Identification of Affective States in MOOCs: A Systematic Literature Review

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Abstract

Massive Open Online Courses (MOOCs) are a type of online coursewere students have little interaction, no instructor, and in some cases, no deadlines to finisch assignments. For this reason, a better understanding of student affection in MOOCs is importantant could have potential to open new perspectives for this type of course. The recent popularization of tools, code libraries and algorithms for intensive data analysis made possible collect data from text and interaction with the platforms, which can be used to infer correlations between affection and learning. In this context, a bibliographical review was carried out, considering the period between 2012 and 2018, with the goal of identifying which methods are being to identify affective states. Three databases were used: ACM Digital Library, IEEE Xplore and Scopus, and46 papers were found. The articles revealed that the most common methods are related to data intensive techinques (i.e. machine learning, sentiment analysis and, more broadly, learning analytics). Methods such as physiological signal recognition andself-reportwere less frequent.

Keywords: MOOCS, affective states, emotions, online learning.

1. Introduction

Massive Open Online Courses (MOOCs) bring together a large number of students, whose platforms store the data generated by navigation and interactions - which can be used for many types os researches, making it possible to detect problems and make decisions that contribute to improve teaching and learning experiences online (Liu et al., 2016).

For this reason it can be said MOOCs have "emotional data" which describe students' affective states while in online learning sessions (Montero and Suhonen, 2014). Affection in MOOCs were underexplored in online courses, because they contain a variety of non-directly accessible behavioral information, which makes it a challenging type of information to extract (Montero and Suhonen, 2014), but have been receiving increassing attention because of the effects positive and negative emotions have in learning (Tzeet al., 2017). If in the context of classroom teaching the students' emotions are more visible to the teacher, in MOOCs - where there is often no interference from teachers or tutors - this identification becomes much more subtle (Liu et al., 2016; Montero and Suhonen , 2014; Rothkrantz, 2017).

Failing to consider affective aspects in the analysis of learning data can impede the comprehension of the students' learning path in an effective way, leading to an incomplete perspective of the online learning process (Montero and Suhonen, 2014). Identyfingstudents' affective states in MOOCs can bring various benefits, such as identify which type of didactic resource/content has potential to boost positive feelings (Xing et al., 2016) and use it as input for the personalization of the learning (Leonyet al., 2015).

By detecting affective states of students of MOOCs, it is possible to identify which elements are related to positive and negative valences, making it possible to correlate affection with learning (Dillonet al., 2016a). This correlations is possible because emotions can be linked to certain behaviours, for example: negative emotions (such as frustration and anxiety)can be related to drop-out (Montero and Suhonen, 2014), while positive emotions may be associated with increased engagement (Tzeetal, 2017).D'Errico et al (2016) have identified that affective states with positive valence have a positive influence on student participation and performance. Rothkrantz (2017) adds that positive emotions can favor the intention to continue studies in a MOOC. On the other hand, negative valenced emotions can trigger undesirable effects in learning, which can affect the educational path of the student, as well as his interest in distance learning (Oluwalola, 2015). Affective states such as engagement, frustration, confusion and boredom may indicate elements that are affecting learning, evidence the level of involvement and interest of students, as well as the state of understanding of content (Gupta et al., 2016).

According to Ez-Zaouia and Lavoué (2017) it is possible to infer students' affective state from information collected from different types of resources, such as: audio, video, self-report tools and interaction analysis. Considering the diverse possibilities of recognition of affective states, in this paper a systematic review of the literature was carried out with the goal of finding studies that address the identification of these emotional aspects in MOOCs, and verify the methods employed.

2. Affective states in Online Learning

In this paper, we consider emotional, affective, mood and feeling as "affective states". According to Ekkekakis (2012), emotion, affection and humor are terms that differ in their meanings. Ekkekakis (2012, page 322) clarifies that affection "can be a component of moods and emotions, but it can also occur in pure, or isolate", while emotions are tied to individuals' reactions to something, for example: anger, fear, jealousy, pride, and love (Ekkekakis, 2012).With regard to moods, Pathak et al. (2011, p. 221) explain that "moods (as feeling cheerful or depressed) are states or frames of mind. They may be occurrent or longer-term dispositional states. Moods are less closely tied to specific objects than emotions. They are not linked to specific patterns of intentional action so they do not afford motives for action. Moods color one's thoughts and pervade one's reflections". On the other hand, feelings differs from emotion because they are enduring (Munezeroet al., 2014).For this reason we use the expression "affective states", because they are broader, and not limited to recognizable states with high valences (such as anger, fear and joy).

