ARTIFICIAL INTELLIGENCE TO SUPPORT THE ASSESSMENT OF EMOTIONAL INTELLIGENCE

INTELLIGENZA ARTIFICIALE A SUPPORTO DELLA VALUTAZIONE DELL'INTELLIGENZA EMOTIVA

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ABSTRACT
Initially, Emotional Intelligence (EI) was defined as an ability to process emotional information measurable through performance tasks. Later, other authors conceptualized EI as a set of aspects related to the recognition and regulation of emotions both in oneself and in others, that could be assessed through self-report instruments. Both performance tasks and self-report instruments present several problems. AI could support the assessment of EI by developing an algorithm that detects emotional states associated with facial expressions in response to viewing videos validated to induce specific emotions. The project proposal aims to present a protocol that involves the use of an algorithm capable of comparing each subject's responses at the level of emotional states experienced. The project also includes the proposal of a comparative analysis of the quality and intensity of emotional states during the video, by monitoring some physiological parameters (HRV, GSR and temperature) through a biofeedback instrumentation. Based on the level of consistency among these data, the algorithm will provide a percentage related to the ability to recognize one's own emotions.

Inizialmente, l'Intelligenza Emotiva (IE) è stata definita come la capacità di elaborare le informazioni emotive misurabili attraverso compiti di prestazioni. Successivamente, altri autori hanno concettualizzato l'IE come un insieme di aspetti relativi al riconoscimento e alla regolazione delle emozioni sia in sé stessi che negli altri, valutabili attraverso strumenti *self-report*. Tuttavia, sia i compiti di *performance* che gli strumenti *self-report* presentano diversi problemi. L'IA potrebbe supportare la valutazione dell'IE sviluppando un algoritmo che rileva gli stati emotivi associati alle espressioni facciali in risposta alla visualizzazione di video convalidati per indurre emozioni specifiche. La proposta progettuale mira a presentare un protocollo che prevede l'utilizzo di un algoritmo in grado di confrontare le risposte di ogni soggetto a livello di stati emotivi sperimentati. Il progetto prevede anche la proposta di un'analisi comparativa della qualità e intensità degli stati emotivi durante il video, monitorando alcuni parametri fisiologici (HRV, GSR e temperatura) attraverso una strumentazione di biofeedback. In base al livello di coerenza tra questi dati, l'algoritmo fornirà una percentuale relativa alla capacità di riconoscere le proprie emozioni.

KEYWORDS
Emotional Intelligence, Biofeedback, Emotions, Artificial Intelligence, Emotion Recognition
Intelligenza Emotiva, Biofeedback, Emozioni, Intelligenza Artificiale

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Introduction[1]

Emotional intelligence (EI) is a complex and multifaceted construct that establishes an interconnection between emotionality and cognition and can encapsulate aspects related to intelligence, temperament, personality, and the ability to process emotional information as well as to self-regulate with respect to it (Stough, Saklofske, & Parker, 2009). However, EI still presents several measurement problems related to the different types of conceptualization available in the literature (Zeidner, Matthews, & Roberts, 2008). To date, there are three main models of EI: the ability model, the trait model, and the mixed model. All of these models view EI as a construct distinct from both "normal" intelligence and other aspects of personality. The first authors to introduce the concept of Emotional Intelligence (EI) were Peter Salovey and John Mayer who defined it as a subset of social intelligence and, specifically, as "the ability to monitor one's own emotions and those of others, to discriminate between them, and to use information to guide one's thinking and actions" (Salovey & Mayer, 1990, p. 189). The authors proposed a four-branch hierarchical model (Mayer et al., 2008) identifying four main aspects of EI: emotional perception, emotional assimilation, emotional understanding and emotional management. Emotional perception is the ability to identify emotions through the detection of emotional signals in oneself and others; emotional assimilation is the ability to distinguish experienced emotions to facilitate thinking about and adapting to situations; emotional understanding, on the other hand, allows one to comprehend complex emotions and the transition between different emotions over time and in different situations; and finally, emotional management involves the ability to control one's own and others' emotions (Mayer, Salovey, & Caruso, 2004). These aspects are organized hierarchically and include both rapid emotional information processing and higher-order cognitive processes (Mayer & Salovey, 1990; Salovey & Grewal, 2005). So, according to this model, EI is an innate ability that, similarly to intelligence, is assessed primarily through objective performance scales i.e., through the results obtained in solving specific emotion-related tasks that involve answers classified as correct or incorrect (Mayer, Caruso, and Salovey, 2016). People with a high degree of emotional intelligence, in fact, should have an advantage in solving problems adaptively, creatively, and flexibly (Salovey and Mayer, 1990). In this regard, Mayer and colleagues first developed the Multifactor Emotional Intelligence Scale (MEIS; Mayer, Caruso and Salovey, 1999) and later the Mayer-Salovey-Caruso Emotional Intelligence Test (MSCEIT; Mayer et al, 2003) to measure different aspects of EI through specific emotional tasks

