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Neurodesign: A Game-Changer in Educational Contexts

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Neurodesign: A Game-Changer in Educational Contexts

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Abstract: In the wake of the COVID-19 pandemic, the importance of assessing students' academic performance has become more critical than ever. With the widespread adoption of remote and hybrid learning models, it is essential to monitor students' progress and identify areas where they may be struggling. Using Artificial Intelligence (AI) to assess students' performance can help prevent the dispersion of educational outcomes that may result from the pandemic. By leveraging advanced techniques such as Deep Learning and Computer Vision, educators can extract features from students' data, including their facial expressions and sentiment analysis, to gain insights into their learning progress and emotional well-being. Through our proposed approach that combines Facial Expression Recognition (FER) and Sentiment Analysis techniques, we can detect stress periods and improve students' academic performance. This can enable educators to identify students who may be struggling with the transition to remote learning or facing other challenges and provide them with the support they need to succeed. Overall, our research highlights how AI-based student performance assessment can play a critical role in ensuring that students' educational outcomes are not adversely affected by the pandemic. By monitoring students' progress and providing targeted interventions to support their learning, educators can help prevent the dispersion of educational outcomes and ensure that all students receive the education they deserve.

***Keywords**: computer vision; deep learning; facial emotion recognition; emotional analysis; academic*

Introduction

The COVID-19 pandemic has had a significant impact on education worldwide, with the closure of schools and universities disrupting normal academic activities. This has made it harder for students to remain motivated and engaged in school, increasing the risk of dropping out. Numerous studies have reported that in many countries, the dropout rate has increased significantly, especially among students in socioeconomically disadvantaged situations, who have not always had immediate access to the necessary technologies to participate in online classes or who have difficulty learning and lack opportunities to receive distance education support. Many students have experienced family and social stress, which has affected their emotional well-being and ability to focus on studies, and inequalities in the education system have been exacerbated.

To address this problem, many schools and educational institutions have sought to adopt measures to support students, such as providing technologies and educational resources to those in need, offering emotional and psychological support to students and their families, and creating recovery programs for students who have lost contact with school. During the lockdown, every teacher was faced with the need to learn how to evaluate their students with different tools, considering the lack of typical interaction in a classroom. Additionally, every teacher had to inevitably modify their teaching methods to make them accessible and effective online. Currently, technology allows us to use artificial intelligence techniques to be immediately notified when our students' attention level drops, making it desirable to change the teaching methodology or modify the proposed work material. In this project, we want to describe the results obtained from an initial classroom experiment and the idea of how these can be improved and expanded to allow for almost total inclusion of the student population we are targeting.

The purpose of this paper is to present the preliminary results of a collaborative project between the University of Genoa and the Merchant Marine Academy (Figure 1) aimed at comparing results coming from an automatic emotion recognition software and a common tool to detect student's stress. The paper is structured into the following sections:

- Introduction
- Literature review
- Methodology
- Results and discussion
- Conclusions

Figure 1. Class experimental setting

Literature Review

Students' stress can negatively affect their academic performance in various ways (Borca, Cattelino, Bonino,2002). This study delves into the examination of school failure and school dissatisfaction as two key indicators of challenges within the educational system. To gather data, the "Io, la scuola e il mio stile di vita" questionnaire, developed by

Cattelino, Begotti, and Bonino in 1999, was administered to a group of 839 Italian adolescents, aged 14 to 16, who were attending high school. The results of the study reveal a correlation between failure and dissatisfaction, as well as their associations with various individual, social, and contextual factors. Notably, the factors contributing to and predicting school failure appear to be quite similar for both boys and girls. However, in the case of dissatisfaction, external factors such as perceived subject difficulties and teacher-student relationships exert a stronger influence on boys. Conversely, girls place a higher emphasis on internal factors, such as low self-efficacy in achieving academic success and monitoring their own learning progress. Firstly, an increase in stress levels can interfere with students' ability to concentrate and learn, making it more difficult for them to memorise information and solve problems. Secondly, stress can cause anxiety and worry, which can distract students from their academic activity. Moreover, chronic stress can have negative effects on the physical and mental health of students, which can lead to school absences or lower academic performance.

The accumulation of stress and the resulting academic difficulties can in turn lead to dropping out of school. In fact, students who feel overwhelmed by stress and who cannot successfully face academic challenges may develop low self-esteem and lose motivation for school. This can lead to a habit of absenteeism, disengagement from school, and in extreme cases, dropping out of school (Fonzi,2002).

Assessing a student's stress levels can be a challenging endeavour due to the subjective nature of stress. Stress is a highly individualised experience, and its perception and impact can vary significantly from one person to another. This subjectivity stems from a variety of factors, including an individual's personality, coping mechanisms, prior experiences, and external stressors. To evaluate a student's stress effectively, it's crucial to consider these nuances and employ a holistic approach that considers both objective and subjective indicators. Objective measures may include academic performance, attendance records, and physical symptoms. However, these should be complemented with subjective assessments, such as self-reported stress levels, open communication, and observations of behavioural changes. Furthermore, it's essential to recognize that what might be a stressor for one student may not be the same for another. This underscores the need for a tailored and empathetic approach to understand and address each student's unique stressors and needs.

Evaluating and detecting stress in students is a vital aspect of an educator's role, but it can be a complex and nuanced process due to the subjective nature of stress. To effectively assess a student's stress levels, teachers and educators can employ a combination of strategies, keeping in mind the individualised nature of stress experiences.

- Open Communication: One of the most direct ways to understand a student's stress is through open communication. Encouraging students to share their feelings and concerns can provide valuable insights. Teachers can foster a safe and supportive environment where students feel comfortable discussing their stressors. Listening actively and empathetically is key to this approach.
- Observation: Teachers and educators can keenly observe students for changes in behaviour, demeanour, and academic performance. Signs of stress may manifest as increased irritability, withdrawal from social interactions, changes in eating or sleeping patterns, and a decline in academic engagement or performance. These observable cues can serve as important indicators.
- Self-Reported Data: Using self-report measures, such as surveys or questionnaires, can provide valuable information about a student's stress levels. While these assessments are subjective and may vary in accuracy, they still offer insights into a student's self-perceived stress and can help identify trends over time. The most common questionnaire are:
- The Perceived Stress Scale (PSS) (Cohen et al., 1983) is a widely recognized self-report questionnaire designed to assess an individual's perceived level of stress. This instrument has undergone comprehensive validation and is frequently employed in research. The questionnaire items are rated on a 5-point scale, and their scores are aggregated to produce a total score. A higher total score indicates a higher level of perceived stress. In our study, we utilised the 10-item version of this instrument.
- The Multidimensional Scale of Perceived Social Support (MSPSS) (Zimet et al., 1988) is a validated self-report questionnaire designed to assess an individual's perception of the level of support they receive from family, friends, and significant others. This questionnaire comprises 12 items, each of which is rated on a 7-point scale. The MSPSS provides three subscale scores: Family Support, Friends Support, and Others Support. Higher scores on the MSPSS indicate a higher perceived level of support from these social sources.
- The life event checklist is derived from Paykel's catalogue of stressful life events (Paykel, 1983). It comprises 60 specific and well-defined events, with an additional open-ended question at the end, inquiring about any relevant event that may not have been covered in the predefined list.