In educational contexts, it is important to emphasize that learning does not only include mental, social and psychomotor character, but also an affective component (Alico, Maraorao and Maraorao, 2017). Affection (an emotion) impact virtual learning, and during this course the student can experience both positive and negative negative emotions, which can be seen as signs of success and frustration in learning

(Kaushik, 2017).

In this scenario, knowing students 'affective states is fundamental to evaluate learning, to identify relationships between emotion and learning, and to establish strategies to adapt students' learning experiences, considering the dimensions affective (D'Erricoet al., 2018). By understanding and improving affective experiences in online learning, it may be possible to contribute to reducing online drop-out rates (Gupta et al., 2016).

3. Methodological procedures for the systematic literature review

This research consists of a systematic literature review based on the guidelines proposed by Aromataris and Riitano (2014). The review protocol begins with a guiding question, then proceeds to defining search terms. Once the keywords are established, one defines the databases and the criterions of inclusion and exclusion for the papers found. The analysis of the papers can include reading the titles and abstracts, and, as the amount of papers is reduced, proceed to a carefull reading. Our research question was:*How has the identification of affective states of students in contexts of MOOCs been performed?*

To answer this question, the search for papers was done using a set of keywords and the boolean operator {AND}: (i) MOOC AND Sentiment analysis; (ii) MOOC AND face recognition AND emotion; (iii) MOOC AND data mining AND emotion; (iv) MOOC AND emotion; (v) MOOC AND affective states; (vi) MOOC AND learning analytics AND emotion.

The search was carried out in three databases: (i) ACM Digital Library; (ii) IEEE Xplore; (iii) Scopus, chosen because they host high quality journals and conferences in the fields related to the subject. Because the identification of affection in contexts of MOOCs can be considered a recent theme, it was decided to search publications from 2012 to 2018.

Regarding the inclusion criteria, only papers written in English were selected because they potentially reach a larger audience. Another inclusion criterion was to choose only the studies that describe how the recognition / identification of emotions or affective states in MOOCs occured. Non-scientific texts; duplicated texts; texts withouththe keywords; texts which does not explain how the identification of the emotions occurred were excluded.For the primary analysis, the titles and abstracts were read, and the keywords were located in the text. The papers which passed the inclusion criterion were then fully read.

4. Results

Regarding the search results, in IEEE Xplore 27 studies were found, 8 of which were selected after application of the inclusion criteria. The search in Scopus returned 644 results, 32 of which were selected for final analysis. In the ACM Digital Library 1265 results were returned, however many were repeated or had already been listed in IEEE and/or Scopus. For this reason, out of 1265 papers, 6 met the inclusion criteria. At the end of the search, 46 papers were included. Table 1 has the number of studies per year of publication and per database of the selected papers. No paper with publication date of 2012 was found.

Table 1 - Publications per year and per database

	2018	2017	2016	2015	2014	2013
IEEE	1	2	2	1	1	1
Scopus	7	7	7	4	6	1
ACM	0	1	3	1	1	0
Sum	**8**	**10**	**12**	**6**	**8**	**2**

After reading the 46 papers, we classified them in 5 categories, regarding the methods used to identify affective states: (1) learning analytics (or educational data mining); (2) machine learning; (3) sentiment analysis; (4) physiological signals; (5) self-report *Figure 1* shows the number of papers per category.

