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INNOVATIVE PROCEDURE FOR INCLUSIVE EVALUATION IN UNIVERSITY: THE ROLE OF EMOTIONAL FEEDBACK

PROCEDURE INNOVATIVE PER LA VALUTAZIONE INCLUSIVA IN UNIVERSITÀ: IL RUOLO DELL'EMOTIONAL FEEDBACK

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Abstract

The increasing number of students with disabilities and Specific Learning Disorders (SpLDs) has led universities and educational policies to start a reflection on teaching, assessment, and organisational practices to achieve inclusive education. Achieving these goals requires a rethink of the overall educational and teaching proposals from an inclusive perspective, including assessment procedures. As emotions significantly contribute to student engagement and positive academic outcomes, providing inclusive assessment paths, ensuring a welcoming atmosphere, plays an important role in improving student academic success, especially for students with SpLDs or disabilities. However only few studies focused on inclusive university assessment. This study, starting from a pilot study conducted at University of Macerata, aims at understanding whether emotional feedback can support the redefinition of the assessment context in a more inclusive way.

Il numero crescente di studenti con disabilità e disturbi specifici dell'apprendimento nei contesti universitari ha portato le politiche educative ad avviare una riflessione sull'insegnamento, la valutazione

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e le pratiche organizzative al fine di raggiungere processi formativi inclusivi. Il raggiungimento di questi obiettivi richiede un ripensamento delle proposte educative e didattiche, comprese le procedure di valutazione, che sappiano direzionarsi verso una prospettiva inclusiva. Poiché le emozioni contribuiscono in modo significativo al coinvolgimento degli studenti e al raggiungimento di risultati accademici positivi, fornire percorsi di valutazione inclusivi, garantendo un'atmosfera accogliente, svolge un ruolo importante nel migliorare il successo scolastico degli studenti, in particolare con disabilità e con disturbi specifici dell'apprendimento. Poiché solo poche ricerche si sono concentrate sulla valutazione universitaria inclusiva, questo studio, partendo da uno studio pilota condotto presso l'Università di Macerata, mira a comprendere se il feedback emotivo possa supportare la ridefinizione del contesto valutativo in modo più inclusivo.

Key-words

Emotion recognition; Gaze tracking; Inclusive university teaching; students with disability and Specific Learning Disorders

Riconoscimento emotivo; Tracciamento oculare; Apprendimento universitario inclusivo; Studenti con disabilità e disturbi specifici dell'apprendimento

1. Introduction

The growing number of students with disabilities and Specific Learning Disorders (SpLDs) attending Universities (Giaconi et al., 2019; Pino and Mortari, 2014; Rivera et al., T2019), is driving inclusive approaches to support the design of training and teaching strategies able to respond to the requirement of personalization, according to individual students' needs (D'Angelo and Del Bianco, 2019; Giaconi, 2015; Perla, 2018). The transition from physical to online presence, which universities have been forced to from 2020 onwards, has also called into the rethinking and redesign of university contests and content from an inclusive perspective. Among these, the reorganization of assessment practices could be considered necessary for all students and, in particular, for those with disabilities or Specific Learning Disorders (SpLDs). In this direction, new solutions to support the analysis and understanding of difficulties experienced by students during their exams and, in general, their academic careers, should be considered (Mengoni et al., 2021a).
In the last few years, research has suggested how emotions influence cognitive processes (Tyng et al., 2017), including attention (Vuilleumier, 2005), learning and memory (Um et al., 2012), reasoning (Jung et al., 2014), and problem solving (Isen et al., 1987).
Studies suggest how emotions significantly contribute to student engagement (Pentaraki and Burkholder, 2017), and also are important to achieve positive academic outcomes (D'Errico et al., 2016). For example, in a study based on emotional development (Romeo, 2021) observed the "emotional availability" of teachers along with their "mood background" and provided a good "shape" to the student's emotional mental states during the final exam of a discipline (Sroufe, 2000). This should be considered as a capacitating feature, and not as a critical feature, of a particular learning context in which not only disciplinary knowledge should be assessed, but above all, the ability to act in front of a given task of the fragile student (Le Boterf, 2000) and therefore his/her resilience in an inclusive perspective (Romeo, 2020). Therefore, emotional feedback in the teacher-student interaction during the final tests can be helpful in assessing the setting and the evaluation process (Mengoni et al., 2021b). Another important factor is represented by the students' engagement, or interest, to accomplish the learning task (Nicholls et al., 2015), in fact, the exam moment is an event full of expectations and anxieties,

