LEVERAGING EMOTIONS TO ENHANCE LEARNING SUCCESS IN ONLINE EDUCATION: A SYSTEMATIC REVIEW

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ABSTRACT

Emotions are vital to learning success, especially in online learning environments. They make the difference between learning success and failure. Unfortunately, learners' emotional state is still rarely considered in online learning and teaching, although it is an important driver of learning success. This paper reports a work-in-progress systematic literature review to provide a current state of research on emotion measurement in online learning environments. The findings will later serve as a basis for creating an emotion-based adaptive online learning environment.

KEYWORDS

Affective Computing, Emotion Recognition, Learning Support, Systematic Review, Learning Analytics

1. INTRODUCTION

Emotions are an essential part of the learning experience (D'Mello, 2017). They are complex psychophysiological states characterized by subjective experiences and accompanying physiological responses to external or internal stimuli (Levenson, 1994). In conventional face-to-face teaching and learning settings, educators have the advantage of being able to discern and address the emotional state of their learners through non-verbal cues and direct interactions. However, this becomes more challenging in online learning and teaching environments due to the absence of physical presence (Collazos et al., 2021). Among other reasons, this is why an increasing part of the scientific community has focused on emotions and learning and the field of affective computing in education. In addition, methods for measuring emotions using artificial intelligence in educational environments offer a very accurate (Jaiswal, Nair & Sahoo, 2022) and resource-optimized way to capture emotions (Huang et al., 2019).

Furthermore, emotions in educational settings are mental states that arise spontaneously rather than through conscious effort (Ifenthaler, 2015) and are regarded as a key driver of learning success (Pekrun, 2017). For example, Pekrun (2017) has found that emotions influence adolescents' learning, including their attention, motivation, use of learning strategies, self-regulation in learning, and performance outcomes. At the same time, online learning and teaching methods are also becoming increasingly important in education and training. Online learning environments, such as Massive Open Online Courses (MOOCs), are thus seen as an online alternative for in-company training and professional development (Egloffstein & Ifenthaler, 2017). Still, dropout rates seem particularly high in this area (Badali et al., 2022). Dillon and colleagues (2016) found that emotions are a significant contributor to dropout rates in such online learning environments. Their findings showed that anxiety, confusion, and frustration were significantly positively correlated with dropouts. But not only dropout rates can be optimized by incorporating features focusing on emotions into online learning environments, as other research suggests that learning success can be improved (Llanda, 2019).

This paper presents a systematic literature review focusing on online learning environments and the use of features to regulate emotions. In particular, the following research questions have been addressed: (a) To what extent is affective computing used in education? (b) Which AI technologies are being used? (c) Which measures are available to facilitate learning success? The findings may provide a sound basis for developing and implementing adaptive features for online learning environments to regulate learners' emotions.

2. METHODOLOGY

This section describes the systematic review approach employed in this study. Our methodology largely complies with the PRISMA guideline for reporting systematic reviews (Page et al., 2021). We began by formulating our research questions. Subsequently, we developed the search strategy, encompassing search strings, databases, and inclusion and exclusion criteria. After eliminating duplicate papers, two reviewers initially screened titles and abstracts. Thereafter, we conducted a full-text search and extracted predefined content on previously defined extraction criteria, including used emotions, applied techniques, and outcome measures for learners. The following section describes the process in detail.

2.1 Database

A scientific database search was conducted in the area-specific leading IT, education, and psychology databases. The following databases were used for the search: ACM Digital Library, ACM Guide to Computing Literature, ERIC, IEEE Xplore, Web of Science, and PsycInfo.

2.2 Searching Strategies

To reflect the diversity of online learning and teaching and affective computing, the search strategies included different synonyms, for instance, variations of online learning environments, such as e-learning or Massive Open Online Courses (MOOCs). Further, the search strategy could have explicitly considered physiological factors, however, in the initial searches, these were always treated under a synonym for affective computing or emotion recognition. Hence, the following search strategy was implemented for this systematic review:

Search string focused on online learning: "E-Learning" OR "Virtual learning" OR "Distance learning" OR "Mooc*" OR "Massive Open Online Course" OR "Remote Learning" OR "Online Learning" OR "Online-Learning" OR "Digital Learning" OR "Web-based learning" OR "Internet-based learning" OR "Cyberlearning" OR "Online-Education" OR "Online education" OR "Web-based instruction*"

