



AFFECTIVE COMPUTING AND EMOTIONAL EDUCATION: A Systematic Review of Emotional Response Inference from Visual Content

MARÍA AUXILIADORA ORDÓÑEZ-JIMÉNEZ ¹

mariaauxiliadora.ordonez@universidadviu.com

¹Universidad Internacional de Valencia, España

KEYWORDS	ABSTRACT
<i>Affective computing</i> <i>Emotional inference</i> <i>Visual content</i> <i>Emotional education</i> <i>Artificial intelligence</i>	<i>Affective AI has established itself as a field focused on inferring emotional responses from visual stimuli, while concern for emotional and affective development occupies a central place in current educational approaches. The aim of this article is to conduct a systematic review focused on understanding how affective computing is applied to infer emotional responses to visual content and to what extent these approaches contribute to students' emotional education. The results highlight the need to develop approaches that take into account not only technological development but also the emotional well-being of the subjects. This consideration is key to ensuring that automated emotional inference will contribute to emotional development in educational contexts.</i>

Recibido: 03/ 05 / 2026

Aceptado: 01/ 09 / 2026

1. Introduction

Interest in the study of emotions has been increasing across multiple scientific fields, especially those that study the symbiosis between technology and learning. Emotions represent a key motivation for developing deep learning, promoting the emotional development of the subject in face-to-face and digital educational contexts (Araya and Espinoza, 2020). Based on this scenario, in which emotions can enhance or inhibit learning processes, a field of study has emerged that focuses on detecting, interpreting, and responding to the emotional states of the subject, through machine learning and artificial intelligence (AI), called affective computing. Affective computing aims to reduce the communication gap between the subject and the computer system itself, using non-verbal language as a reference, to improve the performance of these systems and thus personalise learning (Bosquez et al., 2018).

The number of publications on affective computing in education has increased in recent years, providing results on how affective computing applications are used in the field of education. These studies focus on the domains of learning, with particular emphasis on the emotional regulation required to maintain commitment and performance in learning. Among the predominant affective measurements is the analysis of facial expressions in order to adequately measure the emotional state of students. However, there are still pedagogical gaps in the interpretation of emotional inferences and their relevance to the promotion of emotional well-being (Yuvaraj et al., 2025).

The support available to students has undergone a transformation with the integration of technology and artificial intelligence into educational environments, especially those designed to address students' learning difficulties. In this sense, the role of this technology is focused on recognising emotions to create a more inclusive learning environment and promote improved student performance. Integrating artificial intelligence with assistive technology promotes emotional support and meaningful learning (Vistorte et al., 2024).

Visual content such as images, videos, or simulations used in educational contexts act as stimulators of the subject's emotional response. These stimuli are an essential part of improving the facial recognition systems used by affective artificial intelligence (Yu et al., 2024).

Published studies on affective computing in the field of education suggest that there is a clear imbalance between technological advances and their appropriate application from a pedagogical perspective, as they are being used to personalise the learning process but do not contribute significantly to the development of emotional skills (Yuvaraj et al., 2025; Yu et al., 2024).

Against this background, the main objective of this study is to conduct a systematic review of the existing literature that addresses how affective computing has been applied to the inference of emotional responses, focusing on visual content. In turn, it aims to explore how these contributions benefit the field of education and even the possible limitations found with regard to the development of the subject's emotional well-being. To this end, the review is conducted in accordance with the PRISMA protocol, identifying approaches developed and their possible pedagogical integration. The originality of the study lies in foregrounding the emotional and educational perspective, aiming to contribute a reflective and critical synthesis of affective computing.

2. Conceptual framework

2.1. *Emotion and learning*

Integrating emotional development into learning processes represents an educational model that does not focus solely on academic achievement; rather, it pursues students' holistic development by considering factors such as motivation, engagement in learning, and emotional self-regulation.

The emotions that students experience are related to the perception or value they attribute to the tasks and results they obtain. In this sense, emotions such as anxiety, boredom, or enjoyment influence student learning and involvement (Pekrun et al., 2011).

Emotional regulation is related to different dimensions of the individual, influencing behaviour, cognition and interpersonal relationships (Mendieta and Martínez, 2015). Implementing emotional regulation strategies is therefore linked to higher levels of personal and academic well-being, especially in technology-mediated environments (Gross, 2015).