and the construction of a welcoming context becomes essential to provide the conditions for success, especially for students with disabilities or SpLDs (Mengoni et al., 2021a). Since emotional influences the educational process, it should be carefully considered to maximize learner engagement. 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 (Whitehill et al., 2014).
Today several methods and technologies allow the recognition of human emotions, which differ in level of intrusiveness. In the last years, important progress has been made in the field of facial expression recognition systems, which have allowed the development of more accurate and less invasive systems, so they represent the technology of choice to automatically perform emotion recognition in a learning context (Ceccacci et al., 2021). Most of them implement Deep Learning algorithms (i.e., Convolutional Neural Networks) (Generosi et al., 2018), based on the theoretical model known as "Facial Action Coding System" (FACS) (Ekman and Wallace, 1978), which allows the identification of the "big six" Ekman's emotions (i.e., joy, surprise, sadness, anger, fear, and disgust). 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 (Generosi et al., 2020), which exploits a CNN, based on Keras and Tensorflow frameworks, which has been trained merging three different public datasets.
Automatic engagement prediction can be based on various kinds of data modalities, e.g. student response (Beck, 2005; Johns and Woolf, 2006), LMSs logs (Hussain et al., 2018), physiological and neurological measures (Goldberg et al., 2011; Xiao and Wang, 2017) or features extracted on the basis of facial movements, head postures and eye gaze (Kaur et al., 2018; Whitehill et al., 2014). The last ones are the least invasive, and probably the most suitable to be used in a learning context. Gaze tracking techniques can be classified into two main categories (Hansen and Ji, 2010): feature-based and appearance-based. Feature-based systems are characterized by high accuracy, but they require the use of special equipment (e.g., special glasses / IR cameras) and need for system calibration. In general, appearance-based approaches are less accurate (Zhang et al., 2019). However, in recent years research has aimed to achieve increasingly accurate results, using less and less invasive and off-the-shelf systems (especially webcams). In particular, the solution proposed in (Krafka et al., 2016), based on the AlexNet model (Krizhevsky et al., 2012), represents one of the more solid tools actually proposed for gaze tracking.
Moving from these considerations, the University of Macerata and the Università Politecnica delle Marche have introduced a technological system, which exploits facial coding techniques during the evaluation process. The system is programmed to collect relevant data related to the emotional behavior of both student and teacher, and the level of student's attention, with the aim to help in assessing the evaluation setting and support reflection on the evaluation processes in the light of the different situations and the specificity of the interaction contexts that arise in the final assessment.

2. Monitoring student-teacher emotional behaviour during university exams

To investigate student-teacher interaction, an emotional analysis platform has been developed that enables collection and analysis of data about emotional behavior of students and professors during university exams. The system simply requires the use of at least one webcam and one PC connected to the internet. It is characterized by a desktop client application developed in C++ to analyze the face of students and professors during the exam, and a data visualization dashboard developed using Python and JavaScript to display the data collected by the client