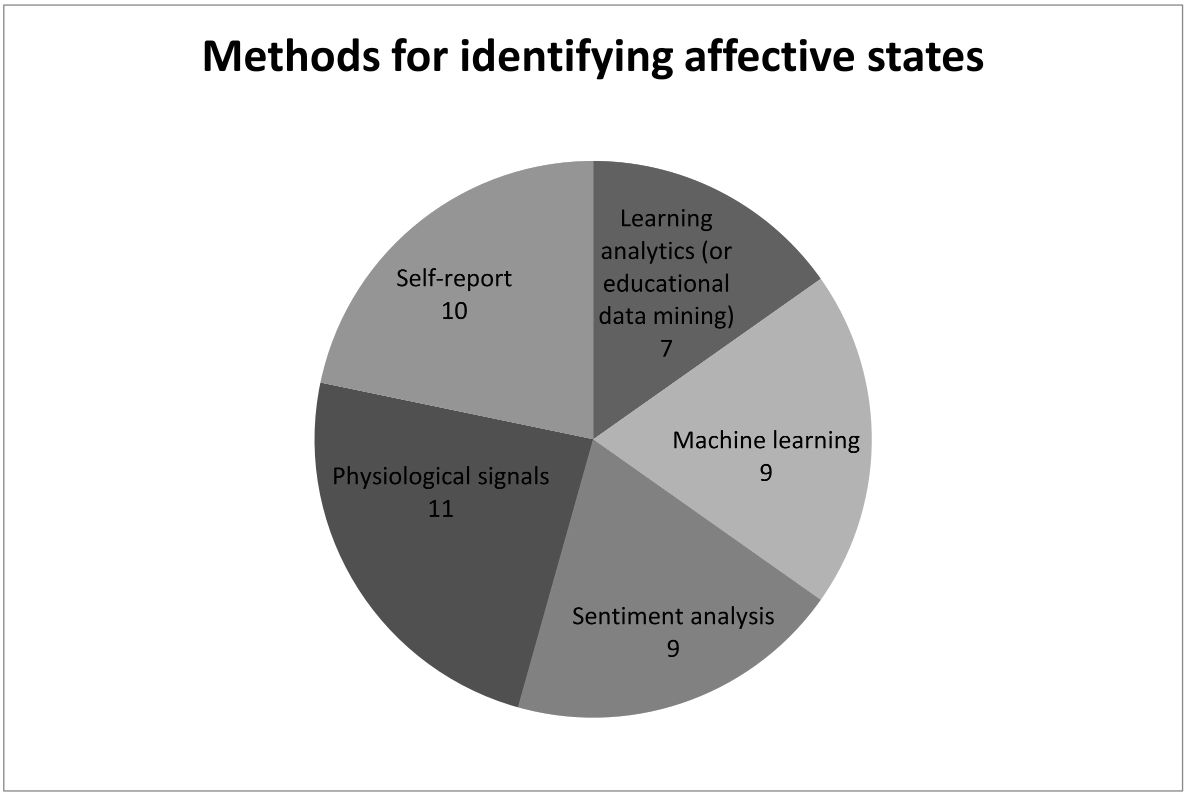

Figure 1 – Amount of papers per category

The number of studies in each category indicates that the identification of affective states in MOOC occurs in different ways, but data intensive methods - machine learning, sentiment analysis and, more broadly, learning analytics – were more numerous.Next sections details the selected papers in each category, beginning with the most used methods.

4.1 Learning Analytics, Educational Data Mining

Learning Analytics (or Educational Data Mining)is a broad label for analysis based on statistical tests and exploratory mathematical methods. This category could include algorithms for Machine Learning and Sentiment Analysis – because these algorithms also use statistical and probabilistic methods, such as Bayes and various types of Regression - but we decided to group these methods in other category, as they share the relevant characteristic of using text as primary input.Learning Analytics techniques have been used in MOOCs for various purposes, but for the specific purpose of analyzing affective aspects, few studies were found.

The first study is a reviewby Montero and Suhonen (2014), and presents a theoretical discussion about the use of learninganalytics in the identification and analysis of emotional states of students of online courses, especially MOOCs.The authors focus the review on the possibilities learning analytics' techniques offer for the extraction of affective data and address how to identify positive and negative affect and use this information to perform interventions in online learning.

Li and Baker (2018) collected and analyzed log data obtained from three MOOCs on Coursera to investigate student engagement and its relationship to learning outcomes. The authors classified students in four subgroups (all-rounders, quiz-takers, auditors, disengagers), and found out that the same engagement measure may be oppositely associated with achievement for different subgroups and that some engagement measures predict achievement for one subgroup but not another. Behavioral engagement was measured using lecture and quiz coverage. Cognitive engagement was measured by counting video interaction events. To measure achievement, the authors used course grade and overall lecture coverage throughout the whole course.

