Facial coding as a mean to enable continuous monitoring of student's behavior in e-Learning

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Abstract

This paper introduces an e-learning platform for the management of courses based on MOOCs, able to continuously monitoring student's behavior through facial coding techniques, with a low computational effort client-side, and to provide useful insight for the instructor. The system exploits the most recent developments in Deep Learning and Computer Vision for Affective Computing, in compliance with the European GDPR. Taking as input the video capture by the webcam of the device used to attend the course, it: (1) performs continuous student's authentication based on face recognition, (2) monitors the student's level of attention through head orientation tracking and gaze detection analysis, (3) estimates student's emotion during the course attendance. The paper describes the overall system design and reports the results of a preliminary survey, which involved a total of 14 subjects, aimed at investigating user acceptance, in terms of intention to continue using such a system.

Keywords 1

E-leaning, Affective Computing, Facial Coding, Facial Recognition, Deep Learning

1. Introduction

In recent years, web-based learning has transformed the way to educate in distance learning settings, by providing personalized delivery of knowledge. Massive Open Online Courses (MOOCs) have strongly contributed to the expansion of the training offer. They represent one of the most versatile way to offer access to quality education, as they allow learners to attend lessons and study anytime and from nearly any location [1]. They allowed to facilitate the access to higher education to a wider audience [2] and represent a means to enable accreditation of prior learning and to support professional development [3].

Despite the undisputed advantages of MOOCs, there are still several challenges that need to be addressed to cover some significant disadvantages that still limit their real potential for education.

The first one refers to how to prove that online students are who they claim to be during e-learning activities, especially in the case of courses with compulsory attendance, and exams [4].

To enable the certification of skills acquired through e-learning courses, institutions need learning management systems (LMSs) implementing continuous authentication tools, so to exclude the possibility that impostors take an online exam or participate in lessons instead of other users. In addition, such systems must ensure that students take the exams without cheating, so that their skills are properly assessed. Over the years, different solutions have been proposed to detect the identity of students based on the acquisition of biometric information, such as face, voice and fingerprints (e.g., [4-6]). However, the use of such tools remained limited to the exam context, as they often are cumbersome and require

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high computational performances. Most of the tracking currently used in LMSs, based on the analysis of actions performed by the students on computer input devices (e.g. keyboard or mouse), are unable to determine who performs the actions [5].

In this context, the present paper introduces a tool able to perform continuous students' authentication, based on face recognition, and to record the actual learning time a trainee spends in a course, with a low computational effort client side.

Another big challenge refers to how to monitor the student interest in various course activities and for various course materials. In a face-to-face lesson, teachers have various tools to appraise students' levels of performance, motivation and engagement (e.g., questioning students, conducting exams) and can easily adjust the topic of the lesson accordingly [7]. While the possibility to capture the student's and dynamically cope with the boredom of the student is missing in e-learning. In web-based systems, students data represent the only source through which instructors can assess student performance and engagement [8]. Thus, there is a necessity for LMSs equipped with proper tools, to enable the analysis of the students' mood in an e-learning environment [9].

Several systems have been proposed to estimate their level of attention [10, 11] and emotional states [12, 13] during their participation in the courses, in order to support educators to inspect and reflect on the students' behavior with web learning applications, by using facial coding. However, based on the best of our knowledge, no system has yet been proposed to support instructors in student performance assessment, that integrates also student authentication capability.

In this context, the present paper introduces a web-based platform for the management of e-learning courses based on MOOCs, which exploits facial coding techniques to enable continuous student authentication and autonomous monitoring of students' behavior to determine the level of attention and satisfaction. By using a webcam at least, the proposed system can:

- Recognizing the user's identity thanks to a face recognition system and detect the presence of strangers within the camera's field of view;
- Monitoring the level of attention demonstrated by the student during the presence at the course, through head orientation tracking and gaze detection analysis;
- Recording the emotions experienced by the student during the course attendance;
- Detect any action the student attempts to perform on the device used to access the platform, which overcome the mere interaction with the platform itself (e.g., access to other web pages, launching other applications)
- Mapping the monitored data related to students' levels of attention and satisfaction with the course dropout rate and/or the results of tests and exams and providing real time statistical information in an easy and intuitive way, useful to drive the instructor in a continuous improvement process of lessons/courses.

