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Real-Time Emotion Recognition and its Effects in a Learning Environment.

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Abstract. The purpose of the article is to understand the current state of both the technology and the implementation of emotion recognition in the educational environment. The goal is to obtain detailed information about the current state of emotion recognition technology and how its practical use is being carried out in educational settings. In this line, it examines the proposals from publications over the last 10 years on the advancement of technology for emotion recognition in education. A total of 1,347 studies were obtained and 43 were included in the review for analysis and discussion. The article demonstrates how the number of studies has increased in recent years, with a higher frequency in online learning. Furthermore, according to the Technological Readiness Level, despite the growing interest in emotion recognition in the educational environment, its implementation is still far from becoming a reality. Most of the research has been conducted from a theoretical perspective and none of them has been fully developed and implemented in the classroom. In addition, many of the studies analysed have not tested the validity of their findings.

Keywords: Emotion Recognition, Smart Classroom, Educational Environments.

1 Introduction

Understanding and acknowledging students' emotions plays a pivotal role in the learning process [1]. This comprehension not only enhances the teaching process but also offers a deeper understanding of students, catering to their individual needs and placing them at the forefront of learning [2]. On the one hand, positive emotions such as joy and curiosity have a positive effect by facilitating self-regulation and focus on the task, and by promoting student engagement [3] and motivation to achieve goals [4]. On the other hand, negative emotions such as boredom and frustration distract students' attention and deplete their cognitive resources, leading to lower engagement [5]. In education, efforts are being made to improve learning processes, knowledge transmission and teaching methods [6]. In this context, understanding students' emotions is crucial to help improve teaching performance [2].

Emotions are emotional states that arise in response interactions [7]. Different emotions and their corresponding facial expressions are associated with different patterns of activity in the nervous system that elicit specific responses in the observer [2]. Identifying emotions in real time is critical to gaining valuable insight into the emotional state of students during the learning process. Emotions play an important role in students' academic lives and have a profound impact on their cognitive learning techniques and performance [8]. By recognising these emotions, educators can adapt their pedagogical approach, provide emotional support, foster motivation and enrich students' overall learning experience. Motivation, which is closely linked to emotions, has a significant impact on task performance as it triggers and sustains students' drive towards their academic tasks [9].

Despite the complexity of the different emotions experienced by students, in most cases positive emotions are associated with learning success and are an indicator of a conducive learning environment. However, there is limited empirical evidence as to whether this is also true in a physical classroom setting [10]. Automated emotion capture is gradually becoming a reality as machine learning methods improve [11].

Recognising emotions is a challenging task, even for people who tend to interpret those emotions from facial expressions, body language, voice and other cues [12]. However, technology can be an ally in this difficult task [2]. Indeed, recognising emotions remains a challenge for technology because of the fuzzy boundaries and individual differences. Emotions affect various aspects of life, and relying only on physiological aspects makes it difficult to detect them accurately. Moreover, emotions can have significant physiological differences in individuals, leading to notable differences [13].

It is still difficult for computers to recognise people's emotions. Several research studies have focused on Facial Expression Recognition (FER), which aims to classify people's expressions into predefined emotions [12]. New biomedical analysis techniques such as the EEG (electroencephalogram) or the ECG (electrocardiogram), together with the analysis of facial features, can help to better understand the psychological characteristics of a person [14].

Emotion recognition (ER) is a component within the Smart Classroom ecosystem and makes sense in this context, as it may not have that much significance on its own [15]. The number of studies on this topic has increased in the e-learning environment, as the lack of emotions and connections between students and teachers reduces motivation and limits the quality of teaching [14].

1.1 Study Objectives and Outline

The general aim of this research is to analyse real-time ER in educational settings. The guiding questions for this review are the following:

- Research Question 1 (RQ1). How can emotions be identified in individuals?
- Research Question 2 (RQ2). What are the benefits and uses of identifying emotions in real time?
- Research Question 3 (RQ3). What is the future of real-time emotion recognition?.

The rest of the article is structured as follows: Section 2 presents the review methodology and its results in relation to the excluded and included articles. Section 3 analyses the results of the review in terms of year of publication, country of authors, type of learning, etc. Section 4 provides a detailed discussion of our research questions, security and privacy issues, and the maturity of the proposals; it also outlines future research in this area. Finally, Section 5 concludes the article.

2 Method

In order to achieve the aim of this study and answer the proposed questions, a systematic review was conducted using an explicit and replicable approach [16].