Guo, Kim, and Rubin (2014)investigated how video watching behavior in MOOCs correlates with student engagement, by analyzing logs of four edX platform MOOCs. The authors report that the start and end times of video watching; playback speed; number of times the student played and paused;the number of attempts of answering questionsafter viewing the videos and total time spent watching videos were observed. The authors considered, in their analysis: the type of video; how these videos were produced; the instructors' speech. They state that shorter videos, in non-formal settings, with enthusiastic speakers are more engaging, and presented a list of guidelines to produce more engaging videos.

Kevan, Menchaca and Hoffman (2016) evaluated students' satisfaction with MOOC conceptualizing four types of satisfaction: content, social, informal learning, and formal learning. The authors tested only the concept of informal learning satisfaction with 26 students, and modeled it as total content views, total design views, check offs, extra discussions and extra peer review. They used Confirmatory Factor Analysis to fit the data to the model, but the result was poor.

Leonyet al. (2015) developed mathematical models for inferring affective states of MOOC students in order to identify frustration,boredom, confusion and happiness, based on exercise data. The authors explain that frustration considers the number of attempts students use to perform the exercises, time spent and level of difficulty. Boredom was calculated considering the mean and standard deviation of the time to answer a question (longer times would indicate boredom). In order to identify confusion, they considered the time and the way the student answered for example: if a student answers correctly, but in the next attempt the answer to the same question is incorrect, the model identifies "confusion". For the analysis of happiness, they considered elements of gamification (winning badges, points and distinctions) and time to answer.

Liu et al. (2016) proposed a system for topic mining and recognition of affective states in MOOCs. The authors performed recognition and emotion extraction in comments posted on 30 online courses hosted on a Chinese MOOC platform called "Goukr." The authors' expectation was to make improvements in students' courses and learning experiences, as well as to mine interests and provide individualized learning strategies.

Drosos, Guo and Parnin (2017) created the Happy Face system, which identifies levels of frustration among students of large-scale online courses, such as MOOCs. In this system, students report their frustration when performing a task, by using a scale with five anchors, each representing a level of frustration (each anchor has a face drawing). The results are sent to the teacher, who can make adjustments in the learning materials.

Summarizing the findings of this review on studies using methods classified as Learning Analytics, there was onereview paper and sixpapers which used data to infer about affective states. Next, studies using Machine Learning are presented.

4.2Machine Learning

Machine Learning methods are also data intensive (the data isgenerated by the users interacting with the platforms). The data can be very heterogeneous, and may include texts, clicks and dates, which is then transformed and used as input to several algorithms (such as Support Vector Machines and K-Nearest Neighbors), statistical procedures (Regression of various types) and/or exploratory methods (Clustering). These algorithms are usually classified as supervised or unsupervised - unsupervised algorithms aim to discover patterns in unlabeled data, while supervised algorithms aims to predict an output variable given a set of mutually exclusive attributes. The studies in this review classified as Machine Learning were differentiated from those classified as Sentiment Analysis because the former had emphasis on methods supervised and unsupervised algorithms, not on dictionaries, lexical tools and natural language processing algorithms. For this reason, the differentiation is not straight clear, and some papers could be on either sections of this review.

Fernández et al. (2017) used text mining and classifiers in forums and questionnaires to find indicators of message type - interventions, questions, comments, or answers. They used KStar, Classification via Regression, Dagging, Decorate, LogitBoost, Rotation Forest, Random Forest, all of them available in Weka[1]. The authors used the Random Forest classifier, as it returned the highest success rate in the identification of messages types. Yang et al. (2015) presented a classification model to identify the degree of confusion expressed in discussion forums of two MOOCs hosted on the Coursera platform, using Logistic Regression and LIWC[2] (Linguistic Inquiry and Word Count).Bakharia (2016) analyzed posts of three MOOCs to compared which technique better classifies text messages as confusion, feelings and urgency – NaïveBayes, Support Vector Machine or Random Forest. They used Support Vector Machine to create a model for classification of each of the categories, as it provided better precision. Harris et al. (2014) used a Naïve Bayes classifier to identify emotions according to six dimensions: positive, negative, neutral, insightful, angry, and joke. Liu et al. (2018) developed a joint probabilistic model (Bayes), called “Emotion Oriented Topic Model” (EoTM) that incorporates an emotion lexicon to the model to calculate the emotion-specific topic distribution over forum posts. It enabled discovering students' emotions in their feedback,