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involving correct or incorrect responses, previously identified as such based on two criteria: a) congruence with responses given by a pool of experts (expert score) and b) similarity with responses given by the majority of a sample (general consensus). Specifically, the MSCEIT test includes eight tasks, two tasks for each of the four branches, and provides a total EI score and a score for each area assessed. Mayer and colleagues (2003) reported that the test has sufficient psychometric indicators of agreement between the two scoring methods and internal consistency However, some subtests of the MSCEIT still have poor reliability (Fiori et al., 2014); MSCEIT scores, moreover, correlate primarily with scores obtained on verbal crystallized intelligence tests (Mayer, Roberts, & Barsade, 2008); such evidence suggests that the test might investigate the use of acquired knowledge about emotions that people possess in theoretical situations rather than the behavior actually adopted in actual social interactions. In line with the model of EI as a skill, tests based on recognition of facial expressions have also been constructed as indicators of EI where the participants' task is to indicate what emotions are present in faces (Roberts et al., 2006). However, these measures do not seem to correlate with the MSCEIT emotion perception tests, suggesting that the tests may assess different aspects of EI.

The main limitation of this test typology concerns the criterion of correctness of answers whereby an incorrect answer may not be indicative of a low level of EI but of a peculiar mode of thinking or specific cultural or social legacies (Extremera Pacheco et al., 2019; Fiori et al., 2014). For these reasons, instruments were proposed to measure EI ability whose responses were evaluated according to the choice of emotional regulation strategies used to solve the given tasks. As such, some strategies are rated as more adaptive than others. However, again, some harmful strategies might be adaptive in some social and cultural contexts, again leading to limitations regarding the correctness of the given responses (Matsumoto et al., 2008). In addition, studies have questioned the hierarchical model because an underlying global EI factor has not been confirmed by factor analysis (Fiori & Antonakis, 2011) and it has been verified that the various components of EI are acquired in a parallel rather than hierarchical manner through a complex learning process involving a wide range of biological and environmental influences (Zeidner et al., 2003, Durosini & Triberti, 2022). These limitations led to the emergence of the trait model and mixed models that expanded the concept of EI by considering it a more compressed construct also including aspects of personality, motivational factors and affective dispositions. Specifically, Petrides and Furnham (2001) defined EI as a trait i.e., a pattern of behavior persisting over time that is part of the individual's personality. According to the authors, EI is a quality of the individual that encompasses fifteen dimensions of personality, grouped into four factors: well-being, self-control, emotionality and sociability (Petrides & Furnham, 2009).