Emotional education involves incorporating pedagogical methods that promote reflective practices that not only encourage collaboration among students but also promote self-regulation processes and

the development of empathy in face-to-face and digital settings (Sarango et al., 2025). Therefore, emotional development contributes to improving student coexistence, which in turn has an impact on subjective well-being. In technology-mediated environments, it is essential to consider the role of emotions from a pedagogical perspective that encourages reflective and formative processes (Durlak et al., 2011). Technology should contribute to the formation of attitudes, the generation of feelings and emotions, and the modulation of behaviour, fostering the development of students' personalities (Rodríguez et al., 2017).

2.2. Affective computing in education

Affective computing aims to achieve recognition, interpretation and response to emotional states, taking into account advances in learning. To understand the benefits offered by artificial intelligence, it is essential to recognise its main components (Molina Saltos et al., 2024). Among the components we find:

- Neural networks: Models that simulate brain function, consisting of nodes that serve to process information and generate responses.
- Deep learning: Machine learning that processes large amounts of information.
- Machine learning: Systems that learn from data to perform tasks without requiring explicit, task-specific programming.

In educational contexts, affective computing has been used mainly for the design of learning spaces following the perspective of technological and emotional education, promoting meaningful learning. It recognises the importance of emotions in the subject's cognitive processes such as decision-making, interaction, or perception, helping to improve learning in human-machine interaction. In this sense, affective systems are capable of recognising emotional states by measuring facial expressions, posture and voice; they process this information using algorithms and generate emotional responses (Rodríguez-Arboleda et al., 2017).

The influence of affective computing should also be considered an ethically sensitive issue because, although it can offer benefits for learning, it also has limitations, providing an impoverished representation of human affective states and even becoming addictive for those who use the technology (Devillers and Cowie, 2023).

3. Method

This section describes the method followed in conducting the study, determining the research objective and the phases for rigorously carrying out the systematic review.

3.1. Objective

The main objective of this study is to conduct a systematic review of the existing literature that addresses how affective computing has been applied to the inference of emotional responses, focusing on visual content. In turn, it aims to explore how these contributions benefit the field of education and even the possible limitations found with regard to the development of the subject's emotional well-being.

3.2. Procedure

The systematic review procedure follows the guidelines set out in the PRISMA protocol to ensure transparency and traceability of results. This procedure has followed four sequential stages, namely:

1. Definition of the research question and objectives.
2. Selection of databases and establishment of eligibility criteria.
3. Design and implementation of the search strategy.
4. Study selection and screening process.

Each of these stages allows for the identification, evaluation, and synthesis of available evidence on emotional inference based on visual content from a pedagogical perspective.

3.3. Stage 1: Definition of the research question and specific objectives

The systematic review is guided by the following main research question:

How is affective computing applied to the inference of emotional responses to visual content, and to what extent do these approaches contribute to students' emotional education?

Based on this general question, the specific objectives defined are:

1. To identify the visual content used in automated emotional inference.
2. Analyse the methodological approach followed in the selected studies.
3. To examine the integration of pedagogical perspectives on emotional education in the analysed literature.
4. To identify limitations and opportunities for the educational integration of affective computing.

3.4. Stage 2: Databases and eligibility criteria

In line with the objectives set out in the study, scientific databases with high quality standards have been selected for their interdisciplinary coverage, such as: Scopus, Web of Science, Proquest and Dialnet.

The eligibility criteria applied are as follows:

Inclusion criteria:

- Articles published between 2020 and 2026.
- Empirical articles written in Spanish and English.
- Open access articles, available in full text.
- Articles focused on automated emotion inference using artificial intelligence.
- Articles on the use of visual content as a stimulus or data source.
- Articles related to learning environments.

Exclusion criteria:

- Articles that do not address automated emotional inference.
- Articles that address emotion without a technological component.
- Articles that do not include visual content as an element of analysis.

3.5. Stage 3: Search strategy

At this stage, the terminology used as keywords for the literature search is defined, both in Spanish and English. Boolean operators have been used to connect search terms related to affective computing, emotional inference, visual content, and education. Specifically, "AND" and "OR" have been used.

The search equation used in English was as follows:

("Affective computing" OR "Emotion recognition" OR "Emotion inference") AND ("Visual content") AND ("Education" OR "Emotional education").