[1]https://www.cs.waikato.ac.nz/ml/weka/
[2] http://liwc.wpengine.com/

thus improving the online learning experience, and identifying at-risk students.Wei et al. (2017) also employed data mining to identify confusion, feelings, and urgency in discussion forums of several MOOCs. The authors proposed a text classifier based on Convolutional Neural Network and Natural Language Processing. Tucker, Dickens and Divinsky (2014) conducted a case study of a MOOC hosted at the Coursera platform, and their goal was to identify students' feelings expressed in discussion forums and their impact on performance. For this purpose, the authors used Natural Language Processing and data mining. Fei and Li (2018) used machine learning techniques to analyze the emotion content in MOOCs discussion forums, using Word2Vect to identify the degree of word similarity, classify affective states of the data set and determine the valence of affect. They trained the classifiers using the classification algorithms Support Vector Machine, Logistic Regression and Decision Tree, and applied it in a set of data obtained from the "xuetangX" learning platform.

The only study mixing self-report and Machine Learning found in this review was Chen et al. (2016), who created a predictor of student personality traits from log data from a MOOC hosted on the edX platform, based on Gaussian Processes andRandomForests, and have also investigated whether personality produces behavioral impacts as well as learning. The authors also applied the Big Five PersonalityQuestionnaire(Goldberg, 1992)in the first week of the course, which included aspects related to emotional stability.

Thenine papers in this review always used a combination of many algorithms. The last section on data intensive methods, about Sentiment Analysis, is presented next.

4.3 Sentiment analysis

Sentiment Analysis is contextual mining of text which identifies and extracts subjective information. In educational contexts, the main sources of data are discussion forums, chats, emails and messages exchanged inside platforms, but could also include social networks such as Facebook and Twitter. Text data is a documentation of students' interactive learning processes, which allows for analyses of students' authentic voices in a non-invasive way. Many of the algorithms used in Sentiment Analysis are also used in studies classified as Machine Learning, but we decided to group then in a separated topic because Sentiment Analysis is a subject on Computational Linguistics.

A distinctive characteristic of this category of studies is using third-party tools as an aid to the analysis - because text data have a semantic layer of meaning which cannot be ignored, and which might not be accessible to untrained databases. For example, Moreno-Marcos et al. (2018) aimed at identifying positive and negative messages in discussion forums, comparing the outcomes of supervised algorithms - Logistic Regression, Support Vector Machines, Decision Trees, Random Forest and Naïve Bayes - and unsupervised – dictionaries and the SentiWordNet[3] (a lexical resource for opinion mining). Chaplot, Rhim, and Kim (2015) tried to predict when students would quit a MOOC using log data and feeding text from forum posts into the tool SentiWordNet and into a Neural Network. The authors also compared the outcomes with and without information related to affective states, and reported the affective information is crucial for the precision of the prediction. However, the authors warn that first week predictions are very weak, and the

[3]https://sentiwordnet.isti.cnr.it/

algorithm's results are substantially improved after this period. Hu et al. (2018) analyzed the relationship between student affiliation and their emotions in MOOCs, tracking discussion forums of five Coursera courses, offered from 2012 to 2015, with more than 59.000 students. The goal was to verify if there were changes in students' discourse regarding positive and negative emotions, according to the iteration of the course (i.e. first time offered, second time offered etc). For this purpose, the authors used the Linguistic Inquiry and Word Count (LIWC[4]) for the text analysis. They found that discussion forums have reflected decreasing affiliation and increasing negative emotions over the years for most courses, with no significant overall change in positive emotions. Lubis, Rosmansyahe and Supangkat (2016) usedPrinceton's University WordNet[5] lexical dictionary with the exploratory algorithms Fuzzy C-Means and K-Nearest Neighbor, to find neutral, positive, and negative emotions in comments made by the students. To find variables that would point the completion of the course the authors used Association Analysis. Shen and Kuo (2015) conducted a sentiment analysis of Twitter in order to find positive and negative tweets related to MOOCs, analyzing its frequency to find out the sentimental tendencies and to verify the variability of the feelings, comparing the data of daily, weekly and monthly posts, using Jan Wiebe's (from University of Pittsburgh) OpinionFinder[6], "a system that processes documents and automatically identifies subjective sentences as well as various aspects of subjectivity within sentences". Fernández, Lujan-Mora and Villegas (2017) conduct opinion mining in e-mails from MOOC students to promote improvements in teaching and learning experiences. The authors used Laurence Anthony's AntConc[7] to calculate frequency terms, as well as the use of Clusters and Support Vector Machine (SVM) for categorization of positive or negative messages.Tucker and Pursel (2014) turned to the analysis of textual data of students enrolled in a MOOC in order to verify if the feelings produced impacts on the performance (measured as grades), using word-sentiment lexicon. In addition, the authors quantified feelings in posts (comments / discussions online) to analyze the temporal variability of feelings during the course.