- The Italian version of the Stress-related Vulnerability Scale (SVS), a short self-completed questionnaire developed by Tarsitani et al. in 2010 to assess an individual's perception of their vulnerability to stress. The Stress-related Vulnerability Scale (SVS) is a self-administered questionnaire that consists of 9 items, each scored on a 4-point scale, ranging from "not at all" to "a lot." It was initially developed two decades ago by carefully reviewing literature related to perceived stress and social support. The pilot version of the SVS was tested on a nonclinical sample of approximately 100 university students and administrative employees. This early version, known as the Rapid Stress Assessment Scale, was subsequently refined based on feedback from participants and proved to be effective in both clinical and non-clinical settings. The SVS was derived from this earlier instrument through a meticulous item selection process, with a focus on psychometric performance, including internal consistency and factorial structure. In comparison to other established stress questionnaires, the SVS places a more explicit emphasis on emotional aspects, such as feelings of discouragement, irritability, and worry. It also includes inquiries about perceived social support, addressing isolation, social activities, and support. The SVS assesses the individual's perceived vulnerability to stress over the past month and provides scores on three distinct subscales, each consisting of 3 items. These subscales are named 'Tension,' 'Demoralization,' and 'Reduced Social Support.' The scores from these subscales are combined to calculate a total score, with higher scores indicating a greater level of stress-related vulnerability. This instrument is designed to provide a comprehensive assessment of an individual's emotional state and their perception of social support, making it a valuable tool in understanding stress-related factors in various settings.
- Attendance and Academic Performance: Consistently missing classes or a significant drop in academic performance can be indicative of heightened stress levels. These objective measures can be reliable indicators of a student's struggles.
- Physical Symptoms: Stress can also manifest in physical symptoms, such as headaches, stomach-aches, or sleep disturbances. Teachers and educators can pay attention to these physical complaints as potential signs of stress.
- Peer and Parental Reports: Sometimes, students may not readily communicate their stress to teachers. In such cases, input from peers or parents can provide a more comprehensive perspective. Teachers can encourage open dialogue with parents and work collaboratively to address a student's stress.
- Educational and Psychological Assessment: In cases of severe or persistent stress, educators may collaborate with school counsellors or psychologists who can conduct more in-depth assessments. These professionals can use validated tools and techniques to diagnose and address stress-related issues.

Lately, thanks to the use of various biometric sensors that detect changes in heart rate, body temperature, cortisol production, prosody, and language used, it is possible to combine these data with the analysis of facial expressions adopted during a specific activity and derive significant assessments about a student's emotional state.

The application of neuroscientific knowledge to design and evaluate products, services, and environments that better meet the needs and preferences of users is called *neurodesign*, according to Darren Bridger (Bridger, 2017). It's important to remember that what may cause stress for one student may not affect another in the same way. Consequently, a personalised and empathetic approach to each student's unique needs and stressors is essential. Additionally, educators should be aware of the resources available within their educational institutions to provide appropriate support and guidance to students dealing with stress. In sum, a multi-faceted approach that combines open communication, observation, self-report data, and collaboration with other professionals can help teachers and educators effectively detect and evaluate stress in students.

Methodology

Introduction

In general, it's important to consider that stress levels can vary over time and that students may exhibit signs of stress in different ways. This is why we decided to consider a multimodal system to monitor our students and we wanted to compare data acquired by a questionnaire, with those derived by the elaboration of an artificial intelligent software.

Purpose

The purpose of this case study is to assess the emotional state of some students by comparing data obtained from an objective measurement through software analysis of video sequences in class, with data extracted from the evaluation questionnaires administered to the students immediately after the recording session.

Research Setting

Our experiment took place in the classrooms of the Accademia Mercantile di Genova, with a class of 9 males and a female, aged between 20 and 22 (Figure 2).

Tools

As for the objective observation, we decided to monitor the emotional stress of the students by recording their activities with two cameras. One camera was positioned in front of them to capture their facial expressions effectively, while the other was placed behind them to correlate their facial expressions with the specific task they were performing at any given moment (Figure 3).

Figure 2. Student's workstation

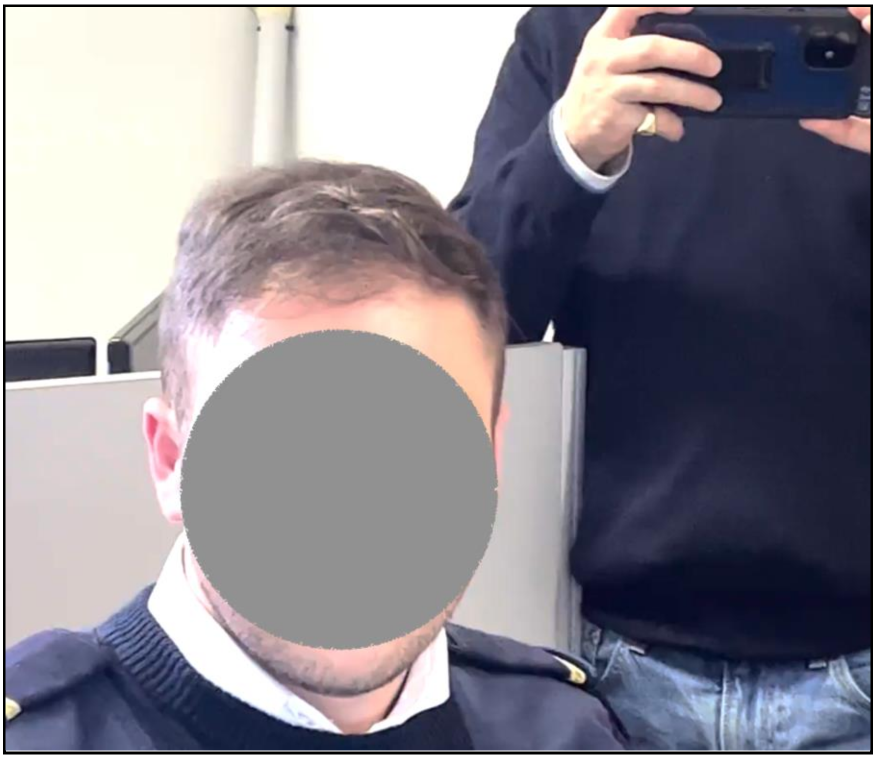

Figure 3. Student at work

Subsequently, the videos were processed using the artificial intelligence software Morphcast Emotion AI, and the emotions for each individual session were extracted. MorphCast Emotion AI is an innovative technology that utilises artificial intelligence to recognize and analyse facial emotions, by using advanced machine learning algorithms to estimate the presence and intensity of facial expressions related to seven core emotions, including anger, disgust, fear, happiness, sadness, surprise, and neutral expression, according to the universal and cross-culturally recognized Ekman discrete model.