Search string focused on emotion recognition: "Affective computing" OR "Emotion detection" OR "Emotion analys*" OR "Emotion classification" OR "Emotional analytics" OR "Emotion tracking" OR "Emotion identification" OR "Sentiment analysis" OR "FER" OR "Fac* emotion" OR "Voice analy*" OR "Emotion tracking"

2.3 Selection Criteria

The search covered scientific literature published until May 2023 and was limited to studies conducted in the English language. The inclusion criteria consisted of the following: (a) the utilization or intended utilization of AI technology for emotion recognition, (b) a focus on online learning and teaching, and (c) the inclusion of emotion technologies that are applicable in real-time or near-time scenarios. Further, (d) studies that derived sentiment from historical data, such as forum posts, were excluded from the selection.

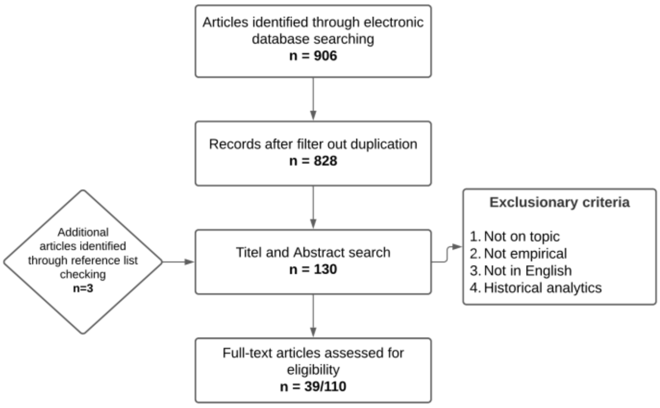

Figure 1. Work-in-progress status of the systematic review

A total of $N = 906$ studies were identified in all six databases. After filtering the duplicates, 828 remained. A title- and abstract search was then carried out, and $N = 130$ potential studies remained. The full-text search is currently in progress. So far, $N = 20$ studies have not been considered to meet the inclusion criteria. A total of $N = 39$ studies were rated as applicable, whereby these also differ again in terms of usefulness. Figure 1 provides an overview of the current status of the systematic review process.

2.4 Extraction Criteria

From the scientific papers that met the inclusion criteria, we are currently extracting information from three distinct areas. These areas include (1) the technical-methodological domain, (2) the emotion-related domain, and (3) the education and learning domain. In the technical-methodological domain, we collect information regarding the selected emotion recognition method, the employed algorithm, and its accuracy. The emotion-related domain is further divided into two sections: 'Number of measured emotions' and 'emotions that are measured'. Here, we focus on determining the number of emotions measured as well as identifying which specific emotions are targeted in the studies. Within the education and learning domain, our interest lies in the type of education context, the derived measures based on emotions, and, ideally, any quantifiable indication of the participants' learning success. We aim to comprehensively analyze and synthesize the relevant findings from the selected scientific papers by organizing the extraction process into these three areas.

3. RESULTS

Various trends can be derived from the studies analyzed so far. Particularly outstanding is that in over 80% of the included studies, the facial emotion recognition (FER) method was used to analyze learners' emotions. Occasionally, this method is combined with other procedures to achieve a possible improvement in recognition. Table 1 provides an overview of the different combinations. In addition, studies report the multimodal approaches for affective computing with more than two techniques.

Table 1. Facial emotion recognition (FER) combinations

Combination with FER	*Reference*
Electroencephalography (EEG)	Gogia et al. (2016)
Voice-Emotion-Recognition	Boumiza et al. (2017)
Mouth- or Eye-detection	Wang & Ding (2012); Liu, Tao & Gui (2019); Zhu et al. (2007)
Text Analytics	Huang et al. (2019)
Feedback from participants	Farin et al. (2015)
Mouse dynamics	Li et al. (2016)
Multimodal	Yang et al. (2019); Anolli et al. (2005)
Gesture	Sarrafzadeh et al. (2007)