Four studies proposed models to identify affective states. Wang, Hu, and Zhou (2018) proposed a Semantic Analysis model to identify the emotional tendencies of students in MOOCs, and predict the likelihood of successful completion of a course based on analysis of students' emotional course of learning. In addition, the authors quantified on different types of positive and negative emotions expressed by students (happy, surprised, proud, in love, sad, angry, disappointed, scared).Rameshet al. (2015) developed a model to detect feelings in MOOCs' discussion forums, using the Natural Language Toolkit and seeded topic models. In this model, a set of words is associated with feelings and valence (positive, negative or neutral), using a probabilistic model of prediction.

In this review sevenpapers used third-party software with Machine Learning algorithms and two studies are model proposals.

4.4 Self-report

The studies in which the subjects are interviewed and/or answered questionnaires were classified as "self-

[4] http://www.liwc.net/liwcespanol/
[5]https://wordnet.princeton.edu/
[6] http://mpqa.cs.pitt.edu/opinionfinder/
[7] http://www.laurenceanthony.net/software/antconc/

report studies". In this review, all the papers adopted a quantitative approach, using questionnaires to create some score which is then correlated to some conclusion. This method has the advantage of obtaining a direct answer from the user about their affective states, which is easier than extract the data from text or navigation tracks. The disadvantages are (1) the amount of data is usually smaller, when compared to log and data mining based methods and (2) the user might not be as thoughtful as it would be necessary to obtain high quality data. Afzalet al. (2017) mention that self-report instruments have the same potential for emotional recognition than other tools such as sensors for signal processing, with self-report having a reduced level of difficulty of use.

Some studies used instruments created by other researchers to measure or identify affection, because developing a validated instrument can be very difficult. For example, Dillonet al. (2016b) carried out the identification of affection of students of a MOOC using the Self-Assessment Manikin (SAM), and Rizzardiniet al. (2014)used the emotional measurement instrument called Computer Emotion Scale. Tsai et al. (2018) proposed a model integrating metacognition (defined by the authors as implicit or explicit information individuals have about their own cognition and about the coping strategies that have an impact on it) and affective states of liking, enjoyment, and engagement, to investigate continuance intention to learn via MOOC. To evaluate metacognition, the authors used the Learning Strategies Survey scale, which evaluates knowledge about the use of coping strategies including planning, monitoring, and regulating. To measure affective states, they used the Online Learning Interest Scale. They found a positive relationship between metacognition and the affective states and continuance intention to learn via MOOCs. Huang and Hew (2017) conducted interviews with students enrolled in MOOCs at the Coursera and Open2study platforms, in order to investigate their motivation. The authors looked at how the instructional design of the courses impacts motivation, and what factors may lead to demotivation, as well as how motivation can influence the completion of a course. For this purpose they used the instrument called "Instructional Material Motivation Survey" (IMMS) that was adapted to collect quantitative data on motivation. Heutteet al. (2014) concentrates on the study of the persistence of students enrolled in a MOOC, using mixed methods - log data, demographic and questionnaire data. For the analysis of affection and persistence PANAS and EduFlow were respectively used.