Again, Reuven Bar-On (1997) and Daniel Goleman (1995) conceptualized EI according to mixed ability models that also include some personality traits. Specifically, Bar-On (2007) views EI as a set of *noncognitive* skills, competencies, and abilities (emphasis added by the authors) that influence a person's ability to succeed in coping with environmental demands and pressures. He postulates five components of EI (or rather, social emotional intelligence (EIS): intrapersonal skills, interpersonal skills, coping skills, stress management skills, and general mood; Goleman (2001), on the other hand, views EI as a more or less stable quality of the individual and comprising four components: (a) recognition of emotions in the self; (b) recognition of emotions in others; (c) regulation of emotions in the self; and (d) regulation of emotions in others. According to these models, EI can be assessed through self-reported measures that tend to describe the person's typical behavior for which there are no right or wrong answers. In these tests, the individual reports his or her beliefs and perceptions about the skills he or she presents within the different components of EI assessed by the different models. Such protocols, however, have reliability limitations in that it is not possible to assess the correctness of a self-assessment considering that respondents may deliberately manipulate and falsify their responses in order to score positively (MacCann & Roberts, 2008); Conversely, not all individuals may be truly capable of assessing their own emotional skills (Dunning, Heath, and Suls (2004); finally, further issues relate to the ecological validity of the tests (Grubb & McDaniel, 2007) and an agreement between scores obtained on these tests that is too high compared with scores on other personality tests and too low compared with scores obtained on intelligence tests De Raad (2005) ; Bastian, Burns and Nettelbeck, 2005; However, in accordance with such models, emotional intelligence can also be conceptualized as a form of emotional self-efficacy or belief about one's ability to manage emotions. In this sense, despite possible inaccuracies in self-assessment of emotional intelligence, trait measures would be able to capture beliefs about personal efficacy that influence behavior and promote learning and self-improvement (Durosini et al., 2021).

In conclusion, the measurement of EI depends on its conceptualization; in fact, different results are derived from tests that draw on the ability model than from those that draw on the trait model or the mixed model (Brackett et al., 2006; BrBru-Luna et al., 2021). To date, the debate about conceptualizing EI as a skill framework or as a personality trait in relation to the respective assessment instruments remains open. It is possible that new technologies (artificial intelligence solutions) offer innovative tools to make EI detection more systematic and accurate.

1.1 Affective computing

The proposed project is part of the vast line of studies of Affective Computing (AC), dealing with the use of digital tools for the detection of affective states. Following the Picard (1997) subdivision of the three types of applications for this purpose:

- Systems that track user emotions.

- Systems that emulate the ability to express emotions.

- Systems capable of experiencing emotions.

Based on these premises, different fields of study have been developed over time that have seen in this branch of knowledge the keystone for the development of increasingly accurate applications of Human-based systems Computer interfaces that are able to meet the needs of users in terms of both cognitive and emotional. In this sense, the challenges posed by the new frontiers of the AC lie in the possibility of developing increasingly subtle recognition systems that can detect fluctuations in the subjective emotional state. As a result, the AC is presented as a multidisciplinary field of study that combines the latest findings in engineering with the evidence emerged in the psychological, sociological and educational fields. It is in this last field that the evidence coming from the context of educational neuroscience with respect to the processes through which emotions influence learning processes is particularly relevant. An important theoretical reference in this sense is the Cognitive-Affective Theory of Learning with Media (CATLM), which has shed light on the effects of specific characteristics of teaching that can elicit the involvement of students in a given subject (Moreno, 2006). Relevant in this context are Leutner's studies (2014) of evidence showing that the functionality of cognitive processes and learning outcomes are strongly influenced by factors such as emotional state fluctuations and situational interest (Quílez-Robres et al., 2023;Wu et al., 2016). In this context, several researchers have used AI to detect subjective emotional states experienced in a given situation. Analysis methods such as Support Vector Machines (SVM), neural network and multilayer perception have been used for this purpose and these tools have proved to be particularly useful for the integration of other profile technologies in the educational field (Wu et al., 2016).