To recognize the above-mentioned cues in the pictures and videos captured by the webcam of devices used by students while attending lectures (i.e., PC, tablet or smartphones), the system exploits the most recent developments in Deep Learning and Computer Vision for Affective Computing, and ensures data security and students' privacy in compliance with the European General Data Protection Regulation (GDPR).

2. Research Background

In the last years, several systems have been proposed to address the main challenges associated with e-learning systems. A lot of solutions have been proposed to ensure students' authentication and to avoid cheating especially during exams.

To verify the effective presence of the students in front of the screen, solutions based on the use of proper objects or devices (e.g., smart cards) are not a suitable alternative [15]. Most of the LMSs adopt knowledge-based tools, which require to retype the password or to answer simple questions at irregular intervals of time. However, the effectiveness of these systems is low, as there is no way to check who actually performed those tasks [5], and the necessity to continuously perform some actions to verify presence is perceived to severely distract the student [14]. Many systems based on the acquisition of passive biometric data (e.g., fingerprints, keystroke and mouse dynamics) have been proposed [16, 17]. Such systems are usually well accepted, despite systems based on fingerprints result intrusive and distracting to the student during exams [18]. Several multi-biometric systems have been introduced to improve the security of the authentication process [19]. However, none of them allow continuous monitoring of the student's identity and avoid cheating during exams. This strongly limits their actual effectiveness in supporting students' identity certification.

Face recognition represents a suitable technology to perform continuous authentication in an e-learning context. However, it is sensitive to student's pose variation, lighting conditions and face occlusion from the camera's view [20]. Moreover, a continuous face authentication process is computationally expensive. To reduce the required computation effort client side, systems based on framework server side have been proposed in the last years, e.g. [5, 18]. To avoid the possibility of cheating, such systems should be able to distinguish printed faces from real faces. However, based on the best of our knowledge, no system actually implements algorithms for liveness detection. To ensure that no stranger may help students during exams, multiple cameras can be used.

Another significant factor that limits the effectiveness of e-learning is the lack of student motivation in various course activities and for various course materials. Several studies suggested that emotions play a vital role in e-learning [21, 22]. In fact, affective intelligence may support students in development of more self-awareness and self-management skills [23]. In the same way, scholars have argued the importance of understanding the students' engagement, or interest, to accomplish the learning task [24]. Measuring the user level of engagement in e-learning can be useful in detecting states such as fatigue, lack of interest and difficulty in understanding the content [25].

Automatic engagement prediction can be based on various kinds of data modalities, which include student response [26, 27], LMSs logs [8], physiological and neurological measures (e.g., electroencephalogram, heart rate, and skin response) through specialized sensors [28, 29], or features extracted on the basis of facial movements, head postures and eye gaze [30, 31]. Among the various methods the last ones are the least invasive, and probably the most suitable to be used in a learning context.

For what concerns emotion recognition systems, in the last years, much progress has been made also in the field of facial expression recognition systems, which have allowed the development of less and less invasive systems. The theoretical model most widely used to develop algorithms for the recognition of emotions is certainly represented by the Facial Action Coding System (FACS) [32]. It allows the identification of six universal emotions (i.e., joy, surprise, sadness, anger, fear and disgust) by tracking the movements of the face muscles. Most facial expression recognition systems are based on Convolutional Neural Networks (CNN) [33]. Several tools have been proposed in literature, such as [34, 35]. Usually these systems refer to trained models using datasets built in controlled environments, where it is possible to obtain the best accuracy scores, or, trained with data obtained by crawlers on the web, with low accuracy but mostly reflecting real contexts. To the best of our knowledge, approaches able to ensure a good accuracy using data obtained "in the wild" have not yet been evaluated. To ensure good accuracy in the recognition of human emotions in different contexts of use, the system introduced in this paper implements the tool described in [36], which exploits a CNN, based on Keras and Tensorflow frameworks, which has been trained merging three different public datasets.

Based on the best of our knowledge, there is still no e-learning platform able to ensure continuous students' authentication and monitoring their engagement through the detection of their attention and emotions, based only on facial coding.