application. The client application processes frame by frame a video stream that can be acquired in real-time from a webcam or from the desktop (i.e. streaming of everything is displayed on the desktop) or processed a posteriori from a pre-recorded video.
The possibility to process different video input formats also allows the system to operate with different architectures and e-learning web platforms: using desktop recordings indeed, it is potentially possible to analyze any video stream, including those coming from teleconferencing applications for remote examinations, very popular at the present time.
Once the source has been selected, the software allows the user to analyze different characteristics of the subject's face (usually synchronizing the analysis of the student's face and the professor's face), which can be configured as required. The client makes use of models trained by specific Convolutional Neural Networks. It implements the solutions described in (Ceccacci et al., 2018; Talipu et al., 2019; Generosi et al., 2020; Ceccacci et al., 2021), to acquire the subject's age and gender, the subject's level of attention to the monitor, the gaze direction, the subject's main emotion among the Ekman's "big six" (i.e., happiness, surprise, sadness, anger, disgust, and fear) plus a Neutral value, and the corresponding emotional valence and engagement. In particular, to allow differentiating between pleasant and unpleasant emotions, the system provides a measure of the emotional valence computed on a scale from -100 to 100, where negative values correspond to negative emotions (such as anger, sadness, disgust and fear), while positive values correspond to positive emotions (happiness and surprise), and the value 0 represent the emotional neutrality. Similarly, the system provides a measure of the emotional engagement (i.e., intensity of the felt emotion regardless of whether it may be negative or positive), providing a value from 0 (total absence of emotions) to 100 (maximum level).
To discriminate the student's face from the professor's in cases where both appear simultaneously on the screen (e.g. when the source is a video recorded from the desktop during an exam session carried out remotely using teleconferencing tools), a Face Recognition model capable of recognizing only the professor's face is applied to every frame, assuming that the other face appearing in the screen belongs to the student, following the method set out in (Ceccacci et al., 2021).
To support qualitative analysis of collected data, the system dashboard displays several tools and specific charts (Fig.1).
More in detail, the interface provides through pie chart information related to:

- the age and gender distribution (two dedicated pie charts);
- the percentage of times in which the system detects the user focused on the monitor (Attention pie chart);
- the aggregated percentage of each of Ekman's emotions (Emotions pie chart).

Moreover, it reports in a proper graph the trend over time of Valence, Engagement, Ekman's emotions and gaze direction, showing the moving average for each time unit, with the possibility of selecting the level of aggregation over time by choosing between 1 second, 30 seconds, 1 minute, 5 minutes and 10 minutes.
The dashboard also enables to filter data according to several specific criteria (e.g., exam session or date, exam results, professor name/surname, student name/surname/matriculation number, certified disabilities).
Furthermore, the interface offers tools that allow you to visualize the relationships between, to support the analysis of student-professor interaction. It provides graphs to support the

comparison of trend lines related to emotional valence, emotional engagement and level of attention, respectively manifested by the student and professor throughout the exam.
The Dashboard also provides the possibility of downloading a report with a pdf printout of all the generated charts and a CSV log with the data collected from the database filtered through the relative widgets, to enable further statistical analysis by means of other commercial tools.