The software can also estimate the emotional arousal and valence intensity of the viewer based on a 2D emotional space and the dimensional model of Russell (Figure 4), which outputs smoothed probabilities of 98 emotional affects. We decided to use Morphcast Emotion AI features because of its strengths:

- accuracy is at the same level as competitors who use server-side algorithms (Dupré et al.,2019)
- empowered by AI algorithms with the minimum computation and size overhead: neither gender nor ethnicity influenced the signalling or recognition of emotion
- flexibility guaranteed by the large number of configurable parameters, such as gender, age, race,
- easy-to-use, very intuitive interface
- modular architecture (since in future developments we will integrate some other biometric sensors)
- dynamic power-save optimizer in terms of CPU/GPU load;
- it is fully GDPR compliant, hyper-optimised, and patented science: each image of the video stream remains in the volatile memory of the device (smartphone, tablet, PC etc.) and it is accessible from the software within the browser sandbox, only for the time strictly necessary for processing the result (about 100ms) after which this image is destroyed and overwritten by the next image).

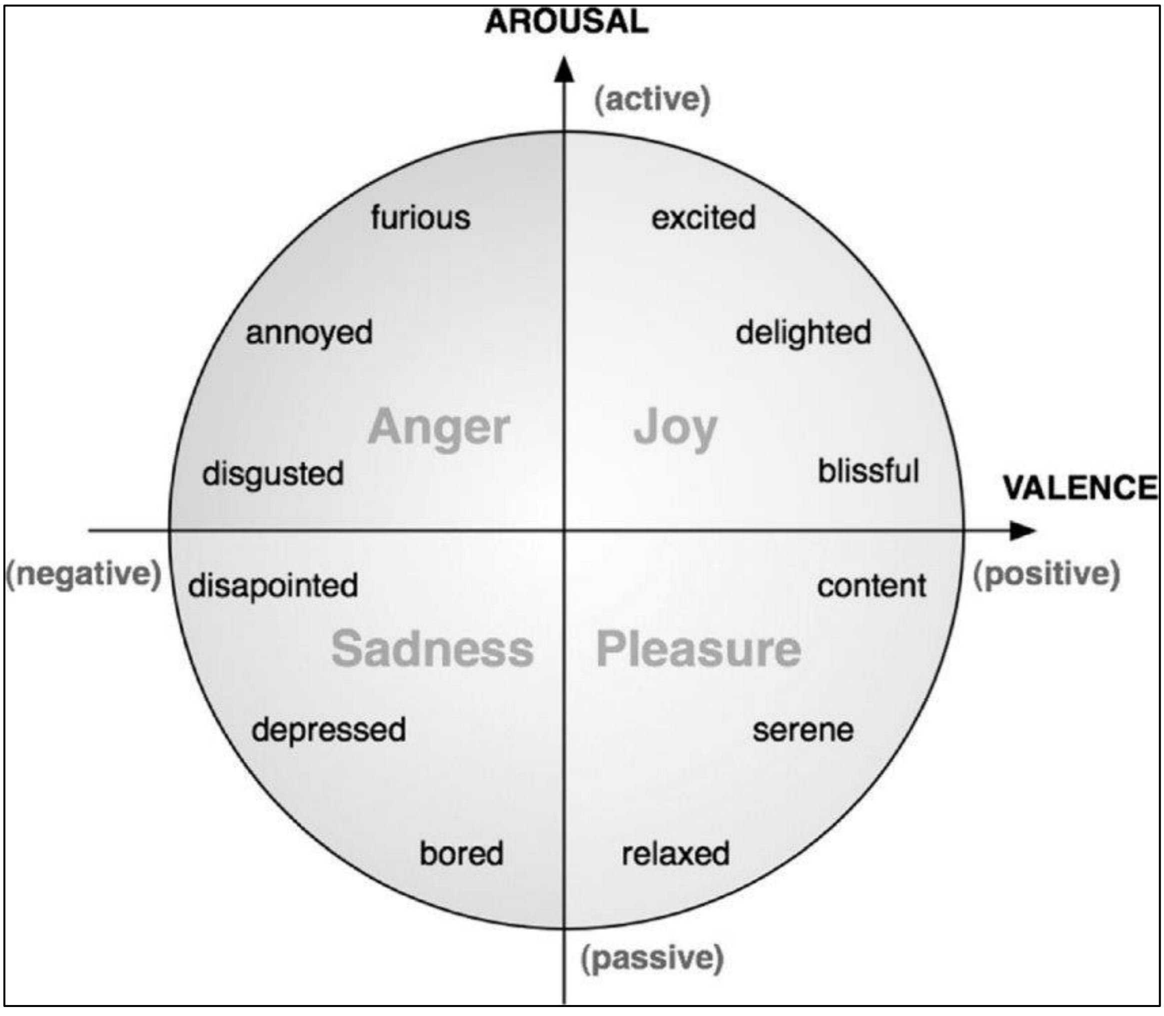

Figure 4. 2D Dimensional Russel Model

As for the evaluation of stress through a questionnaire for the interested students, initially, we had decided to use the Italian version of the SVS test developed by researchers Tarsitani, Battisti, Biondi, and Picardi in 2010. However, we subsequently opted for a different questionnaire, as shown in Figure 5, because the emotions listed in it are the 38 most common out of the 98 detectable by the artificial intelligence software we used.

We chose not to list all 98 emotions for various reasons, primarily because some differed in slight nuances of arousal and evidence, and we were unsure whether the students would recognize these distinctions. Furthermore, our intention was for the students to complete the questionnaire relatively quickly so that their responses would not be biased by the passage of too much time since the experience.

The questionnaire is structured in a way that requires the student to indicate, for each listed emotion, the degree to which they experienced it on a scale ranging from 0 (not at all) to 4 (very much). We also included a column labelled 'Don't know' for those who were uncertain about the meaning of a term. At the end of the questionnaire, students had to compile the valence-arousal diagram as well (Figure 6).

Since the interviewed students were not accustomed to dealing with a diagram of this kind, it was necessary to explain to them the meaning of the terms "arousal" and "valence" in the theory of emotions before completing it. We used HD quality mobile phones (1080p HD at 30fps), at about one metre from the participant (this arrangement seems to be the most suitable for obtaining the best view of the face and of the actions performed by the participants).

HOW DID YOU FEEL?
COME TI SEI SENTITO DURANTE L'ESERCITAZIONE?