3. The proposed system

The proposed system is based on a web platform. Figure 1 describes its overall functioning. As in many other web-based platforms of this type, users can register themselves autonomously through a registration form or be registered by a representative manager. On the first access, the users, whether they registered autonomously or not, are redirected to the "facial encoding registration" page.

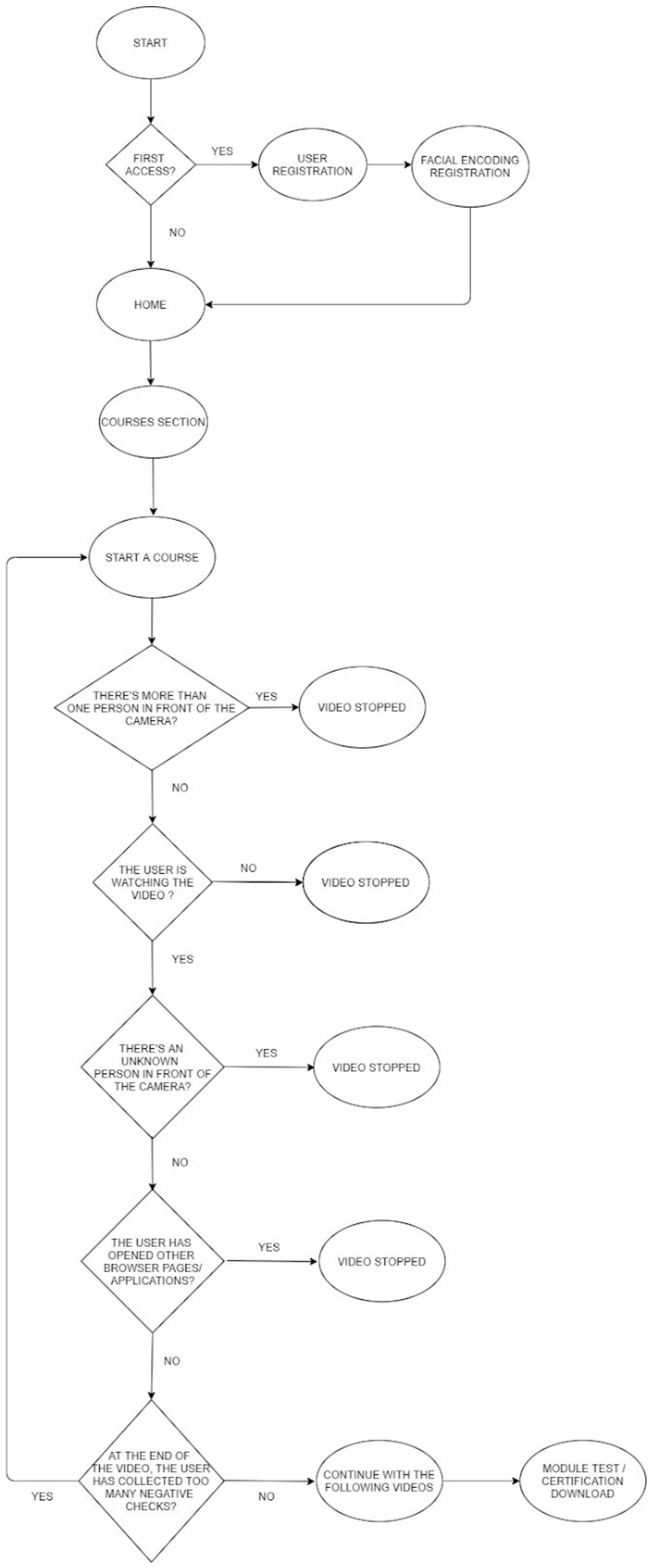

Figure 1: User flow chart

Since the system aims at authenticating users while they're watching the courses, it previously needs to encode the facial characteristics of each user into a numerical array of metadata which can be later used for facial recognition during the viewing. Before proceeding with the actual facial encoding action, the user gets prompted for an Eula popup through which he can acknowledge the end-user-licence agreement and accept it: with this, the user is informed about what kind of data the platform collects about him, where that data is stored and who is responsible for the data collection. After the eula is accepted, the facial encoding phase can actually take place: firstly, a photo through the primary camera of the pc is taken and submitted to the server (Figure 2). That photo is later processed by the backend algorithms of the application which are able to transform the cropped image of the user's face into an array of numerical values which is stored in a MySQL database. Eventually the photo taken by the user could be discarded. No image whatsoever in the whole process is stored anywhere on any physical hard drive, as this would not be compatible with the current legislation in the European Union.