2.1 Data sources and research

The databases used for the search were Web of Science (WoS) and Scopus. They were selected based on the quantity and quality of records according to the JCR and SJR indices, which went through a rigorous process to be included in these databases. The search was limited to the period from 2013 to 2023, which was selected based on the technological changes and advances in recent years in the fields of technology, Artificial Intelligence and ER. The search was conducted using the Boolean operator with the following terms: "emotion*" AND "recognition" AND "real time" AND ("teaching" OR "learning" OR "classroom").

2.2 Inclusion and exclusion criteria

The exclusion criteria applied in this search are duplicates, book chapters, conference papers and dissertations. In addition, the documents that were excluded were those that did not deal with ER or education and the teaching-learning process.

To select the article for this study, its conclusions had to include the recognition of faces and emotions in the context of education.

2.3 Data distribution

As the diagram shows (Figure 1), searches in databases such as Web of Science (WoS) and Scopus found 726 and 621 records respectively. The period defined for the search is 2013-2023. Only those published in English and Spanish were included, limited to the fields of computer science and engineering, and social sciences such as psychology, education and neuroscience. After excluding duplicates (n = 340), a total of 1007 articles remained. The next step was to exclude book chapters, dissertations and conference papers, of which 77 were present, leaving 930 articles. After analysing the titles of the articles, those that did not relate to ER or to the educational environment or teaching-learning process were discarded, leaving 794 articles, of which 117 could be analysed. Of these, 73 were excluded because the conclusions did not relate ER to the educational setting, leaving 43 articles.

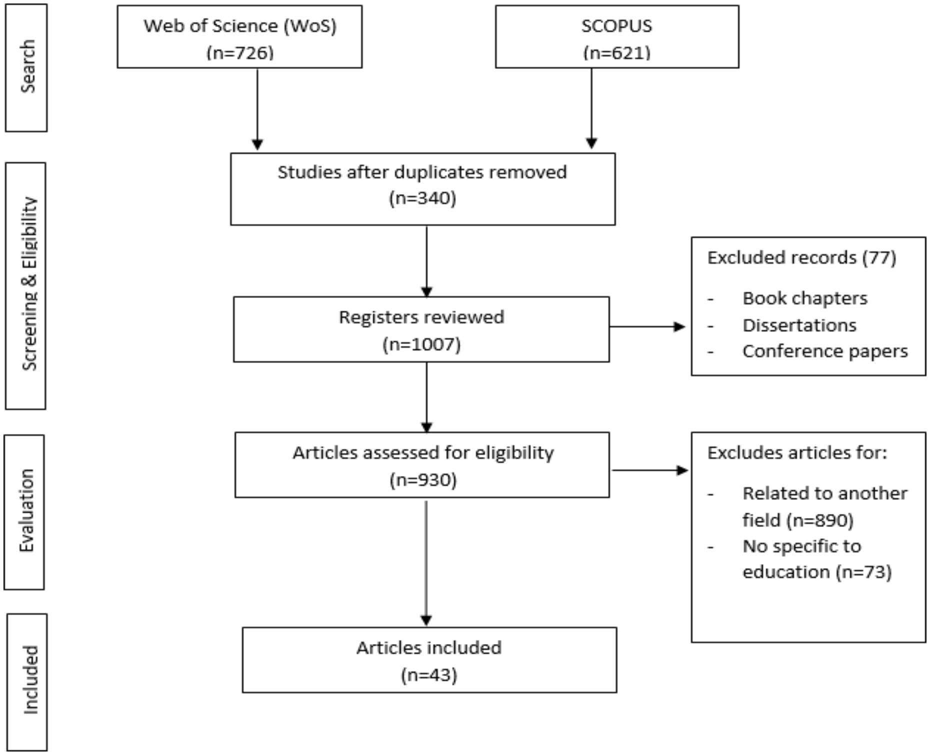

Fig. 1.. Diagram of the process for the systematic review

3 Results

This section analyses the articles included in the systematic review in terms of year of publication, country of authors, type of learning, emotion analysis and methods of data collection.

3.1 Distribution by year of publication

Figure 2 shows the distribution of articles that use ER in education. Looking at Figure 2, a clear increase can be observed in recent years on this topic. The year with the highest number of publications was 2022. As for 2023, the analysis was carried out in January, which explains the lack of articles on this topic in that year.