Furthermore, some techniques extract just parts from the face for emotion recognition. Such an approach is used by Chen et al. (2017), where only the intensity of the smile is measured, while Huang et al. (2019) additionally use the blink rate to assist. Additionally, other emotion recognition technologies are utilized, such as voice emotion recognition, text emotion recognition, or multimodal technologies. One commonly used method is text analysis to create sentiment maps from historical data. However, text analytics is also occasionally used in real-time to measure emotions in educational contexts (Clarita et al., 2018; Tian et al., 2011). An example of the application of text emotion recognition in online learning environments is verifying emotions during interaction with an auto-tutor. By recognizing the learner's emotions, the auto-tutor can react accordingly and take appropriate action (Tian et al., 2011). A similar approach is taken by Seknedy, Fawzi, and Egypt (2021), by proposing a voice emotion recognition for emotion measurement in Human-Computer Interaction. In addition, the systematic search has revealed some other potential methods that have been rarely utilized thus far. These methods include measuring body language (Nguyen, Chen & Rauterberg, 2010), employing predictive questionnaires based on machine learning (ML) (Upadhyay & Kelkar, 2018), and capturing emotions through mouse and keyboard input (Lim, Ayesh & Stacey, 2023). There are also multimodal approaches that combine more than two different measurement methods. For instance, Huang et al. (2019) suggest measuring various combinations involving physiological factors like heart rate, skin conductance, or skin amplitude.

Based on the current state of data analysis of this systematic review, there is a clear trend regarding the emotions measured. In his foundational work in 1999, Paul Ekman identified six basic emotions (happiness, sadness, disgust, fear, surprise and anger). A significant number of the papers covered so far measure these emotions using AI emotion recognition technologies. Incorporating additional emotions, Geng, Meng, and Dou (2022), as well as Wang, Xu, and Niu (2020), include 'contempt' and 'neutral' in their studies. Table 2 presents a comprehensive overview of the measured categories, emotions, or corresponding variables utilized by the measurement technologies.

Table 2. Used emotions

Category/Emotion	Quantity	Reference
Anger; Disgust; Fear; Happiness; Sadness; Surprise	5	Sarrafzadeh, Alexander, Dadgostar, Fan & Bigdeli (2007); Pise, Vadapalli & Sanders (2020); Vivek & Guddeti (2015); Yang, Zeng, Xue & Guo (2019); Huang, Jayaraman, Morshed, Blackburn, Redpath, Guerney, Shahid & Mui (2019); Asaju & Vadapalli (2021)
Anger; Disgust; Fear; Happiness; Sadness; Surprise & Neutral	4	Grewe & Hu (2019); Llanda (2019); Pooliyadda, Peiris, Kurukulasuriya, Hettiarachchi & Hewagamage (2022); Seknedy, Fawzi & Egypt (2021) (CaFe)
Anger; Disgust; Fear; Happiness; Sadness; Surprise, Contempt & Neutral	3	Wang, Xu, Niu (2020); Geng, Meng & Dou (2022)
Positive and negative	4	Clarizia, Colace, De Santo, Lombardi, Pascale & Pietrosanto (2018); Faria, Almeida, Martins, Gonçalves & Figueiredo (2015); Nguyen, Chen, Rauterberg (2010); Liu, Tao & Gui (2019)

Furthermore, variations of the basic emotions are frequently analyzed in the literature (Seknedy, Fawzi & Egypt, 2021; Zhu, Zhou, Jingfang, Cai & Nie, 2007; Anolli et al., 2005), as well as specific emotions such as disgust (Tian, An, Zheng, Qui, Zheng & Yang, 2011; Qi-rong, 2010) or frustration (Leong, 2020; Annoli et al., 2005). Besides the basic emotions, boredom is the most frequently studied, followed by frustration, stress, and joy, which are occasionally queried. In some studies, emotions are included or transformed into academic emotions. These emotions appear during achievement activities or assessments (Pekrun & Stephens, 2012). For example, Asaju and Vadapalli (2021) transformed basic emotions into academic emotions, such as boredom, confusion, frustration, and engagement. Further work has considered self-confidence (Upadhyay & Kelkar, 2018) and negative surprise (Tian et al., 2011) as academic emotions in addition to those mentioned above.

Only a few specific measures are mentioned to ensure a transfer between the IT system and an increase in learning. These measures can be categorized into three main fields of action: learner adaptation, improving the learning experience, and adjusting teaching strategies.

Measures for the adaptation of the learner.