The search equation used in Spanish was as follows:

("Computación afectiva" OR "Reconocimiento de emociones" OR "Inferencia de emociones") AND ("Contenido visual") AND ("Educación" OR "Educación emocional").

The initial search results identified 397 records, distributed as follows:

- Proquest: 391 records.
- Web of Science: 3 records.
- Scopus: 3 records.
- Dialnet: 0 records.

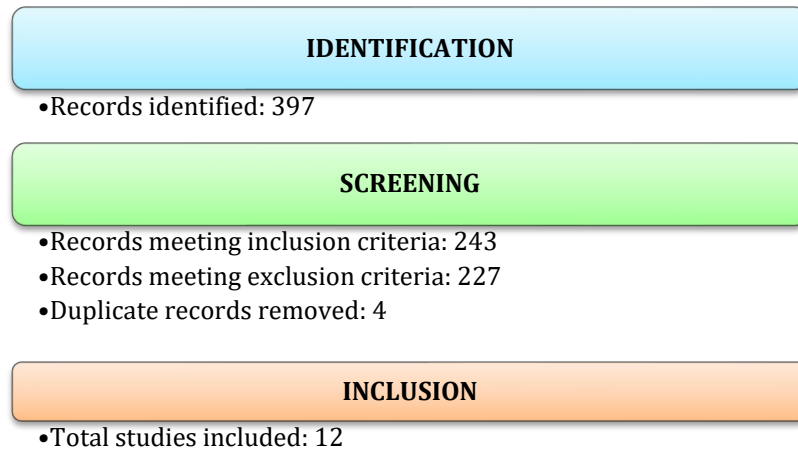
3.6. Stage 4: Selection process

Following the defined search strategy, and taking the initial records as a starting point, the selection process is carried out in several successive phases in accordance with the PRISMA flow:

1. Identification: 397 records are collected in an initial search.
2. Duplicate removal: after cleaning, titles and abstracts are reviewed.
3. Screening: studies that do not meet the inclusion criteria are excluded.
4. Eligibility assessment: the full texts of the selected studies are analysed.
5. Final inclusion: 12 studies that fully meet the established criteria are selected, constituting the final corpus of the systematic review.

This entire process is represented graphically by the PRISMA flow diagram, included as Figure 1, showing the phases followed.

Figure 1. Flow chart based on PRISMA



Source: Autor's elaboration, 2026.

Subsequently, a new analysis was performed applying the pre-established exclusion criteria, resulting in 12 articles on which this systematic review focuses.

The methodological approach adopted allows for a transparent systematic review of the current literature, providing a basis for analysis and subsequent discussion of results.

4. Results

The results presented below are derived from the systematic analysis of the articles selected in the review, in accordance with eligibility criteria and the methodological procedure described.

The presentation of results is organised according to the specific objectives defined in the study, offering a structured view of affective computing for the automated inference of emotional responses to visual content in educational contexts.

First, a description of the general characteristics of the included studies is provided, considering the year of publication, the thematic context, and the type of research conducted. Second, an analysis of the type of visual content linked to automated emotional inference is carried out, assessing its methodological approaches. Thirdly, the integration of emotional education in the studies analysed is addressed and, finally, a descriptive synthesis of the limitations and opportunities found is carried out.

4.1. General characteristics of the studies included

Considering the total set of selected studies, an analysis of 12 empirical studies published between 2022 and 2025 is presented, which highlights an emerging research topic on affective computing applied to emotional inference through visual content in educational contexts. Specifically, since 2023, there has been a significant increase in the number of publications, followed by 2025.

The studies analysed cover thematic areas such as psycho-emotional well-being, digital education, subject interaction with technology, and the application of artificial intelligence. In light of the areas identified, pedagogical and technological approaches are considered, confirming the interdisciplinary nature of the field of study.

Methodologically, the studies show diverse designs, including experimental studies, pilot studies, and model validations, reflecting a plurality of approaches to automated emotional inference.

Table 1. Sample analysed by authorship, year, thematic context, and type of study.