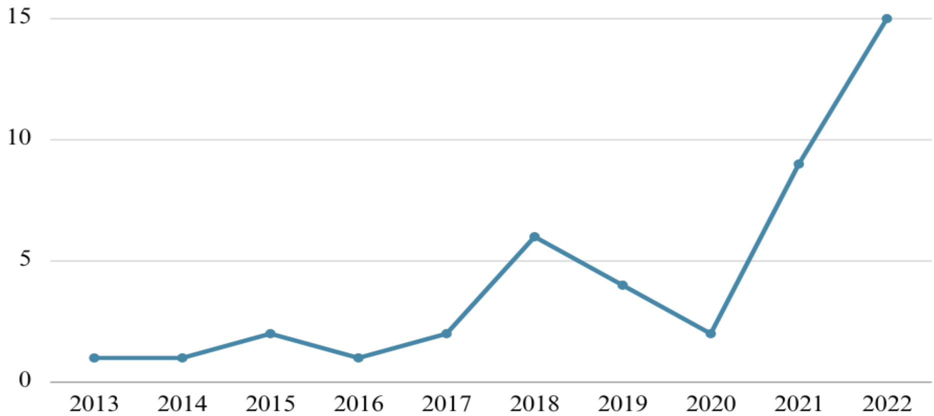

Fig. 2. Distribution of the studies by year

3.2 Distribution by country

Figures 3 and 4 show the distribution of studies included in the review by the continents and countries from the authors that conducted them. When analysing these figures, it can be observed that Asia is the continent with the highest number of studies conducted, with China (n = 12) and India (n = 9) standing out as leading countries in these research efforts.

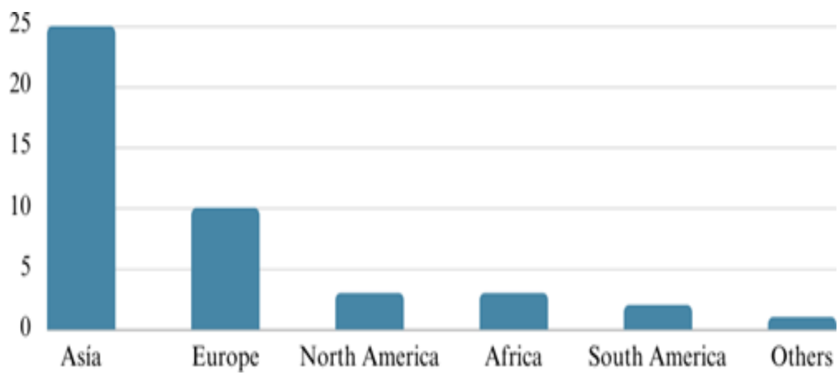

Fig. 3. Distribution of the studies by continent

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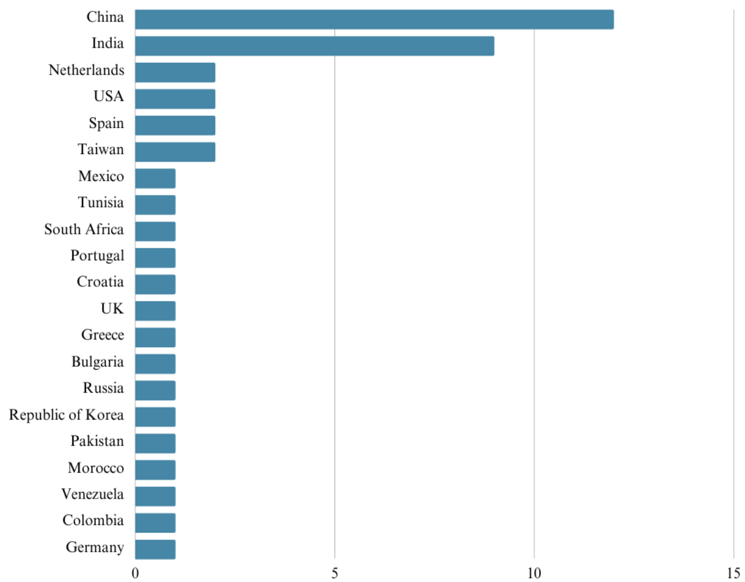

Fig. 4. Distribution of the studies by country

3.3 Distribution by type of learning

Figure 5 indicates the type of learning, whether it is online or in classroom (face-to-face). The analysis of the diagram shows that most of the studies dealing with ER in education are focused on online teaching (n = 30).