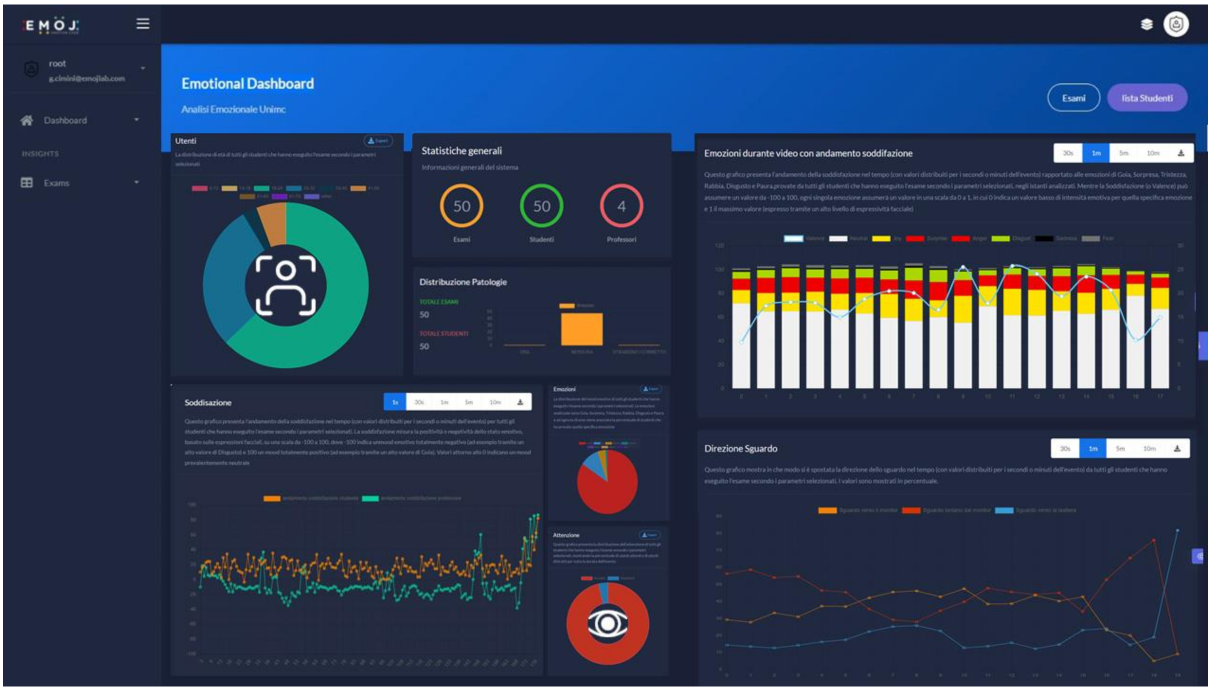

Figure 1 The proposed system dashboard

3. Case study

A preliminary experimentation was conducted with the aim of observing if the information provided by the proposed system can be useful to analyse and understand the dynamics of the relationship between the student and the professor, at an emotional level, during the final exam, and more specifically:

- can be useful to ensure inclusive university teaching and to guarantee opportunities for social inclusion and equity of treatment,
- may support the evaluation of the exam setting followed by the professors during the assessment process.

To this end, a pilot study was carried out at the Department of Education, Cultural Heritage and Tourism of the University of Macerata in the academic year 2020-2021 and was coordinated by a multidisciplinary team composed of experts in pedagogy and special education, developmental psychology and experts in human factors and human-computer interaction.
A total of 50 students, including 5 students with a certification for SpLDs and disabilities, enrolled in the fourth year of Primary Education, have been involved. They were randomly assigned to 4 professors and took the online oral assessment test in Pedagogy and Special

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Education through Microsoft Teams. After collecting the informed consent to participate in the research from each student, the study included an examination registration phase, during which an external observer filled in an Excel table with personal data, the presence of any disability certifications, the year of the course, the frequency of the course delivered online, participation in part of the teaching, and the final grade. Video recording was carried out over the entire duration of the examination, using the tools provided by the MS Teams platform. The videos were collected with specific caution related to recording sitting. Each recording captures audio and video, of both student and professor, and screen sharing activity. Video files have been processed frame by frame through the system described above (see paragraph 3).

4. Results

The analysis of the data collected during the experiment allowed us to evaluate the usefulness of the various tools offered by the proposed system. The Attention and the Emotion pie charts provide an initial overview and allow to compare the students' behavior with different professors.

For example, emotion pie charts related to students respectively promoted by the four considered professors, with a grade equal or higher than 27, are reported in Fig. 2 and Fig. 3.

As can be seen, students who took the exam with Professors 1 and 2 exhibited a slightly higher level of attention (98%) than those who took the exam with Professors 3 (94%) and 4 (96%).

Students who took the exam with professor 2 expressed more positive emotions (i.e., joy = 16%, surprise = 13%) than the others. While students who interacted with Professor 1 showed a higher level of negative emotions (i.e., sadness = 12%, disgust = 2%) than the others.

The other widgets the system displays allow for a better understanding of the differences between professors' individual styles and attitudes toward accommodating students based on their needs and functioning profiles.

In particular, the analysis of the emotional curves allowed to highlight the singularities that characterize the various students during the assessment process.

