. This could simply be related to their levels of confidence on returning to study, and feeling challenged by the online learning environment, for example.

Thus during e-learning activities young adult students with high self-efficacy could be in a 'state of flow' in which cognitive effort can be most likely supported by the willingness to build one's own professional path. By contrast, the presence of states of frustration and boredom in older students with low self-efficacy is probably due to the awareness of the difficulties that need to be overcome to manage the topics that they are facing. Indeed, they expressed boredom: which could indicate a task which is too simple for them or not interesting given their life experiences and prior knowledge**,** but also frustration: which instead indicates the presence of a task too complex for them. This co-presence of these two opposing negative states suggests that for the older students it is more difficult to "enter" into a state of 'flow'. This difficulty seems connected to their perceptions of efficacy and control with respect to the task. However, we cannot exclude that these negative states may be also related to other aspects, such as the difficulties adults have in managing study activities that add to work and family commitments.

Overall these exploratory and preliminary findings provide several practical considerations and implications for teachers and students and future directions for ongoing research. For teachers, the monitoring of cognitive emotions allows the identification of temporary or enduring negative reactions, thereby enabling the design of tailored educational strategies to support students' difficulties with the aim of promoting a positive flow state and positive academic adjustment. For students, the feedback on their cognitive emotional states could represent a useful hint towards regulating their learning tasks, mostly in an online context where emotional communication can be essentially mediated by a technological device.

These considerations lead us to look at cognitive emotions as potential indicators of the quality of the student's learning process. However, at this exploratory stage we need to signal some important limitations of the study: especially the sample and gender of participants. The role played by expressed cognitive emotions in e-learning environments needs to be studied with a larger and more heterogeneous experimental sample of both men and women, increasing the number of learning activities (video-lectures; teacher chats) for each student group and including students not only engaged in the humanistic area, but also technical and scientific students. Future studies would also look at emotions by examining different phases of the video-lectures or chats in order to better understand the emotional dynamics.

Nevertheless the study presents an innovative starting point for exploring both perceived and expressed psychological dimensions of e-learning. It has successfully used *observational* methods, in the detection of cognitive emotions in real time (automatic detection and classification of facial expression), and also trialed previously published, reliable measures and self-assessment tools, together with self-reports on satisfaction and persistence as related to the University course. Finally, it has explored self-efficacy as perceived in learning, mediated by technologies.

Overall, it contributes by extending the emotional education literature, underlining the importance of understanding the interplay between self-representations (e.g. self-efficacy), cognitive emotions expressed in real time, and academic adjustment across ecological and real e-learning contexts.

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