English	Italiano	Per niente: 0	Un po': 1	Abbastanza: 2	Molto: 3	Moltissimo: 4	Non so
Afraid	Paura						
Amused	Divertito						
Angry	Arrabbiato						
Annoyed	Infastidito						
Anxious	Ansioso						
Apathetic	Apatico						
Aroused	Eccitato						
Astonished	Stupito						
Bored	Annoiato						
Calm	Calma						
Conceited	Presuntuoso						
Contemplative	Contemplativo						
Content	Contenuto						
Convinced	Convinto						
Delighted	Incantato						
Depressed	Depresso						
Determined	Determinato						
Disappointed	Deluso						
Discontented	Scontento						
Distressed	Angosciato						
Embarrassed	Imbarazzato						
Enraged	Infuriato						
Excited	Eccitato						
Feel Well	Sentirsi bene						
Frustrated	Frustrato						
Happy	Contento						
Hopeful	Speranzoso						
Impressed	Impressionato						
Melancholic	Malinconico						
Peaceful	Tranquillo						
Pensive	Pensieroso						
Pleased	Lieto						
Relaxed	Rilassato						
Sad	Triste						
Satisfied	Soddisfatto						
Tired	Stanco						
Uncomfortable	Scomodo						
Worried	Preoccupato						

Figure 5. Questionnaire adopted during our experiment

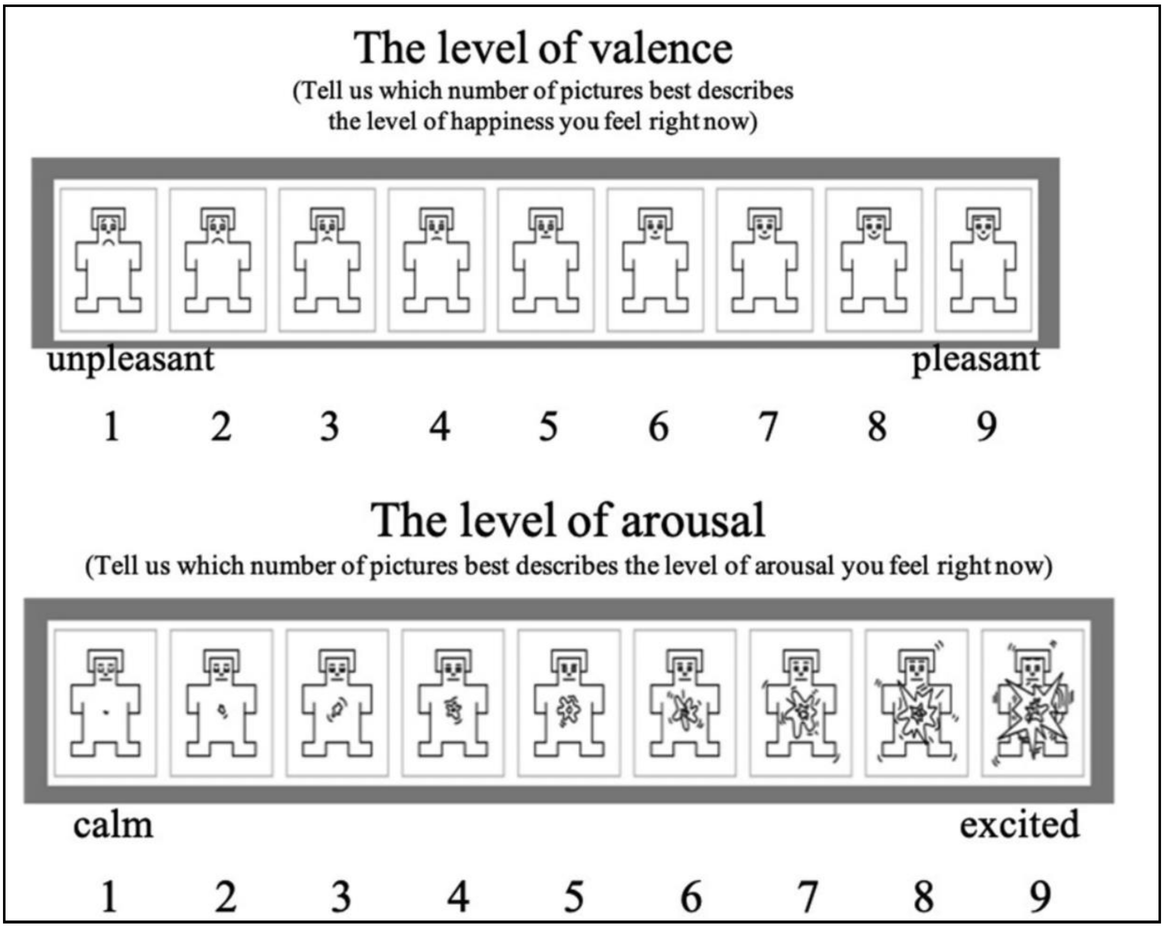

Figure 6. Valence-Arousal emotional diagram

Data Collection Procedure

The experiment can be divided into multiple phases: an initial phase in which students are recorded in their classroom and are asked to complete some challenging tasks, which will be evaluated by the teacher. The element of evaluation was introduced in such a way as to instil a certain level of anxiety in the students and encourage them to perform the tasks with care. In the second phase, students were asked to fill out the questionnaire. Finally, the videos were processed using the artificial intelligence software Morphcast Emotion AI, and the obtained results were compared with those revealed by the questionnaires.

Before the experiment, the students were informed that they would be filmed for approximately two minutes each by a front-facing camera to analyse their facial expressions and by a rear-facing camera that would capture the monitors they would work on, allowing us as observers to correlate their facial expressions with the tasks they were performing. Besides, the necessary permissions for recording and using images for research purposes were requested.

During the exam, the students worked in silence and were monitored by a proctor to ensure that they did not communicate with one another or cheat.

Data Analysis

We processed videos with Morphcast Emotion AI, and we compared the results with the data obtained from the questionnaire using the emotion recognition model to map data with the valence-arousal 2D discrimination (Dai, Wang, Zhang, Zhang & Chen, 2018) such as in Figure 7.