Two studies focused on recreating affective trajectories. Afzalet al. (2017)applied 12 self-report questionnaires (a list of 15 emotions used by Pekrunet (2002)) and from this data, they created trajectories of affective states, in order to observe the transition process between affective states, as well as the occurrence of prevalent states and verified the correlation between affective states, behavior and cognition.Xiao, Pham and Wang (2017) also investigated the temporal dynamics of affective states of MOOC, but focused on video watching. The authors asked the students to indicate their affective states and level of valencein several points of the videos, using a list with nine options: engagement, boredom, confusion, frustration, surprise, pleasure, curiosity, happiness and neutrality.

Regarding studies which created new tools, SandanayakeandMadurapperuma (2013) investigated the relationship of affective states with learning, considering its impact on student performance. The authors proposed a tool called "Online Achievement Emotions Learning Questionnaire" (AEQ), which is a self-report instrument for identifying students' emotional states in Moodle. According to the authors, the AEQ considers 4 positive emotions (pleasure, hope, pride and relief) and 5 negative emotions (anger, anxiety, hopelessness, shame and boredom). The authors conducted an experiment in Moodle, using AEQ and log data such as time spent in activities, chats, navigation, participation in forums and notes, which were correlated with the measures of the self-report instrument.Lavoue, Molinari and Trannois (2017) developed and presented two self-report tools for use in distance learning contexts, encompassing MOOCs. The tools were named EMORE-L (Emotion Report for E-Learning) and CATE (Collaborative Annotation Tool for Emotions). The EMORE-L tool is a questionnaire (uses a Likert scale), which colletcs data regarding affective states related to the pedagogical activities carried out in the course. The CATE instrument can be used to obtain affective feedback in real time when students are in contact with textual material, reading, using emoticons and notes. Chen et al. (2017) developed an emotion classification method based on Kansei Engineering (KE) Type I to identify emotions derived by different types of commonly used MOOC videos (Type I is the simplest case of KE, as it does not uses mathematical or statistical tests). The word list was: refreshed, fun, lively, safe, relaxing calm, comfort, satisfied, interesting, convinced, lost, clueless, fear, depressed, confused, angry and disappointed, and was created by the authors, and they did not used dictionaries or lexical tools. The study was carried out with 50 students who watched 10 types of MOOCs videos, and after visualizing the videos, indicated their feeling from the word list.

In this review on self-report methods seven papers used a third-party instrument to measure affection, and adapted it to their needs, whilethree created new instruments to measure/identify affection.

4.5 Physiological Signs

Phychophysiology refers to any study which correlates a physiological measure with some independent variable (manipulated by the researcher). According to Stern, Ray and Quigley (2001, p. 3) “in the 1950’s a group of physiological psychologistis began referring to themselves as psychophysiologists”.Stern, Ray and Quigley (2001) list the approaches of studies using physiological signs: caracterization of response variables (for example blood pressure and palm sweat); correlation of stimulus and response variable (for example, music and heart rate); correlation of subject variables and a response variable (for example, sleep and heart rate) and application studies.As these studies focus on body responses (such as herat rate, eye tracking, palm sweat, eletromiography and eletroencelafogram, to name a few), the experiments need to be conducted in laboratories. The studies in this review, however, use devices’ camera (personal computer and smartphones), so they can track user data in some form. They are not as precise as, for example, an eye tracking system, but can extract valueble information on affective states.

Pireva, Imran and Dalipi (2015), for example, investigated emotional and sentimental engagement in three different MOOCs (hosted at Udacity, edX and Coursera) analyzing facial expressions to identify states of attention, anger, contempt, disgust, fear, joy, sadness, and surprise. Kamath, Biswas and Balasubramanian (2016) focused on the recognition of student engagement when watching videos of online course, and proposed a engagement recognition model via face recognition, using a Multiple Kernel Learning (MKL) in conjunction with a Support Vector Machine. An experiment was carried out in which students were observed in real situations. According to the authors, affective states such as confusion and boredom can be reflected in engagement.In Augustin (2016a) and Augustin (2016b) one can find the description of the method for detecting student mood in MOOCs, which are intended to identify students' moods by detecting facial points captured by the camera.