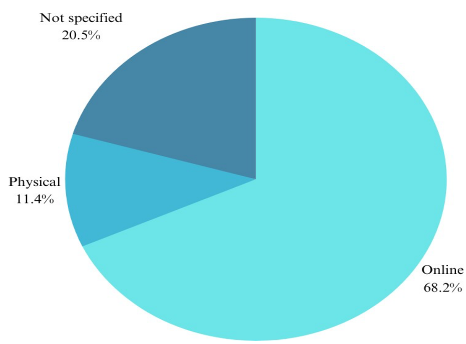

Fig. 5. Distribution of studies by type of learning

3.4 Distribution by the model of emotion analysis

Figure 6 depicts the type of ER models used in the studies analysed. From the figure 66% (n = 29) of the analysed studies used predefined emotions.

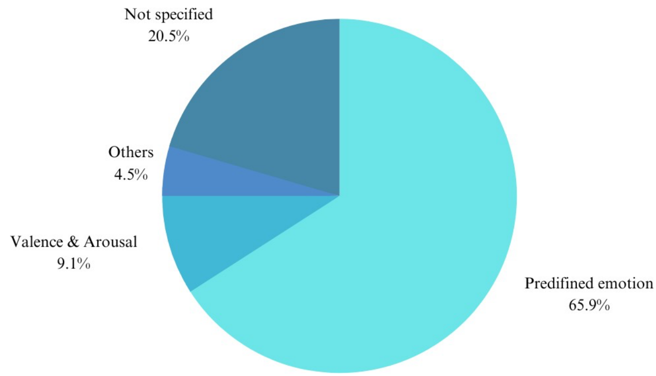

Fig. 6. Distribution of studies by the model of emotion analysis

In Figure 7 displays the distribution of studies based on the emotion model employed in the research and the country where the investigation was conducted, with the predefined emotion model being the most influential in all countries

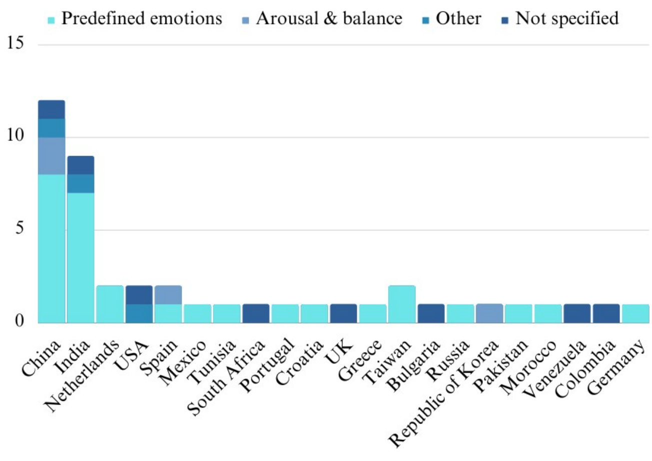

Fig. 7. The distribution of studies based on the emotion model and the country where the study is conducted.

Figure 8 presents the analysed studies that used predefined emotions for ER. The most commonly used emotions are those related to Ekman's theory of six basic emotions: anger, disgust, fear, happiness, sadness, and surprise.

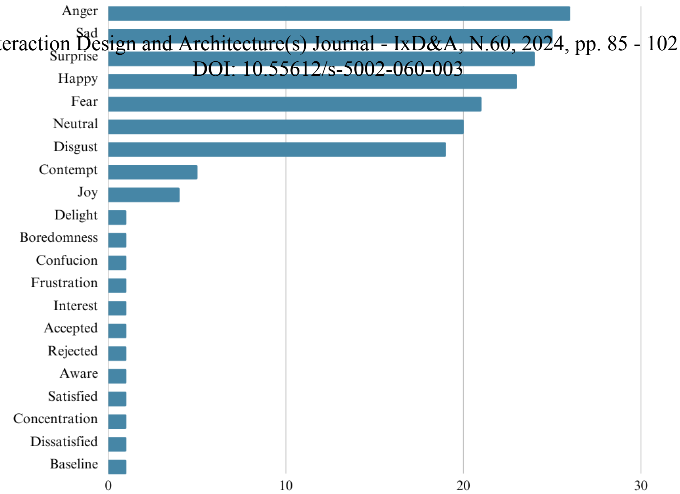

Fig. 8. The distribution based on the predefined emotions used in the analysed studies.