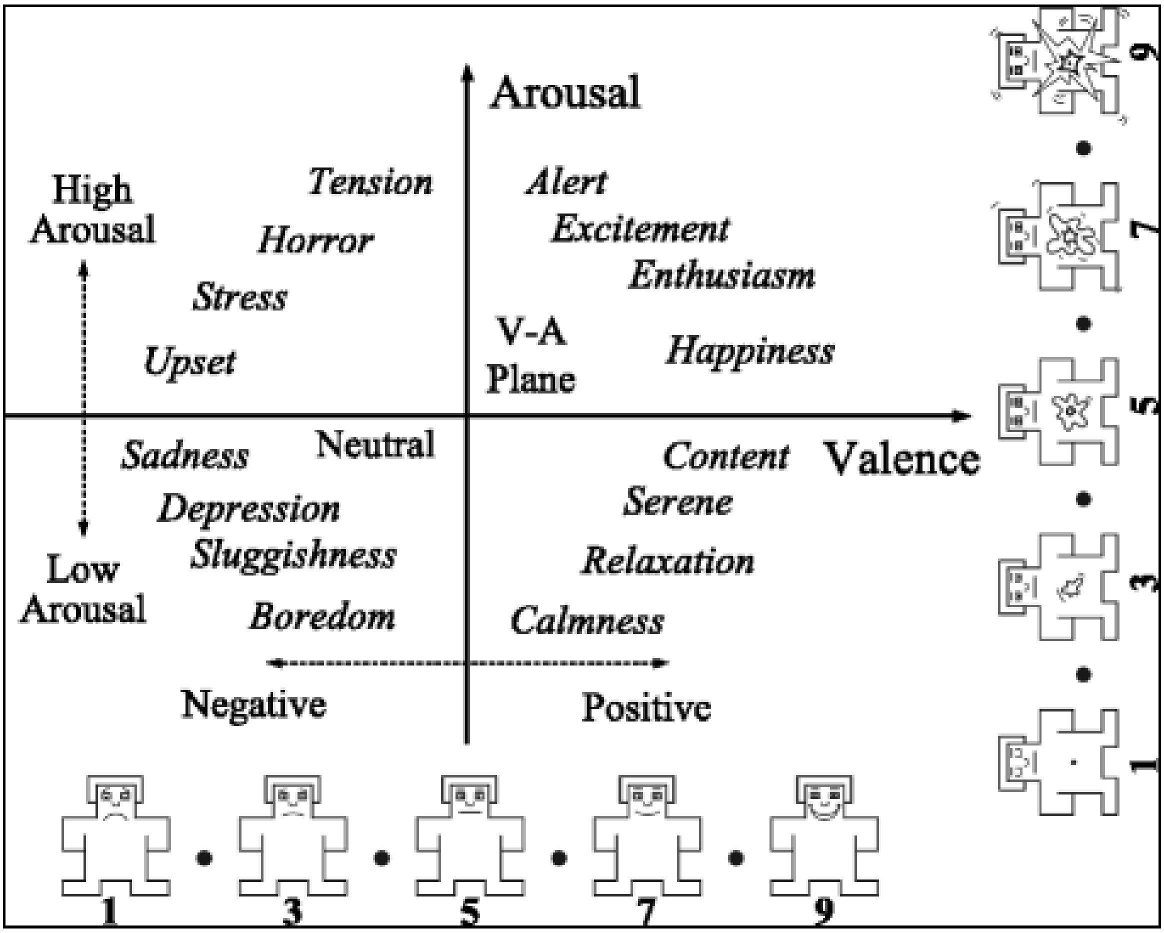

Figure 7. Valence-Arousal plane and 2-D SAM (Self-Assessment Manikin) questionnaire. Image taken from Dai, Yixiang & Wang, Xue & Zhang, Pengbo & Zhang, Weihang & Junfeng, Chen. (2018).

Results and Discussion

During our experiment, we recorded each student for approximately two minutes and asked them to complete the emotional questionnaire immediately after their recording. Furthermore, each student was recorded in the initial phase, right after being asked to perform a specific exercise, to assess their ability to handle a new task. This approach enabled us to collect 10 MP4 recordings and 10 questionnaires, which allowed us to proceed with our analysis.

For each student data coming from Morphcast AI Emotion were:

- ***a quadrant polar area*** (Figure 8), based on the dimensional circumplex diagram of Russell (Russell, 1980).

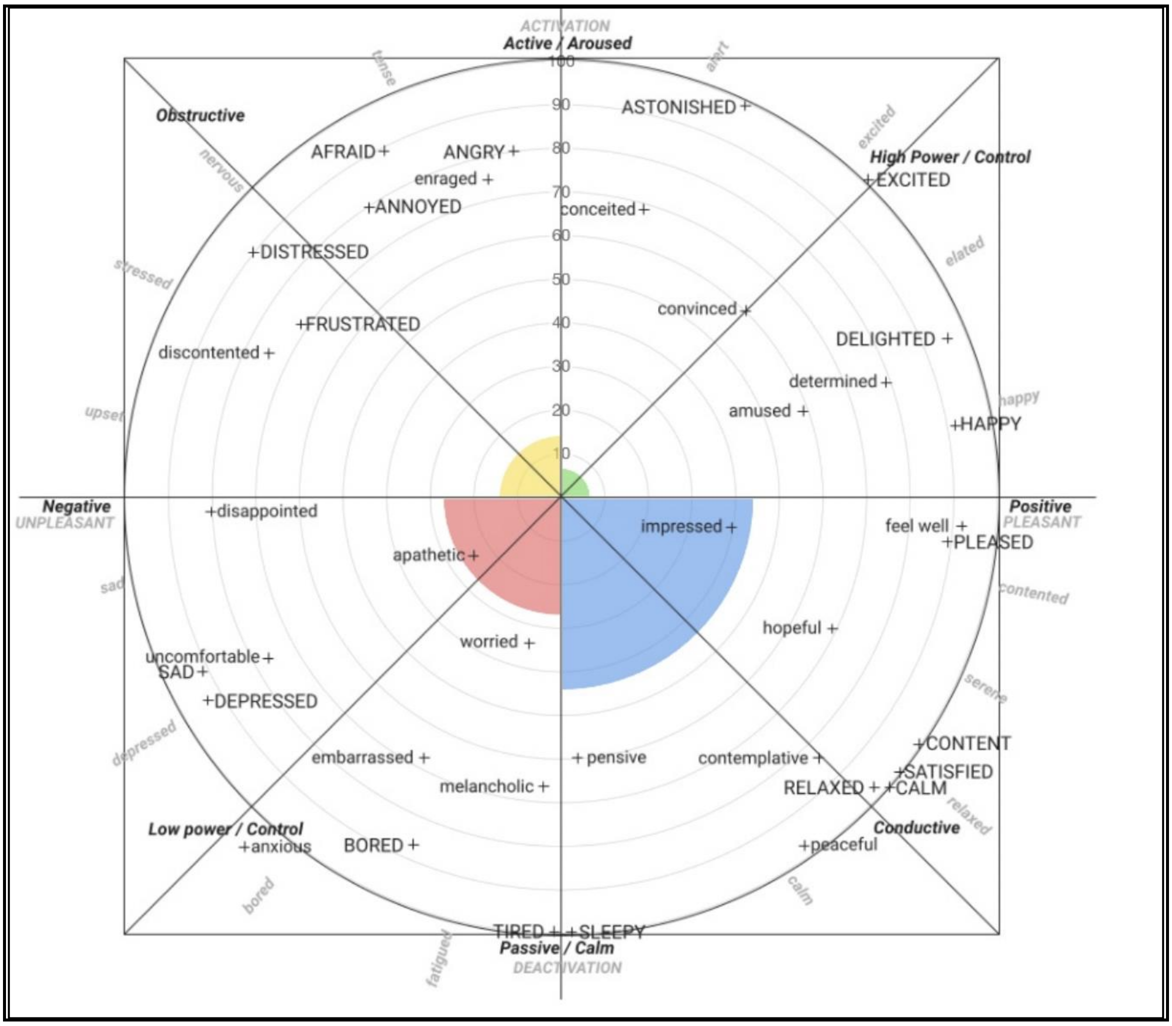

Figure 8. An example of a Student's Quadrant Polar Area obtained during elaboration.