CODE	AUTHORSHIP AND YEAR	THEMATIC CONTEXT	TYPE OF STUDY
A1	Ladas et al. (2025)	Creative education / wellbeing	Pilot study
A2	Wafa et al. (2025)	Multimodal analysis	Model validation
A3	Raza Ur Rehman et al. (2025)	Social networks / visual	Review
A4	Wang (2025)	Digital arts education	Experimental
A5	Wang & Lin (2025)	Emotional regulation	Experimental
A6	Joseph & Maheswari (2025)	Smartphone addiction	Experimental
A7	Dias et al. (2024)	Academic Stress	Model application
A8	Das & Malaviya (2024)	Adaptive learning, learning environments	Exploratory
A9	Yuan (2022)	Classification of emotions in the classroom	Experimental
A10	Jeong et al. (2023)	Psychological well-being of students	Feasibility study
A11	Esfandbod et al. (2023)	Speech therapy	Experimental
A12	Laraib et al. (2023)	Infant facial expressions	Experimental

Source: Autor's elaboration, 2026.

4.2. Types of visual content used in automated emotional inference

Addressing the first specific objective of "identifying the visual content used in automated emotional inference," the results show that visual content is the central axis of emotional inference systems, with variations in its nature and functions among the different studies analysed.

When assessing the type of visual content, there is a higher frequency in the analysis of facial expressions, captured through video sequences or static images. These approaches have been used in educational contexts such as the classroom (Yuan, 2022) or in studies particularly focused on childhood (Laraib et al., 2023), as well as in the detection of disruptive behaviours associated with the use of digital technologies (Joseph and Maheswari, 2025). The main source of visual data for emotional inference in these studies is the students' faces.

Video or visual environments characterised by dynamism are incorporated into other studies as a source of multimodal data or emotional stimuli. This approach is presented in studies aimed at analysing large volumes of data, combining images and videos with other modalities for model accuracy (Raza Ur Rehman et al., 2025; Wafa et al., 2025).

Likewise, proposals focused on interactive virtual environments are identified, such as digital and creative art platforms (Ladas et al., 2025) or systems aimed at the development of arts education (Wang, 2025), placing visual content as a source of data and an element that generates emotional experiences.

It should be noted that, although the studies analysed use visual content as the main source of data for emotional inference, there are works that integrate the visual dimension implicitly, linked to interface design (Das & Malaviya, 2024; Dias et al., 2024).

Table 2. Sample analysed by type of visual content.

TYPE OF VISUAL CONTENT	STUDIES
Facial expressions (image/video)	Joseph & Maheswari (2025); Laraib et al. (2023); Yuan (2022)
Multimodal images and videos	Raza Ur Rehman et al. (2025); Wafa et al. (2025)
Creative/artistic visual environments	Ladas et al. (2025); Wang (2025)
Audiovisual interfaces (visual + music)	Wang & Lin (2025)
Social robotics with visual perception	Esfandbod et al. (2023); Jeong et al. (2023)
Implicit visual content / secondary visual interface	Das & Malaviya (2024); Dias et al. (2024)

Source: Autor's elaboration, 2026.

4.3. Predominant methodological and technological approaches

In response to the second specific objective, "to analyse the methodological approach followed in the selected studies," these studies present an approach based on deep learning. In other words, they rely on artificial intelligence systems designed to analyse images and videos in order to infer emotional states. Along these lines, the approaches are based on the automated analysis of facial expressions or directly observable behaviours within the digital environment.

Complementarily, some studies combine this visual analysis with text and audio information in order to improve the performance of these systems in real contexts (Raza Ur Rehman et al., 2025; Wafa et al.,

2025). These studies prioritise the performance of the model's own, leaving the pedagogical interpretation of the results they obtain in the background.

Other studies adopt an interactive approach, reflecting the integration of emotional inference into educational platforms, social robots focused on well-being, or technological development itself in real-world contexts (Dias et al., 2024; Jeong et al., 2023; Ladas et al., 2025).