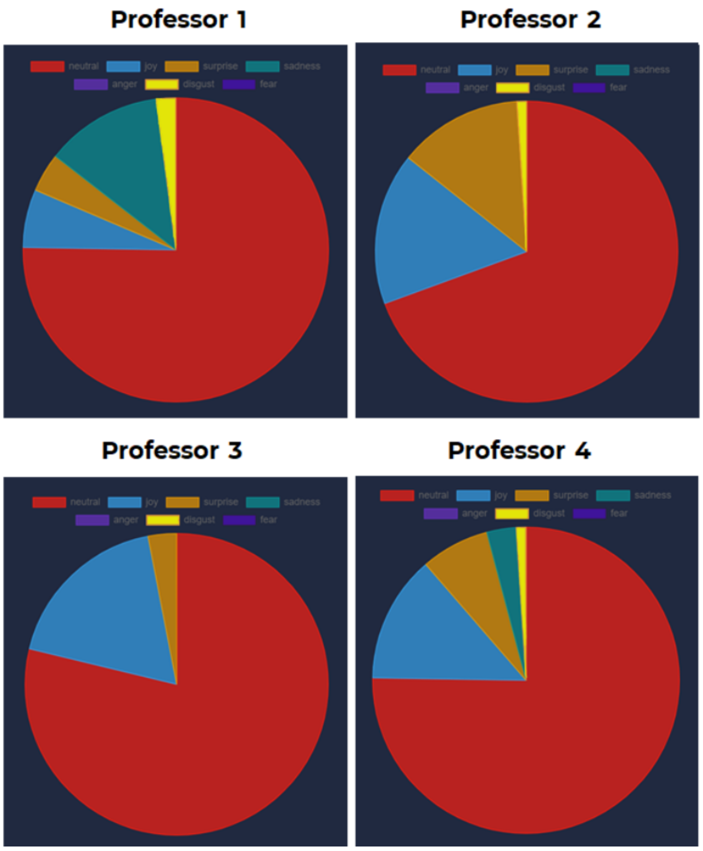

Figure 2 Emotion pie charts related to students respectively promoted by the four considered professors, with a grade equal or higher than 27/30 (red = neutral, green = sadness, blu = joy, orange = surprise, yellow = disgust)

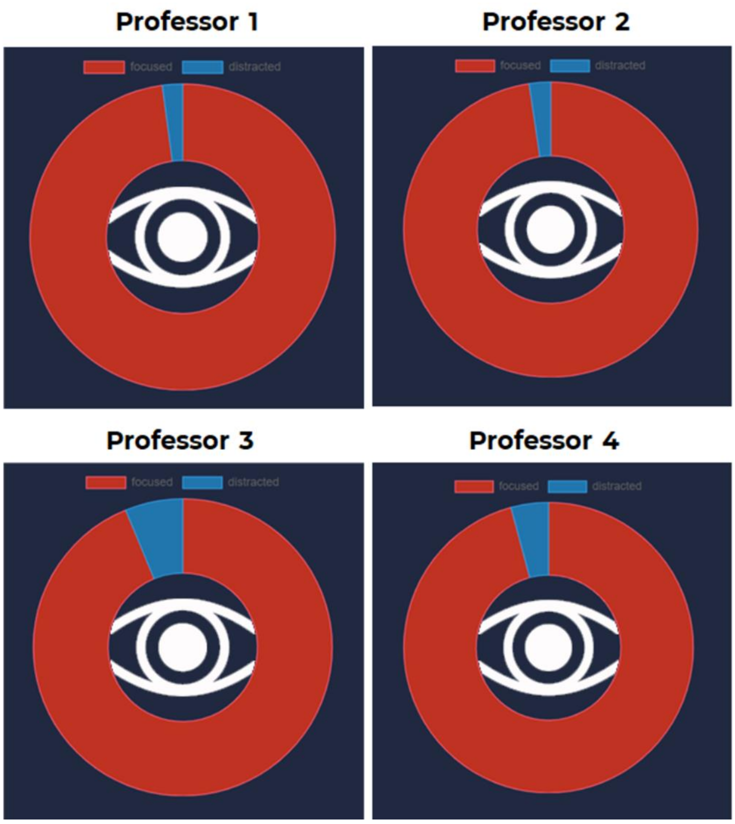

Figure 3 Attention pie charts related to students respectively promoted by the four considered professors, with a grade equal or higher than 27/30 (red = attention, blu = inattention)

For example, in Fig. 4 the valence moving average trendlines (computed considering a period equal to 30 seconds) of three students who took the exam with Professor 1. They are related to:

- a student who failed the exam,
- a student who achieved the high marks,
- a promoted student with dyslexia, who took the exam using compensatory tools.