1.2 Deep Learning Algorithm for Facial Emotion Recognition

Deep learning is a Machine Learning branch that is based on deep artificial neural networks built on multiple layers of computational units that can learn representations of complex data (Paszke, et al., 2019). Deep Learning is very useful in recognizing complex and non-linear patterns in data, such as images, sounds and natural language. Facial Emotion Recognition (FER) using Deep Learning Involves creating a model that can take an input image of a person's face and produce their emotions from a predefined set of categories (Mellouk & Handouzi, 2020). To do this, the model must be able to extract the main features of the face, such as the shape of the mouth, the shape of the eyes, and the position of the eyebrow, and associate them with the corresponding emotion. The Model presented here is a Convolutional Neural Network (CNN) (Arriaga & Plöger, 2017) formed on a data set of 35,685 images annotated with the seven main classes of emotions: happiness, surprise, anger, sadness, fear, disgust, neutral. CNN has a four-level structure: one input level, two hidden levels, and one output level. Network input is a grayscale image scaled to 48x48 pixels. The network has two hidden layers that use convolutional filters and Relu activation functions to extract features from the image. After each hidden layer, max-pooling is applied to reduce the data size, and dropout is used to prevent overfitting. Finally, the output layer uses fully connected layers to classify the emotions of the input image. Among the evidentiable limitations of using this algorithm, it is necessary to emphasize lashow poor ethnic diversity, which can lead to biases and errors in emotion recognition for individuals belonging to minority ethnic groups, such as African Americans, Latinos, or Asians (Dominguez-Catena et al., 2023).

1.3 Biofeedback

The key to structuring realistic models of emotional activation lies in the ability to correctly intercept subjective neurovegetative fluctuations (Pei et al., 2020). In this sense, autonomic responses in relation to different emotions present different activation patterns. Consequently, the use of biofeedback instrumentation for neurophysiological monitoring is crucial (Semerci et. al. 2022). This is because such type of signals is an important marker of the unintentional activity of the subject. Among the most relevant indices, a leading role is played by the Heart rate variability (HRV) (Mendes et al., 2008), whose main components are: high frequency (HF-HRV) and low frequency (LF-HRV). HF-HRV reflects parasympathetic nervous system activity, while LF-HRV can be influenced by both the sympathetic and parasympathetic nervous systems. Additionally, the ratio of LF to HF is examined as an indicator of the balance between sympathetic and parasympathetic activities. Instead, another index found in the Literature is electrothermal activity, specific parameters have been identified to measure skin conductance, considering the amount of sweat present in the eccrine glands as an indicator of such activity. In particular, the level of skin conductance (SC) has been adopted as a measure of mental stress, cognitive load and autonomous excitement (Boucsein et al., 2010). Attention was also paid to skin conductance responses (SCR), which represent electrodermal changes of a specific amplitude that occur over a specific time interval. Finally, the amplitude of the cutaneous conductance (SCA) was considered as a measure of the variation of the cutaneous conductance, observing the transition from the pre-stimulation level to the peak level reached after the stimulus (Rimm-Kaufman & Kagan, 1996). Finally, temperature is also an index to be taken into account for its function of evaluating fluctuations in the context outside the subject that could affect all the other signals previously mentioned at Cascata (Albraikan et al., 2018).

2. Methods/Design

AI could support the assessment of EI by improving the analysis of the understanding component of one's emotions as it can detect the emotions the subject is feeling at a specific time. We propose a novel experimental protocol for the assessment of EI that includes a task that does not involve a correct or incorrect response but whose assessment concerns the degree of agreement between the emotion one claims to have felt and the measured physiological state. Specifically, an algorithm capable of detecting emotional states through facial expressions and certain physiological parameters in response to viewing videos validated to induce specific emotions is proposed. Based on the level of consistency between this data and the stated emotion, the algorithm will provide the percentage of the ability to recognize their emotions.

Participants

It is proposed to recruit a sample of 100 participants of Caucasian ethnicity (this choice reflects the distribution of the reference population and takes into account the bias present in the algorithm's training dataset) aged between 19 and 30 years.