Table 3. Sample analysed by methodological approach

METHODOLOGICAL APPROACH	MAIN CHARACTERISTICS	STUDIES
Deep learning-based visual recognition	Automated image/video analysis, facial expressions	Joseph & Maheswari (2025); Laraib et al. (2023); Yuan (2022)
Multimodal approaches	Integration of visual data with text, audio, or other signals	Raza Ur Rehman et al. (2025); Wafa et al. (2025)
Affective interactive systems	Educational platforms, audiovisual interfaces, emotional regulation	Ladas et al. (2025); Wang & Lin (2025); Wang (2025)
Social robotics with emotional inference	Human-robot interaction with visual perception and expression	Esfandbod et al. (2023); Jeong et al. (2023)
Wearable technologies and neurofeedback	Emotional monitoring and visualisation systems	Dias et al. (2024)
Conceptual-applied approaches in adaptive learning	Integration of affective computing into educational models	Das & Malaviya (2024)

Source: Autor's elaboration, 2026.

4.4. Integration of emotional education in the studies analysed

Regarding the third specific objective, "to examine the integration of pedagogical perspectives of emotional education in the analysed literature," the analysis suggests a heterogeneous integration of emotional education in studies that apply affective computing to the inference of emotional responses to visual content. This dimension is addressed by considering three categories: explicit integration, implicit integration, and absence of pedagogical integration of emotional education.

Studies that explicitly incorporate objectives related to emotional development, emotional/psychological well-being, and/or emotion regulation identify automated emotional inference as a means for pedagogical processes focused on developing resilience, emotional self-regulation, or promoting well-being in educational contexts. This approach has been demonstrated in the use of platforms aimed at emotional development (Ladas et al., 2025), in interactive systems for stress management (Wang and Lin, 2025), and in robotics-mediated interventions aimed at promoting the psychological well-being of university students (Jeong et al., 2023).

Among the studies that present an implicit integration of emotional education, it is noteworthy that emotional inference is used for content adaptation or the personalisation of learning experiences, without establishing an explicit pedagogical framework. The research that demonstrates this is based on arts education through visual systems (Wang, 2025), adaptive learning based on affective computing (Das and Malaviya, 2024), and neurofeedback in academic contexts (Dias et al., 2024).

Finally, studies are identified whose main objective is not emotional education, but rather the development or validation of emotional inference models, and even human-technology interaction. The educational dimension of these works appears contextually, but without any reflection on their contribution to emotional development or (Esfandbod et al., 2023; Joseph y Maheswari, 2025; Laraib et al., 2023; Raza et al., 2025; Wafa et al., 2025; Yuan, 2022).

Overall, the results show that, although affective computing is applied in educational contexts, the true pedagogical integration of emotional education is variable, depending largely on the focus and objectives of the research.

4.5. Descriptive synthesis of limitations and opportunities for the educational integration of affective computing

Following the fourth specific objective, "to identify limitations and opportunities for the educational integration of affective computing," limitations and opportunities related to affective integration applied to emotional inference in response to visual content were detected.

Analysing the limitations present in the studies analysed, there is a notable lack of pedagogical interpretation of the emotional data obtained, with a particular emphasis on the importance of the

performance of emotional inference systems. In the absence of pedagogical frameworks to support the proposals, it is difficult to promote the transfer of knowledge to educational fields.

It is important to highlight the opportunities identified in light of the selected studies. The results demonstrate the potential of affective computing for the socio-emotional development of students, using interactive approaches based on the analysis of visual content. The promotion of emotional regulation can be carried out through creative emotional *feedback* platforms, as proposed by some of these studies.

Considering the context and population of the studies, there is a possibility of replicating the use of the proposed tools, following a defined pedagogical structure. The results, therefore, reveal opportunities to improve technological approaches for the emotional development of the subject.

5. Discussion

The main objective of this study was to conduct a systematic review of the existing literature addressing how affective computing has been applied to the inference of emotional responses, focusing on visual content. In turn, it sought to explore how these contributions benefit the field of education and even the possible limitations found with regard to the development of the subject's emotional well-being.

In light of the results analysed, there is evidence of an emerging field focused on the development of affective computing, with the aim of perfecting facial analysis systems, as well as images and videos, inferring emotional states.

Visual content has been the focus of emotional inference systems, representing the main source of data for detecting emotions and the input for generating emotional experiences. However, the results show that there is a clear prioritisation of model performance without delving into the pedagogical interpretation of the inferences generated. Therefore, this technical perspective may contribute to a purely computational view of emotion, ignoring the educational component.

Visual content as an emotional stimulus highlights the affective potential that we can detect in virtual environments, thus generating meaningful emotional experiences for students (Mayer, 2002). This potential is realised as long as there is appropriate integration of pedagogical proposals.