Surprisingly, it is possible to observe that the emotional curve tends more toward high positive values in the case of the student who failed the exam than in the case of the students who passed. This occurs mainly in the final phase of the examination.

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Figure 4 Valance moving average trendlines (30 sec) related to: a failed student (on the left), a student promoted with high marks (on the right), a student with dyslexia, promoted with high marks, who took the exam using compensatory tools (in the middle).

By analyzing the emotional outcomes of the two promoted students, we can also observe that the curve related to the student with dyslexia is less regular than the other. In fact, while the first has several peaks of positive valence, the second is almost flat.

The reason for these differences can be investigated by looking more closely at the dynamics of the relationship between students and teacher during the exam. This can be seen by analyzing the relationships between the emotional and attention data of a student and his/her professor during a particular exam (Fig. 5).

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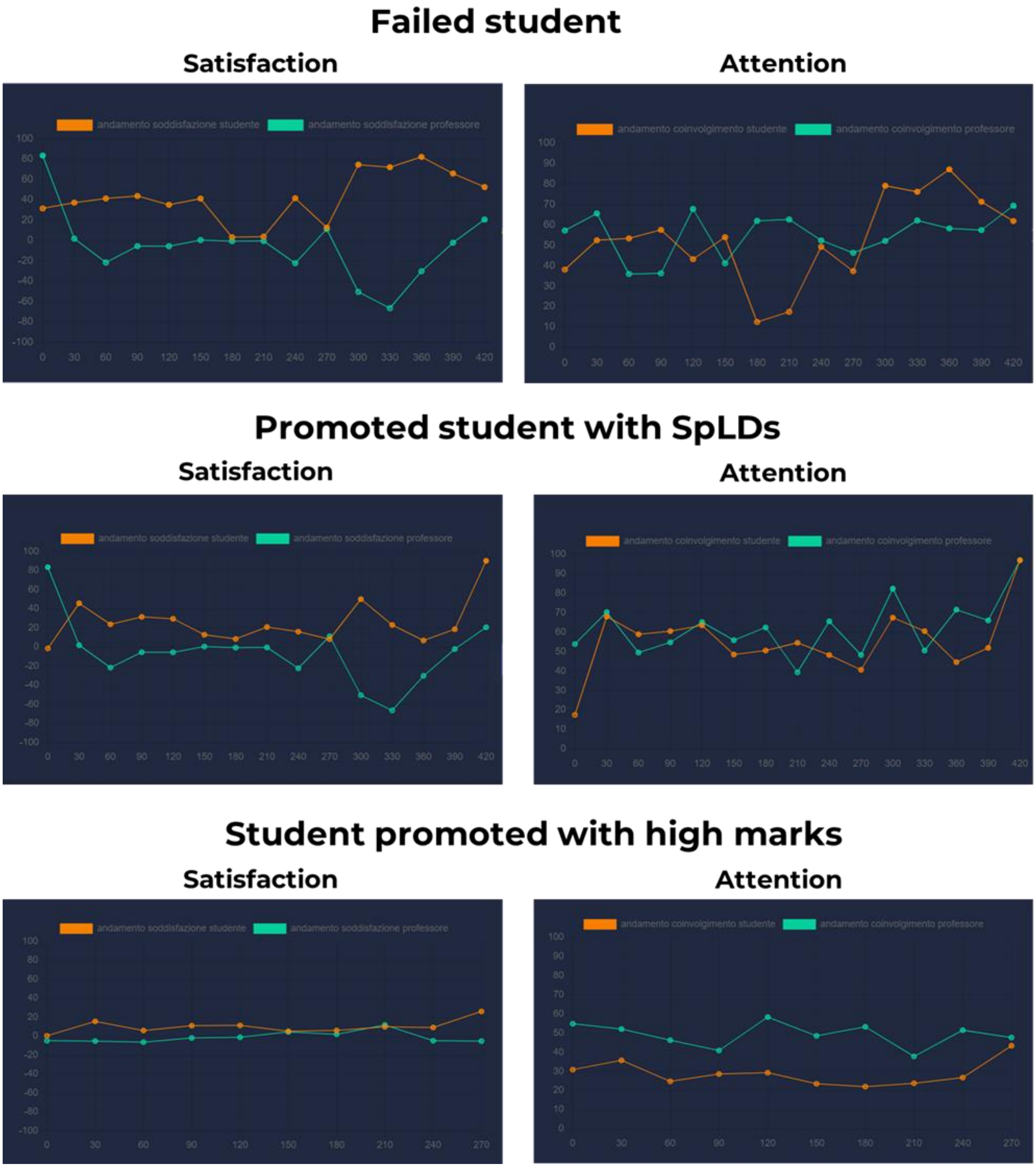