Learners can proactively initiate actions to enhance their learning experience by cultivating awareness of their emotional state. For instance, Jaiswal, Nair, and Sahoo (2022) propose the automatic notification of learners about their attention level through online messages. Alternatively, if a decline in attention is observed, the system could consider options like automatically pausing or providing alternative resources (Gogia et al., 2016). In the event of frustration, learners may be encouraged to review the material (Llanda, 2019) or receive additional information for support (Grewe & Hu, 2019). Detecting signs of stress, the emotion recognition system can display a message such as 'Take a break or stay tuned,' as suggested by Yang and colleagues (2019). Teaching agents may evaluate this comprehensive information about the emotional state, tailor feedback to the learner, and provide advice regarding their current learning process (Qi-rong, 2010). A specific focus could be placed on measuring task difficulty, fatigue or exhaustion levels, and the degree of engagement. Concrete measures can be derived from this data, enabling adjustments to the pace of learning. Additionally, identifying whether a course participant requires further examples or content can be accomplished (Clarizia et al., 2018).

Measures to improve the learning experience.

Visual adaptation of the interface or content can significantly enhance well-being during the learning process (Al-Omair & Huang, 2019). Additionally, it is essential to consider variations and individual preferences in learning methods, which can be identified through measures like capturing the degree of perceived effort (Huang et al., 2019) or the cognitive demands on the learners (Faria et al., 2015). To further improve the learning experience, it is advisable to minimize the use of long texts when learners experience stress (Lim, Ayesh & Stacey, 2023). Excessive typing of long texts should also be avoided as it can lead to learner demotivation (Lim, Ayesh & Stacey, 2023). Implementing these adaptive measures can create a more positive and engaging learning environment for the students.

Measures to adapt the teaching strategy.

Additionally, providing real-time or near-time feedback to teachers can be a valuable means of enhancing the overall learning experience for students. Huang and Bo (2023) propose adapting the pedagogical strategy based on the learner's emotional state. This adaptive approach may involve modifying the teaching rhythm (Qi-rong, 2010) or adjusting the learning speed (Al-Omair & Huang, 2019) to suit the learner's needs and emotions better. Furthermore, automatic adjustment based on the learner's cognitive level presents another promising opportunity. If the cognitive level appears to be low, transitioning to a video mode can be beneficial. And if confusion persists, switching to a demonstration mode might be more effective (Zhu et al., 2007). These adaptive measures not only support teachers but also create a more personalized and optimized learning environment for the students.

Only a limited number of papers provide specific values regarding learning enhancement. For instance, Llanda (2019) conducted a study indicating the effectiveness of an emotion-supported environment. Learners who received additional support during moments of frustration performed 12.26% better than those who did not have access to such tools. Moreover, positive emotions have been shown to be beneficial for learning. A study by Pooliyadda et al. (2022) suggests that positive emotions can enhance the learning process and success. However, it is essential to note that this reference does not mention concrete values of learning improvement. These findings highlight the potential of emotion-supported environments to influence learning experiences and outcomes positively. Nonetheless, more research is required to provide comprehensive and quantifiable data on the overall effectiveness of such approaches.

4. CONCLUSION

It is evident that the subject of emotion measurement in conjunction with online learning environments represents a current and diverse area of research, with various approaches emerging. While much of the work is dedicated to improving emotion recognition algorithms, there is a notable scarcity of studies focusing on concrete measures to enhance the learning experience and outcomes for learners. Initial findings from our systematic review indicate a lack of holistic design in existing online learning environments, despite the evident demand for it. Among the predominant approaches in current research is the utilization of face emotion recognition, likely attributed to its universality (Ekman, 1973), capability to identify complex mental states

(Kaliouby & Robinson, 2004), and feasibility. Most of the mentioned emotion recognition systems primarily use basic emotions, according to Ekman (1973), but often do not offer an in-depth explanation of the specific utility of these selections for the learning process. One potential approach that could help improve the depth of explanation is to transform these basic emotions into the context of academic emotions and performance emotions. In terms of algorithms, Convolutional Neural Networks (CNNs) are widely employed for both face recognition and feature extraction, with ResNets being a notable example (Geng, Meng & Dou, 2022; Pooliyadda et al., 2022; Grewe & Hu, 2019; Huang & Bo, 2023; Asaju & Vadapalli, 2021). Lastly, regarding the third research question, the integration of emotion-based measures for individual learner support appears to be underrepresented in the existing literature. In particular, specific educational interventions for emotional states appear to be few to nonexistent, let alone evidence that they are empirically well supported. Another finding is the existence of twosome research gaps to date. There is a lack of sufficient representation of emotion-based measures for individual learner support, and there is a lack of experimental studies investigating the effectiveness of such support measures. To address this gap, based on the results, we will develop a well-grounded and emotion-based adaptive online tool to measure its effectiveness in learning outcomes.

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