Among the most notable findings of this review is the limited pedagogical integration of emotional education in the studies analysed. While it is true that some studies incorporate it in relation to psycho-emotional well-being objectives, a significant number of studies address emotion mainly in a functional way. There is a risk of instrumentalising emotion in training environments guided by digital technologies, without promoting true reflection on the part of students (Gross, 2015; Pekrun, 2006).

Emotional education involves the recognition of emotions, as well as their understanding, regulation and contextualisation, variables that are not usually considered in the technological approaches that have been analysed.

From an educational perspective, the results highlight that affective computing linked to visual content can support processes of emotional well-being and personalisation of the learning process for students. Opportunities can be found to promote educational designs that include the appropriate pedagogical integration of affective computing.

6. Conclusions

After analysing how affective computing has been applied to the inference of emotional responses, focusing on visual content, and exploring how these contributions benefit the field of education, it is concluded that affective computing is currently an emerging field of great interest.

Overall, the study offers a critical and pedagogical assessment of the application of affective computing to the field of education, emphasising the need to generate approaches that take into account not only technological development but also the emotional well-being of the subjects. This consideration is key to ensuring that automated emotional inference will contribute to emotional development without focusing exclusively on technical aspects.

References

- Araya, S., & Espinoza, L. (2020). Contributions from neuroscience to the understanding of learning processes in educational contexts. *Purposes and representations*, 8 (1), e312.
- Bosquez, V., Sanz, C., Baldassarri, S. S., Ribadeneira, E., Valencia, G., Barragán Arnal, R., Camacho, Á., Shauri Romero, J., & Camacho Castillo, L. A. (2018). Affective computing: Emotions, technologies and their relationship with virtual education. *Talents Research Journal*, 5(1), 94–103.
- Das, A. & Malaviya, S. (2024). AI (Artificial Intelligence)-Enabled Affective Computing in Adaptive Learning: An Integrated Approach to Learning. 20. 30.
- Devillers, L., & Cowie, R. (2023). Ethical considerations on affective computing: An overview. *Proceedings of the IEEE*, 111(10), 1445–1458
- Dias S.B., Jelinek H.F., & Hadjileontiadis L.J. (2024). Wearable neurofeedback acceptance model for students' stress and anxiety management in academic settings. *PLoS One*, 24 October;19(10):e0304932. doi: 10.1371/journal.pone.0304932.
- Durlak, J. A., Weissberg, R. P., Dymnicki, A. B., Taylor, R. D., & Schellinger, K. B. (2011). The impact of enhancing students' social and emotional learning: A meta-analysis of school-based universal interventions. *Child Development*, 82(1), 405–432. <https://doi.org/10.1111/j.1467-8624.2010.01564.x>
- Esfandbod, A., Rokhi, Z., Meghdari, AF et al. (2023). Use of an emotional robot capable of lip synchronisation in robot-assisted speech therapy sessions for children with language disorders. *Int J of Soc Robotics* 15, 165–183 (2023). <https://doi.org/10.1007/s12369-022-00946-2>
- Gross, J. J. (2015). Emotion regulation: Current status and future prospects. *Psychological Inquiry*, 26(1), 1–26. <https://doi.org/10.1080/1047840X.2014.940781>
- Jeong, S., Aymerich-Franch, L., Arias, K. et al. (2023). Implementation of a positive psychology robotic coach to improve the psychological well-being of university students. *User Model User-Adap Inter* 33, 571–615. <https://doi.org/10.1007/s11257-022-09337-8>
- Joseph, C., Maheswari, P.U. (2025). Detection and prevention of smartphone addiction based on facial emotions using deep learning and video-based learning. *Sci Rep* 15, 18025. <https://doi.org/10.1038/s41598-025-99681-7>
- Ladas, A. I., Katsoridou, C., Gravalas, T., Klados, M. A., Stravoravdi, A. S., Tsompanidou, N., Fragkedaki, A., Bista, E., Chorafta, T., Petrovic, K., Vlotinou, P., Tsiakiri, A., Papazisis, G., & Frantzidis, C. A. (2025). Creativity and Resilience Through Arts, Technology and Emotions: A Pilot Study on the Feasibility and Validity of the CREATE Platform. *Brain Sciences*, 15(11), 1171. <https://doi.org/10.3390/brainsci15111171>
- Laraib, U., Shaukat, A., Khan, R. A., Mustansar, Z., Akram, M. U., & Asgher, U. (2023). Recognition of Children's Facial Expressions Using Deep Learned Features. *Electronics*, 12(11), 2416. <https://doi.org/10.3390/electronics12112416>
- Mayer, R. E. (2002). *Multimedia learning principles*. Learning and Instruction.
- Mendieta, F. J., & Martínez, A. (2015). Emotional regulation and presence in adolescent relationships. *Divulgare Scientific Bulletin of the Actopan Higher School*, 2(4).
- Molina, L., Guerrero, R., Bravo, B., & González, A. (2025). Artificial Intelligence: most widely used trends in education and medical simulations. *Social Development Studies: Cuba and Latin America*, 13(1), 121–133.
- Pekrun, R. (2006). The control-value theory of achievement emotions. *Educational Psychology Review*, 18(4), 315–341. <https://doi.org/10.1007/s10648-006-9029-9>
- Pekrun, R., Goetz, T., Frenzel, A. C., Barchfeld, P., & Perry, R. P. (2011). Measuring emotions in students' learning and performance: The Achievement Emotions Questionnaire (AEQ). *Contemporary Educational Psychology*, 36(1), 36–48. <https://doi.org/10.1016/j.cedpsych.2010.10.002>
- Raza Ur Rehman, H.M., Saleem, M., Jhandir, M. et al. (2025). Detecting hate in diversity: A multilingual mixed-code analysis study of images and videos. *J Big Data* 12, 109. <https://doi.org/10.1186/s40537-025-01167-w>
- Rodríguez, V. M., Gallar, Y., & Barrios, E. A. (2017). Theoretical considerations on affective computing in the teaching-learning process in higher education. *CienciAmérica*, 6(3), 170–175.