Figure 2: Facial encoding during the registration phase

As the facial encoding phase is terminated, the user is redirected to the Homepage (Figure 3) and left free to use the application as any other of the same kind.

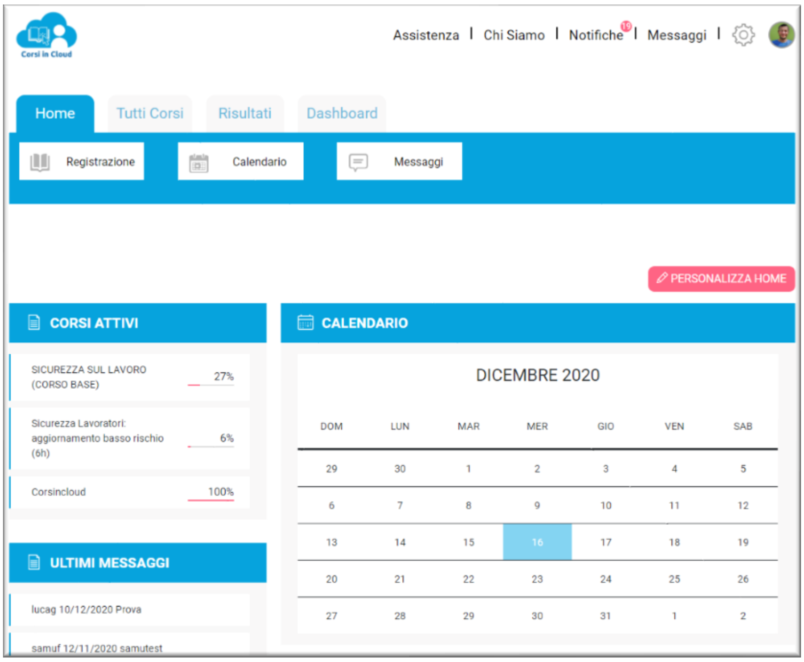

Figure 3: The platform homepage

After being enrolled in a course, the user can finally be able to watch its content.

As previously indicated, one of the main differences with other web platforms for online courses, is that during the viewing of the videos the user is constantly monitored through the proprietary APIs of the application.

When a video page is opened, in fact, the user is asked to grant permission to the application to access the camera, and the video playback is allowed only after those permissions are granted.

When the user actually starts the video playback, a javascript loop handler is launched, accessing the frontal camera to periodically check the user identity, attention and satisfaction.

This period has been empirically set to 5 seconds. The flow is as follows:

Every 5 seconds a photo is captured through the frontal camera. Such photo is analyzed to retrieve the following information:

- Number of people present in the frame
- Attention metrics regarding the user
- Identification of the user
- Satisfaction of the user

If more than one person is found in the image, the check is considered to be false: the platform certifies only one user at a time and multiple viewers are not allowed.

Moreover, the attention level of the use and his facial expressions are evaluated, as well as his identity through a facial recognition algorithm that makes use of the data registered in the facial encoding phase.

If the attention level doesn't reach a minimum threshold level or the user is not recognised the video check is considered to be false: in such an eventuality the playback of the video is stopped and the user is forced to manually restart it after restoring the optimal conditions for monitoring.

The evaluation of the Attention Level is performed in the following way: as for the Facial recognition module, the third-party library Dlib [37] is used in order to retrieve a mapping of the user's facial characteristics, in particular, the distances between six couples of landmarks have been considered to estimate the head orientation with respect to the screen. The platform also integrates a gaze tracker [36] to predict in which direction the user is looking at while it is following the course.

Another condition, but controlled at runtime from the client side, is that the video page does not lose the focus, i.e. is not placed in background respect to other applications: this can happen if, for example, the user changes browser tab or opens another application; in such situations the playback of the video is stopped.