3.5 Distribution based on the type of teaching and the data collection methods

Figure 9 shows the relationship between the type of learning (online or in class) and the type of medium used to collect information about students' emotions. The analysis of the graph shows that for both online and face-to-face models, the camera is the most frequently used element (n = 25).

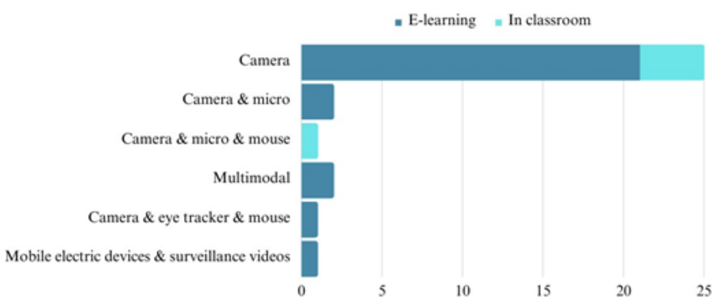

Fig. 9. The distribution of studies based on the type of teaching and the data collection methods.

3.6 Number of studies regarding the model of emotions used for classification and data collection methods

Table 1 relates the type of model and the data collected for emotion identification. Analysis of the table shows that the majority of the studies use the given emotion model and collect data from the face (n = 18). As can be seen from the table, most of the studies analysed use facial expression in the recognition of predefined emotions (n = 18), followed by studies that, in addition to facial recognition, add voice as an element in identifying the students' emotional state of the students (n = 4). The studies analysed that used the Arousal & Valence model use a multidimensional approach (n = 2) to emotion analysis, introducing variables such as face recognition and biometric variables, among others.

Table 1. The distribution of studies based on the model of emotions used for classification, the data collection, and the number of research studies using them.

Model	Collected data	Research
Predefined emotions (basic emotions)	Face Face & voice Face & body	18 4 1
Enjoyment, confusion, fatigue, distraction, neutral	Face	1
Blinking, yawning, nooding, shaking head and leaving	Face & head gestures	1
Arousal and valence	Face Multimodal (face and sensors to measure the body's responses such as EEG or ECG)	1 2
Non specified		9

4 Discussion

After analysing the selected articles, we will aim at discussing the questions formulated as the objective of this article. To this end, we first deal with the question of how emotions can be identified in individuals. Then we address the benefits and uses of identifying emotions in real time. Furthermore, we analyse to what extent security and data privacy are considered in the proposals examined and discuss the technological maturity of the proposals. Finally, we address the future of real-time ER.

4.1 Identifying emotions

Facial emotions are considered important cues for predicting people's reactions to external stimuli, mental states or intentions [17], [18]. Face recognition is one of the most widely used techniques for analysing emotions based on facial expressions, head or eye movements and other facial features [14]. Many studies dealing with face recognition classify facial expressions into predefined emotions, with the camera or webcam being the most used elements.

The recent literature on teaching and learning using affective computing methods, which involve the utilization of technology and computational approaches to recognize, understand, and express affective and emotional data from individuals [19], is concerned with the recognition of students' emotions in e-learning environments where motivation and attachment to the teacher are reduced [9] but student behaviour is easier to capture [20]. Difficulties exist with the hardware used to capture data, both in online training due to the quality of cameras or webcams, and in face-to-face sessions where certain cameras limit the number of students the model can capture, limiting its potential in large classrooms [11]. Apart from the difficulty of correctly identifying emotions, teachers also need to know how to respond to negative emotions in order to steer in the right direction. Therefore, the use of ER methods to infer emotions to support the learning process is conceivable to promote greater interaction in challenging moments in the classroom and to provide teachers with more information about the reception of certain content [11].

Another aspect that is analysed is speech, where speech features can be distinguished in terms of prosody, sound quality, and spectral features [21]. In the literature, prosody is proposed as a factor that contains emotional elements [22]. These prosodic features are divided into pitch, energy, temporal patterns and pronunciation. Emotional features, on the other hand, are reflected in the spectral features, which refer to the distribution of energy in the frequency spectrum. The Mel Frequency Cepstral Coefficients (MFCC) are an instrument that can be used to determine the spectral features of emotional voice signals [21].