- Rodríguez-Arboleda, V., Gallar-Pérez, Y., & Barrios-Queipo, E. (2017). Theoretical considerations on affective computing in the teaching-learning process in higher education. *CienciAmérica*, 6(3).
- Sarango, M. P., Calero, A.C., Ortiz, K. A., Morocho, M., & Ortiz, I. L. Á. (2025.). The socio-emotional approach to improving learning: An experience from innovation. *Prosperus*, 2, 1074-1093.
- Vistorte, A. O. R., Deroncele-Acosta, A., Ayala, J. L. M., Barrasa, A., López-Granero, C., & Martí-González, M. (2024). Integrating artificial intelligence to assess emotions in learning environments: A systematic literature review. *Frontiers in Psychology*, 15, Article 1387089. <https://doi.org/10.3389/fpsyg.2024.1387089>
- Wafa, A.A., Eldefrawi, M.M., & Farhan, M.S. (2025). Advances in multimodal emotion recognition in big data through rapid engineering and deep adaptive learning. *J Big Data* 12, 210 <https://doi.org/10.1186/s40537-025-01264-w>
- Wang, C.M., & Lin, C.H. (2025). Design of an Interactive System by Combining Affective Computing Technology with Music for Stress Relief. *Electronics*, 14(15), 3087. <https://doi.org/10.3390/electronics14153087>
- Wang, Y. (2025). An AI-based personalised recommendation system for simulation-based digital media arts education. *International Journal of Computer-Mediated Games and Simulations (IJGCMS)*, 17 (1), 1-15. <https://doi.org/10.4018/IJGCMS.396267>
- Yu, S., Androsov, A., Yan, H., & Chen, Y. (2024). Bridging computer and education sciences: A systematic review of automated emotion recognition in online learning environments. *Computers & Education*, 220, 105111. <https://doi.org/10.1016/j.compedu.2024.105111>
- Yuan, Q. (2022). Research on an emotion recognition algorithm in the classroom based on visual emotion classification. *Computational Intelligence and Neuroscience*, 6453499, 10 pp. <https://doi.org/10.1155/2022/6453499>
- Yuvaraj, R., Mittal, R., Prince, A. A., & Huang, J. S. (2025). Affective computing for learning in education: A systematic review and bibliometric analysis. *Education Sciences*, 15(1), 65. <https://doi.org/10.3390/educsci15010065>