Once the video is terminated the user can press the button "next" and this will bring him to the next video or to the end page of the course if that was the course's last video. When the user moves to the next video the platform controls that there are a minimum amount of "attention checks" for that specific video: for this control, the considered threshold is not fixed but depends proportionally to the length of the video. If the number of checks for that video is inferior to the considered threshold it means that the user either has tried to move to the next video without actually watching it or he has tried to tamper the javascript functions intended for monitoring. The user in this case is therefore forced to rewatch the video one more time.

Optionally the user can be forced to take some tests in order to assess or evaluate his retention of the course's information, if such tests are failed the user can be optionally forced to rewatch the course or limited section of it.

Once an entire course is completed the user is allowed to download his personal certificate. In the award page of the platform, each user can track their progress within each course, see their results and download certificates.

To enable satisfaction detection, the system makes use of a module specialized in emotions recognition tasks, based on a Convolutional Neural Network (CNN) implemented in Python using the Keras and Tensorflow frameworks and presented in [38].

For the content managers of the platform, i.e. users who upload and manage courses, an additional section is also available, that is the statistics dashboard of the platform. Through this dashboard content creators have the opportunity to observe statistical data for the courses they have published on the platform. In particular, admin accounts can access general statistics about their courses, such as *Attention*, *Authentication*, and *Satisfaction* for an entire course or a specific video of the course (Figure 4).

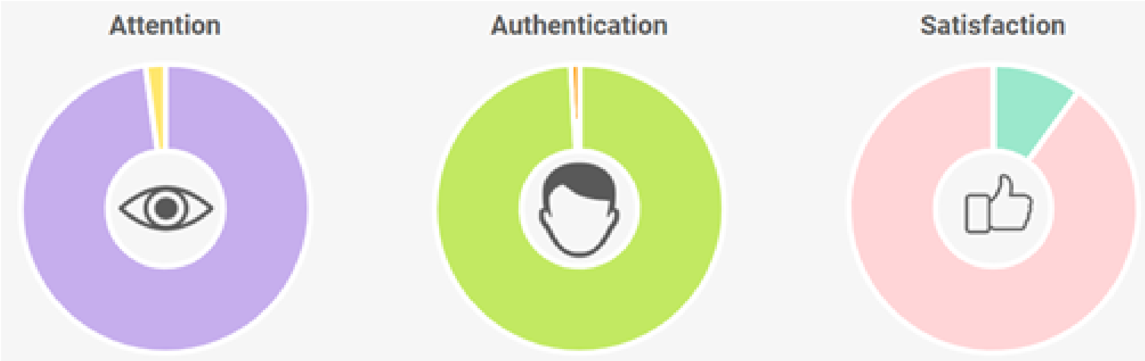

Figure 4: *Attention*, *Authentication* and *Satisfaction* pie charts.

The Attention pie chart represents the percentage of times in which the system detects the user focused on the course , the Authentication pie chart shows the percentage of times in which the face recognition proved the user's identity, and lastly, the Satisfaction pie chart is a summary about the emotions felt by the users (they are aggregated in 3 classes: satisfied, neutral and unsatisfied).

This information is general and is about all the courses, but in the case more specific information is needed, a dashboard is provided for each course. In particular, the mean value of *Satisfaction*, *Attention* and *Authentication* are shown for each video (Figure 5). Moreover, it is also possible to check the criteria described above for each second of a selected video, as shown again in Figure 5.

Figure 5: *Attention*, *Authentication* and *Satisfaction* bar charts representing mean values for each video of the course (on the top), and an example of their related values plotted for a video, mapped using line charts throughout its duration (on the bottom).

4. Preliminary test

A preliminary survey has been carried out in order to investigate user acceptance of the proposed system, in terms of intention to continue using such a system.

4.1. Materials and Methods

As evidenced in [39], the strongest predictor of user's continuance intention are satisfaction and attitude. User's satisfaction with a system is determined by the user's confirmation of expectations and their perceived usefulness [40]. Attitude is ‘‘the degree of a person’s favorable or unfavorable evaluation or appraisal of the behavior in question” [41].

Accordingly, the following questionnaire adapted from [39] has been developed (Table 1).