Emotions can be detected by behaviour, voice, facial expression or physiological cues, although facial expression, voice and behaviour can be subjective [23]. Individuals may mask or show emotions that are contrary to their true feelings. Other signals that have been less explored in the literature are physiological signals such as the electrocardiogram (ECG), electroencephalogram (EEG) or galvanic skin response (GSR), which are more reliable and impartial for ER [24]. Both ECG and GSR provide rich emotional information and can be obtained at low cost and through non-invasive techniques [25]. ECG has been shown to be a reliable source of information for emotion detection [26] and can identify emotional states such as joy, sadness and stress. GSR signals detect the activation of the sympathetic nervous system in response to a stimulus and reflect cognitive and emotional processes [27].

According to [25], an appropriate combination of multiple models can enhance the robustness and effectiveness of an automated ER system [28]. Humans use multiple methods to detect emotions and process signals, and an automated machine may exhibit similar behaviour. Using a multimodal approach and integrating different sources of information such as facial expressions, voice and physiological signals can improve the accuracy of ER in automated systems.

4.2 Benefits and uses of identifying emotions in real-time

Applied Artificial Intelligence can help improve the teaching and learning process by providing information to the teacher. Understanding students' emotions provides access to their genuine reactions to the learning environment. If the teacher detects emotions that are not conducive to effective learning, based on the premise that positive emotions enhance the process, the teacher can intervene by adjusting learning activities or focusing on a particular student [2].

During the learning process, real-time information provides awareness and helps students improve their communication skills and become more aware of their own emotions [29]. It also facilitates the process of learning in the classroom [30]. According to the study conducted by [30], students' facial expressions fluctuated during class, which was directly related to classroom learning. Several variables within the classroom had a significant impact, such as spatial positioning, with students in the front rows being more satisfied. The difficulty level of the topic also had a significant impact, as statistics show that topics with higher difficulty levels cause students to have a negative facial expression during learning.

In the teaching process, students' facial expressions contain valuable information for the teacher to grasp and understand students' emotional state to improve their teaching practise [12] and regulate teaching strategies in real time [31]. In addition, accurate detection of classroom behaviours can help teachers and students better understand classroom learning and promote the development of a smart classroom model [7]. Monitoring the emotional state of students, when used properly, can improve pedagogical processes, such as teacher decision-making in the classroom, as well as optimise attention to students by adjusting teaching methods or focusing on specific individuals [2], as only timely responses can improve the experience of human interaction [25].

The emotional state revealed by facial expressions is related to the activities being performed at that moment [12] and can be a useful indicator for assessing the level of immersion in learning [32]. It can help teachers understand the learning state of their students and enable them to adapt the material to the student's level of difficulty and concentration [33].

The teaching task can be delivered while monitoring student engagement. Real-time analysis of facial expressions would allow instant monitoring of a student's dynamic emotional state. This would be useful in providing the teacher with information about the level of student engagement in learning situations [32] and to encourage greater interaction when there are difficulties in the classroom [11]. Even when dealing with groups of students rather than individuals, the level of engagement can be quantified, and teachers can be provided with colour-coded information similar to a traffic light [32]. This can be potentially useful for a teacher in a group setting, especially an inexperienced educator or a teacher with empathy issues [11].

Research can be improved by including an analysis of the progression of detected emotions over a period of time to create a predictive model of when students are likely to drop out or fail a subject [33]. Additionally, combining variables such as emotions and time of day could help school administrators and education authorities to assess and change timetables in a justifiable way to optimise student well-being and academic performance. This opens the possibility of not only preventing and identifying learning problems, but also health issues [2].

Knowing the students 'emotions is beneficial, however, it should be taken into account that according to [12]'s study, women were more likely to show emotions in almost all types of activities. Moreover, the emotion of happiness was the most likely emotion in all types of activities, regardless of gender.

In the classroom, it is feasible to use computer vision- based methods to derive emotions to support the learning process, promote greater interaction during low points in the class and provide teachers with more information about the reception of certain content. This demonstrates that emotion inference can be potentially useful for an educator even in a small group, especially for novice educators or those with empathy issues. It may also justify further research, particularly in considering an emotion-based average indicator in cases with minimal emotional outliers within the group [11].

4.3 Security and privacy

In the context of the development of information and communication technology, security and data protection are crucial aspects. On the one hand, computer systems are vulnerable to attacks aimed at hijacking information or disabling the services they provide, either temporarily or permanently. In addition, information stored in these systems can be stolen or altered, highlighting the need for safeguards to minimise risk and loss in the event of an attack. Finally, most ER systems rely on data that can identify individuals, such as facial images. Therefore, safeguarding the privacy of the individual is of utmost importance.