Experimental procedure

Laboratory procedures will be conducted in a controlled environment, so as to reduce the impact of environmental variables on neurophysiological findings. The steps provided are as follows:

- 1 minute of monitoring the neurophysiological baseline through biofeedback;
- Administration of BEIS-10 and MAAS scales.
- Viewing of a series of validated videos aimed at elicitation of certain emotions (facial expressions will be recorded by webcam) _ The Chieti Affective Action Videos database (CAAV);

- Administration of the self-assessment Manikin.
- Evaluation by the subject of the degree of pleasure perceived after watching the videos (Likert scale from 1 to 10) and qualitative attribution of a discrete emotion (anger, fear, sadness, joy, surprise, disgust).

The experimental phase will be followed by the analysis of the recording by webcam through the AI algorithm (Marsico, et al., 2023; Deng, et al., 2019) and simultaneously the tracks obtained from the monitoring carried out through biofeedback will be evaluated.

Measures

- The Brief Emotional Intelligence Scale (BEIS-10; Davies et al., 2010) is a 10-item scale, which pertains to five dimensions: appraisal of one's own emotions (which explores people's ability to recognize emotions in themselves and identify factors that might lead to change in emotions), appraisal of others' emotions (which explores people's ability to interpret others' emotions based on their visual and verbal cues), regulation of one's own emotions (which assesses people's perception of control over their emotions but also the individual's ability to regulate emotions through various activities), regulation of others' emotions (which assesses people's personal ability to promote positive feelings in other people), and use of emotions (which explores people's ability to use positive emotions to aid in problem solving). The BEIS-10 has been validated in Italian (Durosini et al., 2021).
- The Mindful Attention Awareness Scale (MAAS; Brown & Rayan, 2003) provides 15 items and for each the subject is asked to answer, on a scale of 1 (almost always) to 6 (almost never), how frequently he or she experiences the daily experiences described. Higher values indicated higher levels of awareness.
- The Chieti Affective Action Videos database (CAAV) (Di Crosta, et al.; 2020): a collection of videos of human actions with standardized affective values on a two-dimensional scale of valence and arousal. The videos were acquired from subjects performing different actions, such as hugging, kissing, crying, laughing, greeting, and walking. The database was created to provide a visual and auditory stimulation tool for research on emotions and their psychophysiological correlations.
- The Self-Assessment Manikin (Bradley and Lang, 1994) represents an emotional assessment tool based on images, designed to objectively and standardizedly probe and measure human affective responses. The approach is based on the premise that emotional states can be

characterized by three fundamental dimensions: valence/pleasure, perceived arousal, and dominance/control

3. Discussion

In the present study we have discussed an algorithm capable of assessing consistency between subjective reports of one's own emotional activation and on-line psycho-physiological response that could be associated with specific emotional categories. Moreover, we have proposed a preliminary research protocol to assess feasibility and effectiveness of the prefigured solution. We discussed the methodology for data collection, statistical analysis and evaluation of results. The expected results of the experimental protocol are to provide an accurate and reliable assessment of the emotions expressed by the participants through the analysis of their facial expressions and their physiological parameters. The algorithm in question trained based on data collected during the protocol can achieve high performance in the recognition of emotions, both in terms of accuracy and generalization to new subjects and stimuli. In addition, it is planned to identify significant relationships between recorded physiological data, detected emotions and psychometric measurements. It is hypothesized that physiological parameters such as sweating and HRV can provide valuable information to evaluate the emotions expressed by participants. Therefore, the analysis of data collected during the protocol should reveal specific physiological patterns associated with different emotional expressions.