Figure 4 Emotional valance moving average trendlines (on the top) and engagement moving average trendlines (on the bottom) registered from a failed student, a promoted student with SpLDs and a promoted student with high marks (in orange) and from the professor (in green).

5. Discussion and Conclusion

The system introduced for the collection of relevant data related to the emotional behavior and attention of both student and teacher during the examinations, allows us to drive our reflection into pedagogical questions.

In the case study section, it is possible to observe that the professor showed a higher level of attention with the failed student and the student with dyslexia than in the case of the student promoted with high marks. Moreover, the first two cases are characterized by a stronger emotional student-teacher interaction: as confirmed through a manual video analysis of the exams, the teacher intentionally attempts to activate feedback to support the student's exposition, support the student with SpLDs to recover from specific difficulties of people with dyslexia, and take care of the communication of not passing the exam. In this way, the failed student managed from the interaction with the teacher to face the rejection as an opportunity to improve his/her preparation and not as a failure, consequently the emotional curve presents high values of valence also at the end of the evaluation process. On the other hand, where the student does not need support, the emotional involvement of the teacher is low.

These results suggest how the system can enhance the assessment process that, while necessarily having to comply with the standards, must be appropriately customized according to the peculiarities of each student, to ensure a path that can best support the process of self-evaluation and learning.

The novelties introduced by the proposed system in the context, in terms of the opportunity to obtain insight useful to train university teachers in the principles and practices of inclusive assessment is discussed.

Considering the need to support assessment procedures capable of supporting reflection on learning, allowing students to arrive at adequate forms of self-assessment (Rossi et al., 2018), results of a preliminary experimentation suggest that the application of the platform is useful for more equitable construction of judgments and therefore to support the redefinition of the evaluation context in a more inclusive way. The system allows the acquisition of important information in the structuring of inclusive processes, highlighting the alignment (or not) between the different functioning profiles of the students, the discipline, the attitude, and the style of the teacher (Rossi et al., 2018; Giaconi, 2015; Rossi, 2011).

Starting from these premises, the evidence that emerged from the case study shows how the application of the emotional recognition system can allow, in this initial phase, reflection on the evaluation processes in the light of the different situations and the specificity of the interaction contexts that arise in the final assessment. It allows researchers to reflect on the teacher's perception about compensatory tools and, more generally, on accommodation exams strategies for students with disabilities and SpLDs.

In this latter direction, we highlight the importance of training university teachers in the principles and practices of inclusive assessment through specific training actions that can support student-centered teaching that is attentive to their needs (Giaconi, 2015; Mengoni et al., 2021a; Mengoni et al., 2021b).

Future developments should aim at providing real time information about emotional feedback, to provide a better support professor in preparing interventions aimed at improving the climate and context of the examination, and the identification of procedures for a more accurate assessment. Future studies should be also conducted to investigate the applicability of the proposed system also in the classroom.

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