We have analysed to what extent the selected articles address these aspects. Specifically, we distinguished four scenarios and classified each work based on what is written in the article text. Specifically:

- SP0. The article does not mention at any point either aspects of computer security or personal privacy. We have found 29 articles in this category.
- SP1. The article mentions security and/or privacy as aspects to be taken into account. In this category we place 7 articles.
- SP2. The article develops strategies to ensure security or privacy. There are 3 articles that explains that their system is secure and that the data is encrypted.
- SP3. The article develops strategies to ensure security and privacy. There is only one article that addresses these aspects.

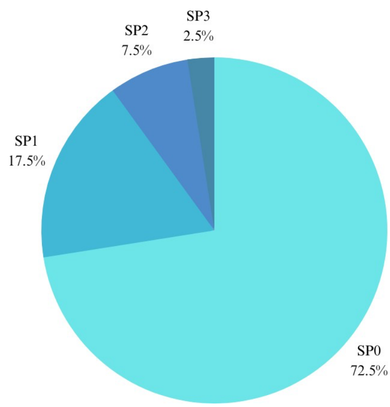

Fig. 10. Classification of the studies based on security and privacy.

It should be noted that despite the fact that ensuring information security and preserving the privacy of individuals is crucial in the ER scenario, almost three out of four papers do not address this issue.

4.4 Technological maturity of the proposals

In this paper we have listed several proposals for recognising emotions in the classroom by analysing data from cameras and sensors. It is interesting to analyse the state of technological development of each proposal in order to assess to what extent the topic of our research has more or less chance of becoming a reality in the classroom.

For this purpose, we have used the Technological Readiness Level (TRL) defined by the ISO 16290: 2013 scale. For simplicity, and given the limited information generally published in the literature on the state of technological maturity, we have classified each proposal into one of the following groups of levels:

- TRL 1-2. Basic principles and formulation of the technology, without demonstrators or testing.
- TRL 3-4. Proofs of concept and technologies validated in a laboratory.
- TRL 5-6-7. Validation and demonstration in a relevant or operational environment (in our case, in the classroom).
- TRL 8-9. Complete and real system working in the classroom.

We found that 12% of the articles analysed are classified in TRL 1-2, i.e. formulated theoretically. 73% of the works are classified in TRL 3-4, indicating that the studies were conducted in laboratory settings. In addition, 14% of the articles are classified in TRL 5-6-7. It is important to note, however, that none of the selected articles has developed a complete system that works in the classroom. So, despite the growing interest in this topic, its use in real environments is still far from becoming a reality. Not only are the articles not applied to real or relevant contexts, but many of them have not tested the validity of the results.

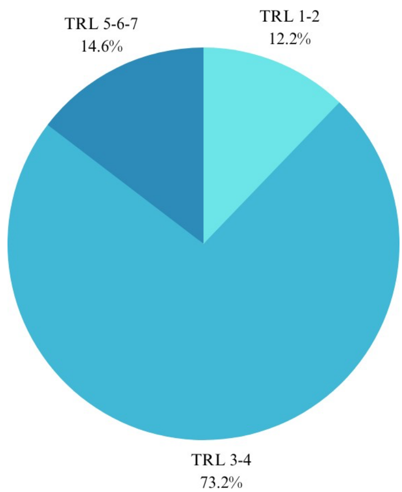

Fig. 11. Number of articles analysed according to the TRL

4.5 The future of real-time emotion recognition

In the ER, most of the studies reviewed used basic emotions in their analysis. Broadening the range of emotions could contribute to a more accurate classification of learners' emotions [24]. Furthermore, predicting arousal and valence [34], in addition to facial expressions, may provide the teacher with additional information about the attitude of individual learners [35]. Although research focuses on the recognition of students' emotions, observation of teachers' emotions can provide important information because of its importance for classroom climate, emotional development and student outcomes [2].

The recognition of emotions can be achieved based on specific learning content, methodologies, teaching styles, and classroom environment [2], helping to bridge the gap between the student and the learning material/concepts/skills during the content delivery process. This can facilitate, especially in e-learning education, the automatic adaptation of the content according to the student's level of concentration, making the learning process more effective [9]. A study with a larger sample would be necessary to analyse the combined influence of emotions, academic performance, and time of day [2].