Implementing such a complex system would improve our ability to assess emotional intelligence beyond the issues inherent to classical approaches such as ability-EI (i.e., difficulty in designing reliable emotional tasks) and trait-EI (i.e., susceptibility to people's inaccuracy in self-assessment) (Durosini et al., 2021). The approach proposed here supports people's emotional self-report with information on consistency with objective measurements. For what regards the component of understanding one's own emotions, the solution outlined here would permit researchers to access a multi-componential account of EI. This is relevant especially for contexts where EI has been found connected to desirable performance and positive outcomes, such as health management (Durosini et al., 2022) and education (Humphrey et al., 2007). Indeed, EI plays a role especially in higher education, especially for what regards abilities of recognizing and using one's own emotions, as it supports involvement in educational activities, resilience against challenges and obstacles and ultimately influences final outcomes (Halimi, AlShammari, & Navarro, 2021; Zhoc et al., 2020). For these reasons, it is important to develop reliable methods for assessment and possibly improvement of EI in different populations.

The proposal is not exempt from limitations:

Across multiple theoretical conceptualizations of EI, the same comprises multiple characteristics, usually associated with abilities in understanding (and managing, and using) one's own *and* others' emotions. That considered, the proposed solution assesses only the first part of the competences associated with EI. Secondarily, the algorithm solution indeed requires a complex setting, instrumentation and qualified operators in order to collect usable data from a human subject and provide any information about their EI level. While it is possible that such procedures will be more and more automated in the future, it is important to take into account that the current solution is certainly not applicable to the evaluation of EI in the wild (e.g., field research, health interventions…), but only within laboratory-based experiments.

An important construct limitation is related to the concept of meta-emotions. Recent research in emotions psychology is emphasizing the importance of appreciating the complexity of the emotional world, which could be hardly reduced to the immediate responses to experimental stimuli. People do not only passively-experience quick responses to stimuli present in the environment, rather they enact complex processes of appraisal and reappraisal even days or years after experiencing an emotion-genic event. Specifically, people have emotional responses to their own emotions, or meta-emotions (Miceli & Castelfranchi, 2019; Bailen, Wu, & Thompson, 2019; Durosini & Triberti, 2022). Meta-emotions have been studied extensively in the last decades, originally by media psychology (Bartsch, Appel & Storch, 2010; Koopman, 2015), in that media fruition is often associated with complex emotional experiences (e.g., crying but reporting joy after seeing a sad movie). Clearly, any solution, test or tool that relies heavily on the here-and-now emotional activation as the one typically analyzed by laboratory-based psycho-physiological indexes could not do justice to the complexity of meta-emotions. For instance, one could show a facial activation commonly associated with fear when seeing some fear-inducing image, but then they could report experiencing fun as a horror estimator. The subjective response is not "wrong", rather it makes a synthesis of appraisal of emotion and meta-emotion. As based primarily on psycho-physiological indexes, the algorithm may be incapable of recognizing the complexity of the emotional experience. Therefore, any implementation of similar solutions should take into account that the immediate response to validated stimuli could not be indicative of the entire emotional experience as it is lived by the subject over time.

The limitations do not imply that the algorithm-based solution proposed here is not applicable, but only that researchers and practitioners should be cautious when interpreting the results. Besides testing the proposed solution, future research entails the development of even more complex and multi-componential tools that could analyze the complexity of emotional intelligence and, more generally, the ways emotions are lived and understood by ourselves and others.

Conclusions

In this project proposal, we have described a study protocol useful to identify the unintentional characteristics of EI through an algorithm of emotion detection by facial expressions comparing outputs with biofeedback. Finally, it is expected that the results obtained can be used to create an adaptive learning tool that provides support in educational and formative contexts that allow to implement the knowledge of EI in educational contexts. However, there are some limitations to this proposed study. For example, the sample on the basis of which the algorithm was trained may not be representative of the general population, which could influence the generalization of results. Moreover, the neurophysiological monitoring through biofeedback presents the strong limit due to the fragmentation of the reference literature in relation to the presence of specific datasets for each manifestation of the emotional state at the level of regulatory samples of reference (Albraikan, 2018)). Therefore, it is necessary to adopt strategies to control and separate these factors to isolate the desired emotional effects. In the future, it would be interesting to expand research by including the integration of multimodal data and exploring individual variability in relation to the subjective manifestations of EI at the physical, neurophysiological and psychological levels.

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