For instance, in this scenario, it's evident that the student was considerably impressed by the assigned task and concerned about their performance.

- ***an emotion distribution graph*** (Figure 9); according to the Ekman discrete model (Ekman, 2013). In the diagram below, provided as an example, we can see how Ekman's basic emotions emerged during the test (plus the neutral state, when no emotion is expressed). The neutral state is the predominant one, but it is immediately followed by a state of anger and frustration, probably because the student did not expect a certain task to be assigned and is uncertain about the outcome they may achieve.

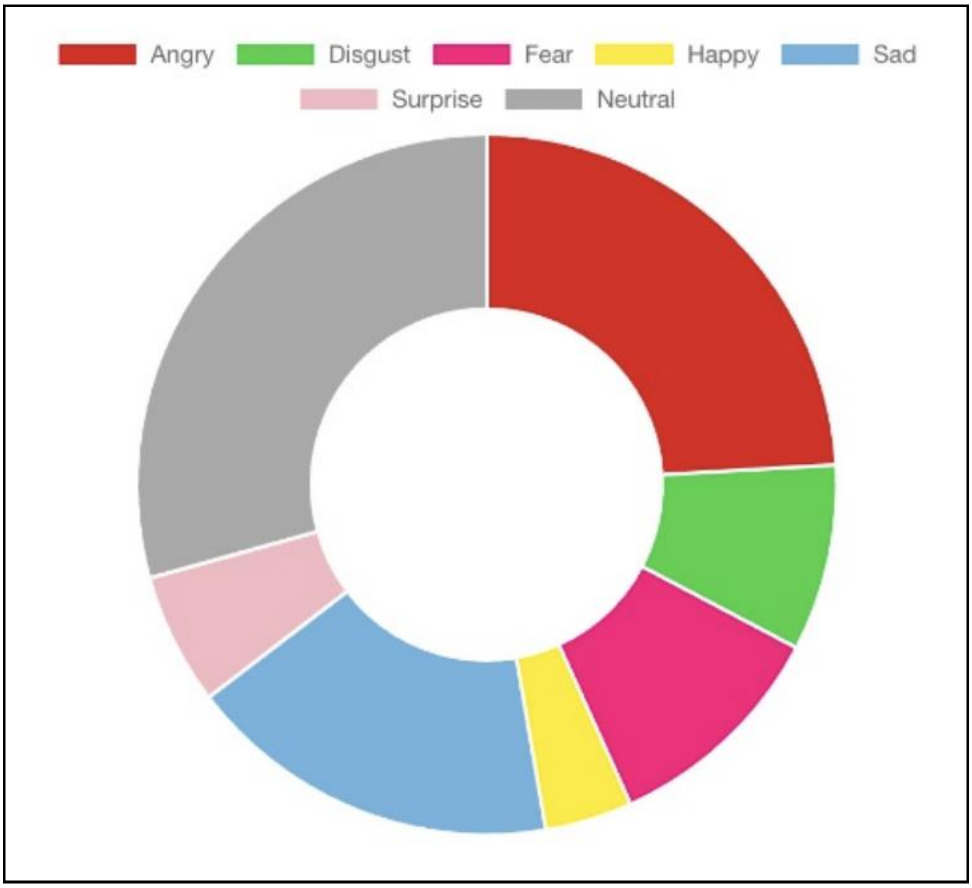

Figure 9. Student's emotions distribution graph

- ***an emotion over time graph*** (Figure 10): in this graph, we can observe the percentage at which each of Ekman's basic emotions appears at a 1-second interval (plus the neutral state). Even in this diagram, it's evident how the emotion of anger predominates over the other emotions.

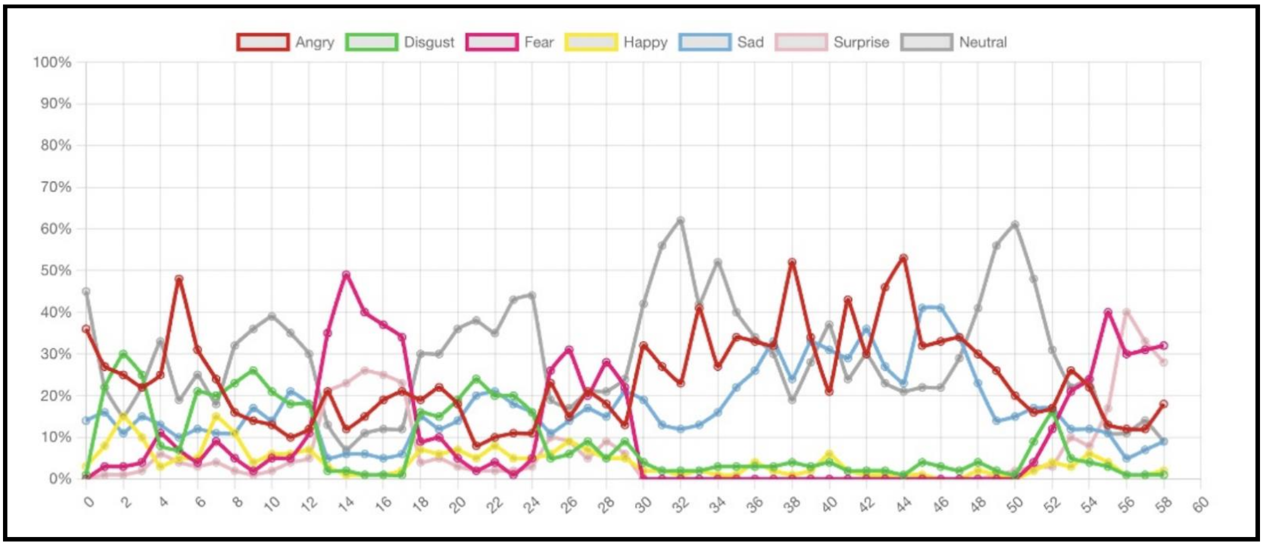

Figure 10. Student's Emotions over time (at 1 sec interval)

- ***an engagement over time graph*** (Figure 11): In this graph, you can observe the level of attention and valence experienced by the student over time. As we have seen in Figure 8's graph, it's noticeable that the curve related to positivity remains high throughout the entire interval, as well as the valence, indicating the intensity of the emotion experienced. On the contrary, we can observe that the level of attention has an initial peak as soon as the task is presented, and after some time, when the student understands what needs to be done to solve it.