The uncertainty in recognising a particular emotion remains open. Perhaps this could be overcome by using multimodal sources for ER [29]. In multimodal use, different sensors are combined to provide more accurate recognition, creating a better intelligent education system [14]. In this multimodal system, facial recognition could be combined with audio or sound [12], [36], the use of heart rate, EEG or EGG signals [5], [36], [37], electrodermal activation or galvanic skin response [38], oxygen levels [9], body movements [21], eye or facial movements [5], [38] and the attentional learning state in the classification label. In this way, a comprehensive affective recognition system would emerge [21].

With the data collected, feedback can be given to teachers that includes self-reports of student emotions and indicates effectiveness in conveying ideas to the audience [38]. The data can also be shared with students to evaluate their perception and usefulness for self-regulation regarding the recorded emotions [2].

With regard to the security and privacy of individuals in data collection, it is necessary to incorporate the optimisation of protocols in cloud computing systems, placing more emphasis on security and coordination [25]. While the need for privacy is universal, individuals' judgment and privacy preferences largely depend on the context. Therefore, it remains to be studied whether video-based person-computer interaction can be widely used in teaching [39].

Regarding the limitations encountered, the hardware of certain cameras limits the model in large classrooms [11]. Additionally, following [36] guidelines, ECG or EEG sensors could also be used in the future, but only for research purposes, as these solutions are not considered suitable for learning applications.

Additionally, further research is needed regarding the characteristics of the participants and languages, as emotions and expressions may vary depending on the country or culture [29]. Cultural factors play a significant role in shaping emotional experiences and expressions. Therefore, ongoing research and consideration of cultural diversity is crucial to ensure the accuracy and effectiveness of ER systems across different populations and languages.

5 Conclusions

This study has undertaken a comprehensive systematic review of the existing literature on ER within the educational setting. Specifically, the aim was to assess the current state of the art in this area, including the stage of development and the progress made so far. We have observed that the number of studies conducted has increased, with 2022 being the year with the highest number of publications on the topic. From 2021 onwards, there has been a noticeable surge in the number of studies on this topic. This trend could possibly be due to the COVID -19 pandemic and the rise of online education [40], which poses challenges to the teacher-student relationship. Consequently, most of the studies analysed were conducted in online environments.

Examination of the studies included in this systematic review revealed a predominant concentration of research conducted in China and India. This observation can be attributed to the status of these countries as pioneers in technological innovation. As claimed by [40], research and development are the main focus of researchers in developed countries.

In terms of the theoretical framework used to analyse emotions, the majority of the selected studies focused on identifying specific emotions and linking facial or other behavioural cues to the corresponding emotional states. According to [14], most of the research focuses on the recognition of facial expressions and head pose. Recognition of dynamic facial features can provide valuable information about students' emotions, although computers still struggle to recognise human emotions. Analysis of facial features using cameras can offer precision and is suitable for online learning. Additionally, there are other biometric techniques that can capture students' psychological characteristics, such as electroencephalogram and electrocardiogram analysis [14]. The combination of these techniques can provide more accurate information about students' emotions.

When examining the type of education in which ER is conducted, a larger number of studies on online learning were observed. Online education offers advantages such as maximising the use of resources and flexible learning methods. However, one of the drawbacks is the lack of emotional connection between teachers and students as interaction takes place through machines [14]. Moreover, it is easier to gather information in online environments [20]. In contrast, face-to-face teaching makes it difficult to identify emotions in the classroom. This is due to the cost and impracticality of implementing sensors and hardware in many real-world classroom environments, as well as concerns about the intrusiveness of the systems and the privacy and use of the collected data [11].

Regarding the limitations in this analysis, it is still at an early stage despite the growing interest in the subject. Most of the research has been conducted from a theoretical perspective and none of them has been fully developed and implemented in the classroom. Therefore, it is still far from becoming a reality in the educational environment. In addition, many of the studies analysed have not tested the validity of their findings.

For future research, more implemented, refined and mature instruments and studies should be developed to measure the impact on teaching performance. It should also analyse how real-time ER can help students improve their learning and how it can help teachers manage classroom activities and adapt and personalise teaching methods to students' needs.

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CRediT author statement. **Oihane Unciti:** Investigation, Formal analysis, Writing – original draft preparation. **Antoni Martínez Ballesté**: Investigation, Formal analysis, Writing – review and editing. **Ramon Palau**: Formal analysis – review and editing.

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