Table 1
Measurement Model

Construct		Evaluation Metrics	Questionnaire items
Intention to Continue	Satisfaction	*Utility*	I find this e-learning system to be useful to me
		Confirmation	My experience with using this e-learning system was better than I expected
		Control	I found this system too coercive
		Concentration	This e-learning system allowed me to concentrate fully on the course content
		Ease to use	Overall, this e-learning system is easy to use
	Attitude	*Desirability*	It is desirable to use this e-learning system
		Approval	I am pleased with the experience of using this system
		Enjoyment	Using this e-learning system is pleasurable
		Attitude to Recommend	I will strongly recommend that others use it

Note: The order of questionnaire items has been randomized.

A total of 14 subjects have been involved (11 males, 3 females) aged between 27 and 54 (Mean = 37,64; SD = 6,67). Six of them had no previous experience with e-learning courses based on MOOCs.

All the participants are employed in a company working in the field of software development and were asked to use the proposed system to attend a mandatory safety course for employees. The course lasts four hours and its primary objective is training the workers on general concepts of prevention and safety, according to the Italian regulation about health and safety in the workplace (i.e., Art.37 of D.Lgs. 81/08). The course is organized in several modules, lasting an average of 15 minutes. At the end of each module, the learner is asked to answer a multiple-choice test. In order to pass the test and move on to the next module, the learner must answer at least 70% of the questions correctly. At the end of the course, trainees must also pass a final test.

After completing the course, participants were asked to answer the questionnaire described above using a Likert scale 1-7 (1 = strongly disagree; 7 = strongly agree).

Participation in the test was entirely voluntary. The administration of the questionnaires was handled completely anonymously, using Google Survey.

4.2. Results

Scores related to the “Intention to Continue” and the considered dimensions (i.e., Satisfaction and Attitude), were calculated by averaging the respective item values per participant. Internal consistency of all the scores was good (Cronbach’s on the pooled values: “Intention to Continue”, α = .91; Satisfaction, α = .75; Attitude, α = .90).

The effect of the factor “previous experience” has been assessed using the non-parametric Mann Whitney U test, due to the categorial of variables and the lack of normality of the distributions. The results showed no statistically significant differences in the ratings given by subjects with previous experience compared with MOOCs to those given by subjects without experience. Consequently, the data were analyzed as a single group. Overall results are reported in Figure 6.

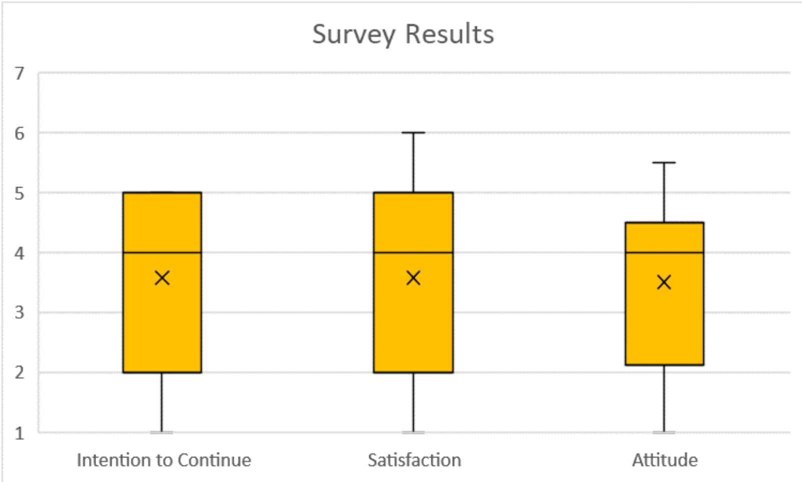

Figure 6: Results related to the participants' Satisfaction, Attitude and Intention to Continue using the proposed system

As it can be observed, the overall judgement related to the Intention to Continue using the proposed system resulted quite low (Mdn = 4). This is due both to low levels of Satisfaction (Mdn = 4) and Attitude (Mdn = 4).