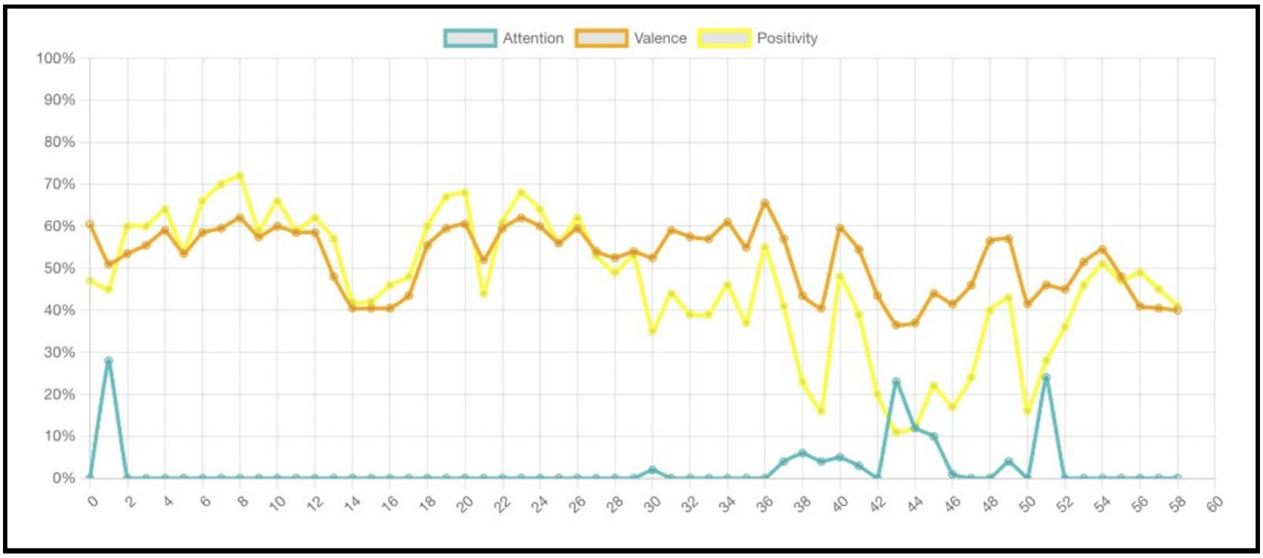

Figure 11. Student's engagement over time (at 1 sec interval)

- ***the top 5 circumplex emotions*** (Figure 12) based measuring the smoothed probabilities in the range 0.00, - 1.00 of the 98 emotional affects, computed from the points in the 2D (valence, arousal) emotional space, according to the mappings of Schrerer (Scherer, 2005) and Ahn et al. (Ahn, Gobron, Silvestre, Thalmann, 2010).

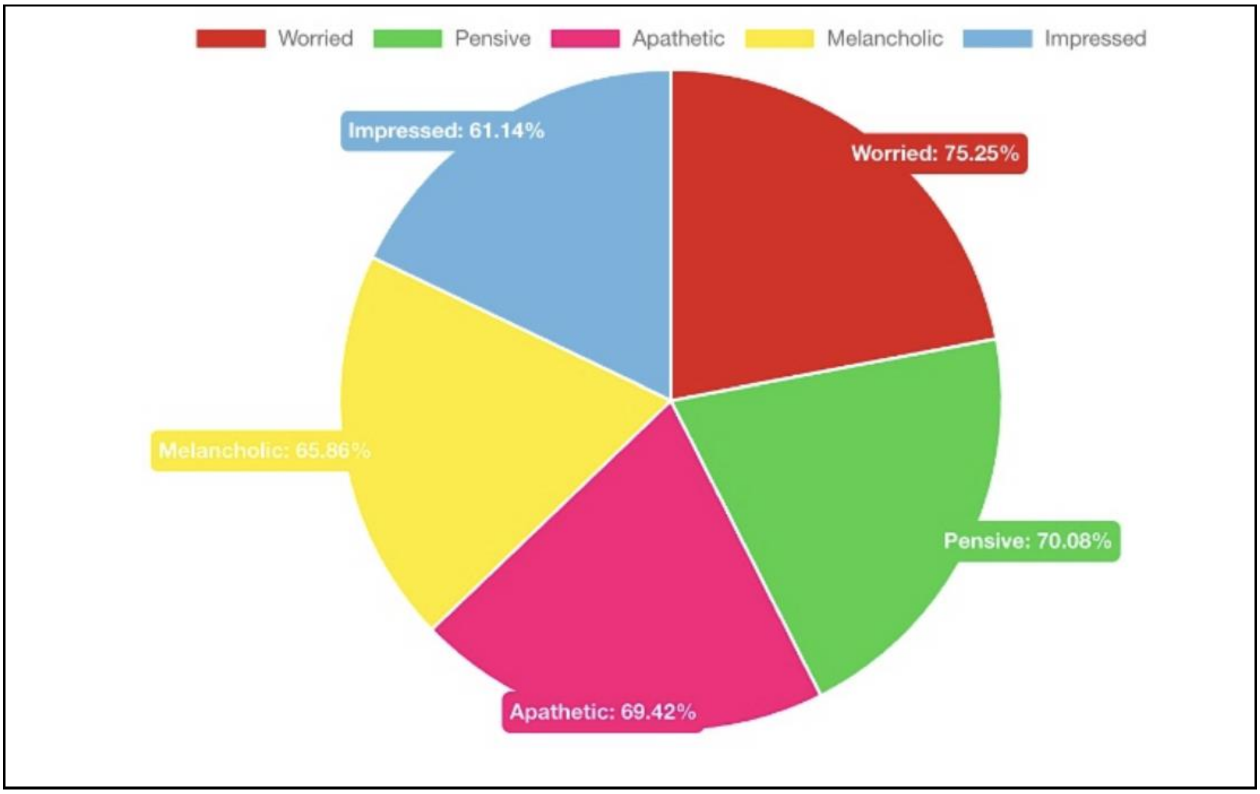

Figure 12. Top 5 student's emotions

In Figure 13, we can see how the two modalities (software analysis and questionnaire analysis) have been processed to highlight any discrepancies or similarities for each student. Specifically, in the case presented here, we can observe that the emotions that the student indicated as being the most experienced are also those that emerged during the software processing.