Caballé et al. (2014) presented a tool called "SmartBox", which identifies students' emotions in contexts of distance education, and performs a behavioral monitoring through a sensor that captures body movements, acting with stimuli aimed at increasing motivation and concentration of students. For example, if a student stops triggering the mouse or keyboard, the system recognizes ir as"loss of concentration", and some stimuli are triggered, such as a chair vibrator or sound activation. Xing et al. (2016) performed the recognition of emotions from the analysis of pupil diameter variation of students when they are interacting in MOOCs using computers or cell phones. The recognition of affective states resulted in a recognition model based on Machine Learning, trained witha database composed of characteristics of pupil variation. The authors also developed an application called "Emotional MOOCs", to act as an informative resource to the teachers about students' emotions, so they know students' affective states and identify which type of material causes a particular reaction. Xing et al. (2016) explain that when students use a MOOC by means of a cell phone or computer, short videos are recorded at different moments of visualization of the learning material, capturing the behavior of the pupil, and at the end of the course the MOOC has a report containing the emotions detected, with statistical results delivered to the teacher through the EMOOC application.The research of Xiao and Wang (2016) is inserted in the context of mobile MOOC, regarding the monitoring of student behavior. The authors have presented an intelligent system that captures signals from the user's rear camera, and accompanies the movements of the user's fingertips. This system is able to infer boredom and disinterest and to identify a possible drop-put. According to the authors, the inference occurs in real time while the students access MOOCs through the cell phone.Soltani, Zarzour and Babahenini (2018) is aimed at the detection of emotion from facial expression of MOOCs students, through webcam, analyzing the following states: anger, disgust, fear, happiness, neutral, sadness, contempt and surprise. The authors presented an architecture composed of three layers: data, logic and learning. The data layer acts in the collection of information related to the student's profile, learning data and general business rules. The logical layer is specifically responsible for the adaptative MOOC deleverd to the students. The learning layer has a facial analyzer, the adaptive MOOC and pedagogical agents. From the detection of students'emotions,the pedagogical agent provides information to the students concerning their emotional states as well as orientations.Pham and Wang (2017) developed a system called "AttentiveLearner2" whose focus is to make affective and cognitive inferences about students accessing MOOCs through smartphones. The recognizes and tracks boredom, confusion, curiosity, frustration, happiness and self-efficacy, using a dual tracking system that uses the rear camera to track signals obtained from users' fingertips and the camera's front camera to capture facial expressions.

One study did not used face monitoring - Wang et al. (2013), who used a single-channel EEG headset in adults watching MOOC videos, and trained and tested classifiers to detect when the student is confused while watching the course material. The EEG displayed a weak but above chance performance distinguishing confusion, while the classifier performed comparably to a human observer (who monitored body language and rated the students' confusion levels).

Finally, Sharmaet al. (2016) are cited in this review because they used a mixed method study. They used eye tracking to monitoring students watching videos in MOOCs and provide notifications about their state of attention, using measures such as: student's first look at a page; time the student stayed on a single page; number of times the student revisited a content by looking at a specific item; frequency of looking to an element of a page. In addition to the focus on attention states the authors investigate whether there was correlation of patterns of visual inspection of the pages and learning gains.

Nine studies out of the eleven studies in tis category correlated face recognition to affective states, while one used a different approach and one presented systems which recognize affective or emotional states and give feedback based on this information.

5. Conclusion

This systematic review had the purpose of answering the following question: how has the identification of student emotions in the context of MOOCs been performed? The 46 studies found in the review pointed out that emotional recognition in MOOC environments is performed through several techniques, especially data intensive methods, but also physiological signals detection and self-report. The review revealed the importance of studying affect in online learning environments in an integrated form, and suggested different methodological possibilities, including the feasibility of integrating more than one method, using a mixed approach, so that quantitative and qualitative information can be used.

Identifying affective states can be an important element in online and offline learning analysis because there are behavioral and cognitive associations between affection and learning. In this direction, this systematic review has revealed that the identification of affective states in MOOCs is feasible through different methodological paths, allowing the recognition of elements that cause positive or negative reactions, in many intensities, and the results can be used to make improvements in the learning environment, in the educational content and on students' online learning experiences.

The results also revealed that the most exploited methods are data intensive methods mainly using text data as source (25 papers). Methods using self report (10) and physical indicators (11) were less frequent. We consider important to study the different methods aimed at the recognition of affective states, so that important information can guide the instructional design of the courses, recommendation of contents and personalization of the learning experience

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