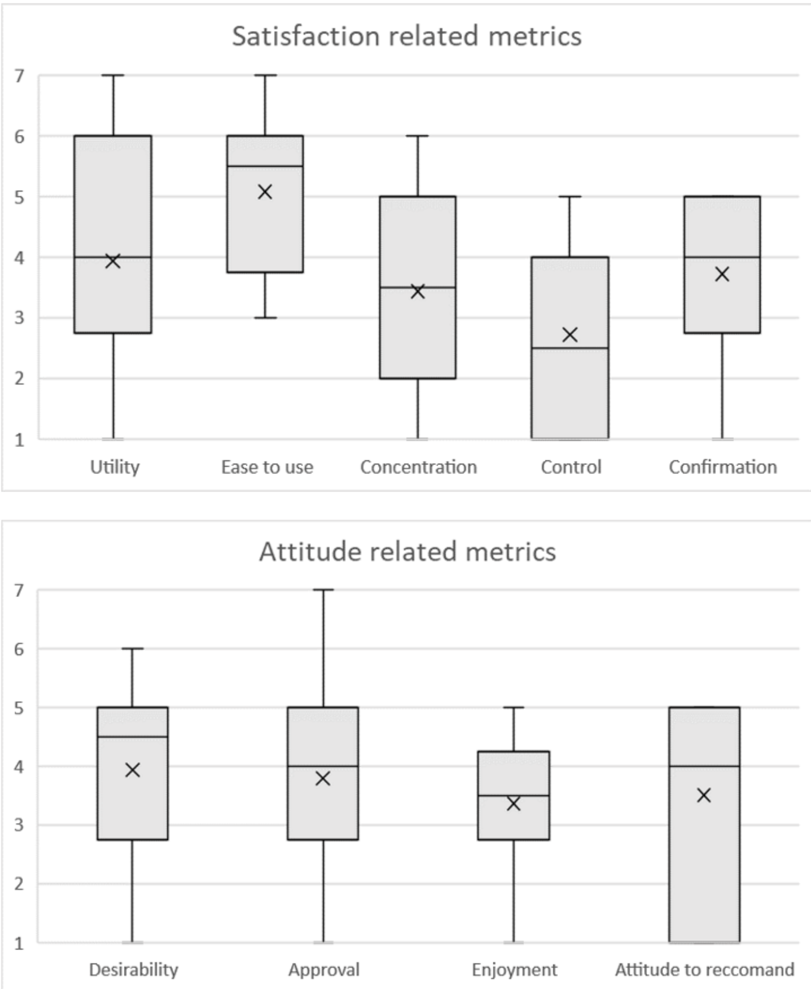

Figure 7: Participants judgements referred to *Satisfaction* and *Attitude* related metrics

By analyzing the collected judgements referred to Satisfaction related metrics (Figure 7), it is possible to observe that the most satisfactory aspect is the *Ease to use* (Mdn = 5,5), while the least satisfactory one is the perceived *Control* (Mdn = 2,5). Participants found the proposed system too coercive. *Concentration* (Mdn = 3,5) has also negatively impacted the overall perceived *Satisfaction*.

These results have been confirmed by the analysis of messages that participants have sent to each other via the slack live chat related to the course attendance. In fact, most of them complained that the system did not allow them to take their eyes off the screen, and that they could not carry out any other activity while watching the MOOCs. Some expressed their disappointment regarding the fact that they were required to maintain a certain posture: they argued that this did not help them to concentrate on the lesson, but rather distracted them from it. This could also explain the reported low level of enjoyment (Mdn = 3,5), and the relatively low levels of *Confirmation* (Mdn = 4) and *Attitude to Recommend* (Mdn = 4).

It is also worth reporting that most participants tried to bypass the system in some way, but even though they had strong computer skills, none of them succeeded.

5. Conclusion

This paper described the overall system design of an e-leaning platform able to ensure student's authentication, monitoring student's behavior during the course attendance through face coding techniques and provide useful insight for the instructor.

The results of a preliminary survey suggest that the system is effective and robust. Participants judged the system as ease to use. However, overall, it resulted in a low level of acceptance by end users. Participant perceived it as too coercive, as it requires users to stay in front of the device with their eyes focused on the screen throughout the course. This may be partly due to the management criteria and threshold values that have been empirically chosen to discriminate whether a person is attentive or not. Several experimentations should be carried out in the future to better adapt these criteria in order to improve the level of acceptability by users, while maintaining the effectiveness and reliability of the system.

Future studies should extend the experimentation to a wide range of users, in order to accurately assess the real performance of the system and better understand its actual impact on students' self-regulation, engagement and learning performance.

Moreover, several researches should also aim to better investigate the actual usefulness of the insights that the system is able to provide to the instructor, in order to support him/her in the continuous improvement of the lessons.

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