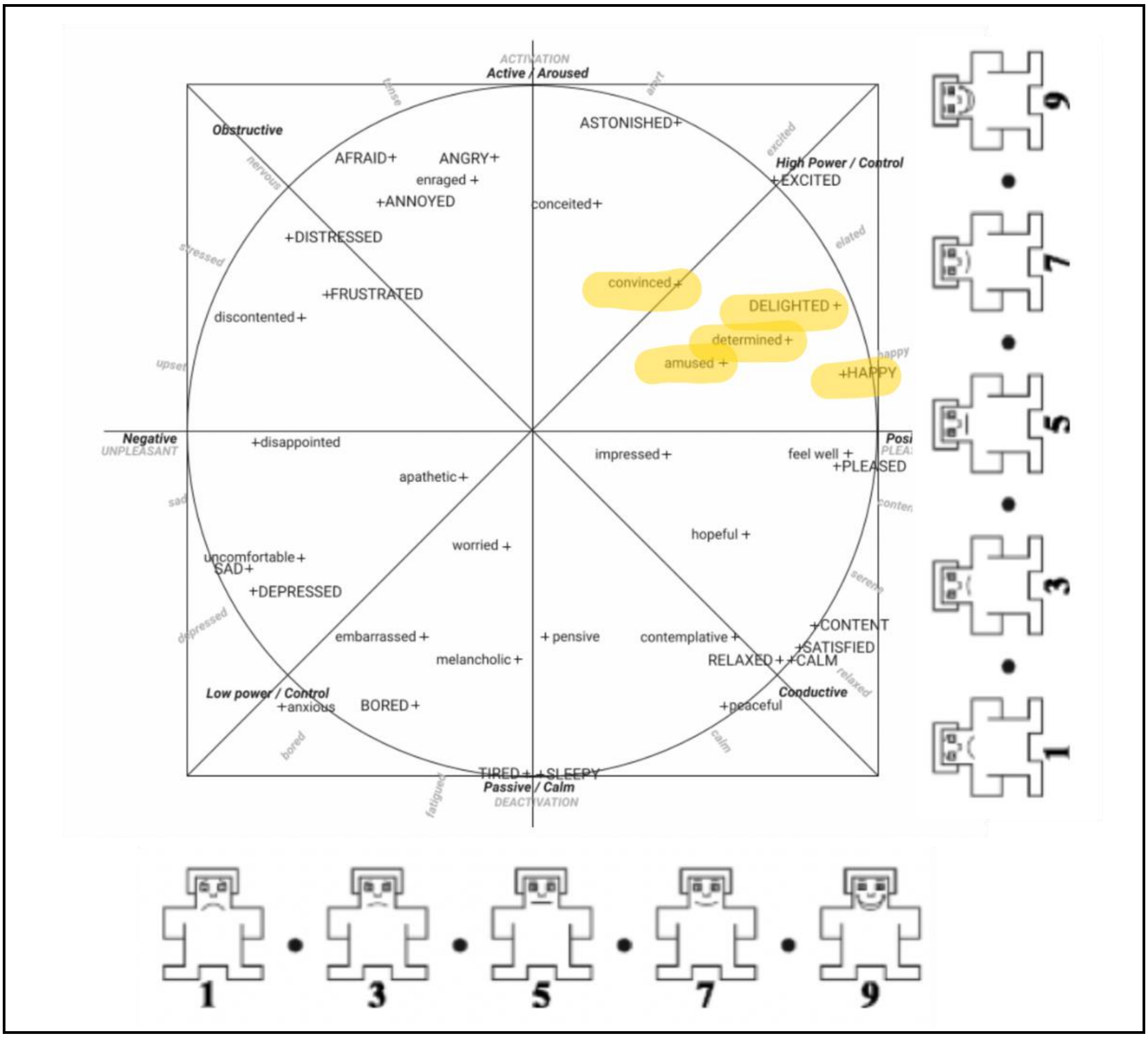

Figure 13: Comparison of the results

As expected, several typical problems during the questionnaire have emerged. These include:

- Response bias: which is the tendency of respondents to answer questions in a way that they think is socially desirable or that aligns with the interviewer's expectations. This can lead to inaccurate or incomplete data.
- Self-assessment bias, which occurs when respondents have difficulty assessing their own emotions and expressing them accurately using consistent language and terminology. Emotions are complex and subjective, and different people may have different interpretations of the same emotion.

Many of the emotions selected with their maximum degree were correctly identified, as well as “amused”, “delighted”, “convinced”, “happy”, while they found it difficult to recognize emotions such as “conceited” and “uncomfortable”.

Besides, many emotions could not be distinguished properly, because many students declared they didn’t know the exact meaning of the word provide.

Conclusion

Emotional well-being is a significant concern in contemporary society. Irregular emotional states can lead to potential risks or unfortunate incidents in an individual's life, particularly for specialized groups like drivers, pilots, and soldiers, whose emotional health issues can impact the stability of communities and the public interest.

Historically, the evaluation of emotional states relied on the subjective judgment of medical professionals or psychologists using various questionnaires, which lacked the scientific rigor necessary for everyday emotional health monitoring. There are several advantages to employing an automatic emotion recognition system in contrast to questionnaires and surveys:

- Objectivity: Automatic systems offer impartial assessments of emotions, eliminating the potential for bias or self-reporting errors.
- Efficiency: Automatic systems can process emotions in real-time, enabling immediate feedback and intervention, whereas questionnaires and surveys require time for administration and analysis.
- Non-intrusive: Automatic systems can operate discreetly without disrupting an individual's natural behavior, while questionnaires and surveys necessitate participants to pause and complete forms.
- Comprehensive data: Automatic systems can gather extensive data over extended periods, offering a more thorough understanding of emotional states and trends compared to questionnaires and surveys.
- Cost-effectiveness: Automatic systems can be a more cost-effective option compared to questionnaires and surveys, which demand human resources for administration, analysis, and interpretation.

The paper explores the potential of automatic emotion recognition systems in delivering precise and objective insights into emotional states, applicable across various domains. It advocates the utilization of emotion-sensing and recognition frameworks that harness multiple biosignals for the objective interpretation of people's emotional states. This approach can significantly enhance emotional health monitoring and the primary diagnosis of mental disorders.

The findings of this study could be valuable in understanding and addressing stress levels among students during examinations, ultimately leading to improved academic performance. Additionally, the field of neurodesign can enhance teaching and learning by customizing educational materials and environments to suit the preferences and needs of learners. For instance, certain visual aids like infographics and diagrams have been shown to boost memory retention. Neurodesign can also optimize classroom settings to support learning by minimizing distractions and enhancing cognitive functioning.

Furthermore, neuroscience can assist educators in monitoring students' attention and the effectiveness of their teaching methodologies, allowing for prompt adjustments to facilitate the learning process for students of varying abilities. The paper also underscores the necessity of introducing additional biosensors to obtain unbiased biological data. Potential inputs include respiration rate (Zhang, et al., 2017), eye tracking (Saadon et al., 2023), EEG (Nikolova et al., 2018), electrocardiogram (Gannouni et al. 2021), electromyography, electrodermal activity (Kipli et al. 2022), galvanic response, and natural language processing (Guo, 2022).

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