



Emotions and Technology in Education: a Review Focused on Motivation

*Emoções e Tecnologia na Educação: uma Revisão com Foco na
Motivação*

*Emociones y tecnología en la educación: una revisión centrada
en la motivación*

AUTOR:

Hernan Isaac Ocana Flores

School of Information Technology, The University of Queensland, Brisbane
Australia

kaliman.hernan@gmail.com

<https://orcid.org/0000-0001-6258-3828>

Fecha de recepción: 2025-02-08

Fecha de aceptación: 2025-04-14

Fecha de publicación: 2025-04-24

ABSTRACT

This study analyzes the impact of emotional intelligence on motivation, subjective well-being, academic burnout, and the use of affective technologies within human-computer interaction (HCI) in these settings. Through a systematic literature review, the study explores the relationships between emotions, educational technologies, and academic performance, highlighting the importance of considering the emotional dimension in the design of learning environments. The author bases a strong postulate on recent findings on the educational and psychological space that showed that students with higher levels of emotional intelligence exhibit greater intrinsic motivation, lower academic burnout, and higher levels of subjective well-being. At the same time, how technologies allow the possibility for pedagogical and psychological strategies to be adapted improving the personalization of learning and therefore aiding to a desired educational performance.

KEYWORDS: Emotional intelligence; affective technologies; human-computer interaction; motivation; educational ethics.



RESUMO

Este estudo analisa o impacto da inteligência emocional na motivação, no bem-estar subjetivo, no esgotamento acadêmico e no uso de tecnologias afetivas na interação humano-computador (IHC) nesses contextos. Por meio de uma revisão sistemática da literatura, o estudo explora as relações entre emoções, tecnologias educacionais e desempenho acadêmico, destacando a importância de considerar a dimensão emocional no design de ambientes de aprendizagem. O autor baseia-se em fortes postulados em descobertas recentes no âmbito educacional e psicológico, que demonstraram que alunos com maiores níveis de inteligência emocional apresentam maior motivação intrínseca, menor esgotamento acadêmico e maiores níveis de bem-estar subjetivo. Ao mesmo tempo, analisa como as tecnologias permitem a adaptação de estratégias pedagógicas e psicológicas, melhorando a personalização da aprendizagem e, portanto, contribuindo para o desempenho educacional desejado.

PALAVRAS-CHAVE: Inteligência emocional; tecnologias afetivas; interação humano-computador; motivação; ética educacional.

RESUMEN

Este estudio analiza el impacto de la inteligencia emocional en la motivación, el bienestar subjetivo, el agotamiento académico y el uso de tecnologías afectivas en la interacción persona-ordenador (HCI) en estos entornos. A través de una revisión sistemática de la literatura, el estudio explora las relaciones entre las emociones, las tecnologías educativas y el rendimiento académico, destacando la importancia de considerar la dimensión emocional en el diseño de entornos de aprendizaje. El autor basa un sólido postulado en hallazgos recientes en el ámbito educativo y psicológico que demuestran que los estudiantes con mayores niveles de inteligencia emocional presentan mayor motivación intrínseca, menor agotamiento académico y mayores niveles de bienestar subjetivo. Al mismo tiempo, analiza cómo las tecnologías permiten adaptar las estrategias pedagógicas y psicológicas para mejorar la personalización del aprendizaje y, por lo tanto, contribuir al rendimiento educativo deseado.

PALABRAS CLAVE: Inteligencia emocional; tecnologías afectivas; interacción persona-ordenador; motivación; ética educativa.

1. INTRODUCTORY FRAMEWORK

1.1 Contextualizing Emotion in Educational Technologies

Traditional methods for education had often overlooked the role of human emotion especially as external factors to the cognitive process (Sarnou & Sarnou, 2023). However, during the last decade with the raise of technology and development of mental models through in which the users perceive and interact with it had led to the establishment of HIC Human Computer Interaction (Ocaña et al., 2024; Luna et al., 2025). Alongside with the raise of new technological applications that had aid various sectors such as is education is worth mentioning that the emotions have a direct impact over attention, memory,

motivation and self-check process, key elements for an effective learner in the digital age (Villamarín et al., 2023).

Thus, this paper presents an overview not only for HCI and emotional learning but also investigates emotional intelligence. This is defined by Zhao et al. (2022) as the capacity to self-regulating the internal and external emotions. The purpose of this focus is that has been identified as one of the variables of the academic performance. (Lee et al., 2022; Pacheco-Mendoza et al., 2023; Alenezi, 2024).

1.2 Human-Computer Interaction as a Framework for Emotional Responsiveness

Previous studies have shown that emotion-sensitive technologies possess methodological challenges (McStay, 2020; Roemmich & Andalibi, 2021; Härting et al., 2021). At the methodological level, there is a fragmentation of knowledge that is derived from the multiplicity of approaches (Flores, 2025) for example, engineering, psychology, pedagogy. Therefore, both technological and psychological studies have opted for systematic reviews to build more integrated theoretical frameworks (Ding & Zou, 2024). Human-computer interaction is no longer confined to usability alone but has expanded to encompass the quality of user experience (Nicolescu & Tudorache, 2022; Kivijärvi & Pärnänen, 2023), in different levels (Guallichico et al., 2023; Ocaña et al., 2022) and subjects (Bazurto Palma, & Ocaña Garzón, 2023).

According to Kim et al. (2022), affective responses play a crucial role in shaping behavior, fostering trust, and sustaining user engagement. Therefore, developing emotion recognition functionalities enables organizations to more accurately analyze both user interaction behaviors and learners' emotional states (Flores, 2023). Researchers also suggest that such systems possess real-time adaptive capabilities, allowing for dynamic adjustments in content pacing and feedback intensity, tailored to the emotional and cognitive conditions of each individual (Kaklauskas et al., 2022; Liu & Yin, 2024; Glickman & Sharot, 2025).

Similar models in emotion recognition technology can also be employed to enhance learners' self-regulated learning capacity, support cognitive processing, and minimize distractions (Chen et al., 2024; Ngo et al., 2024; Shi, 2025). Thereby promoting the development of more responsive educational environments and advancing the modes of interaction within broader social contexts.

1.3 Literature Review

Originating from the control-value theory of achievement emotions, Pekrun (2024) proposed the hypothesis that learners' appraisals of task control and value directly influence the formation of emotions, thereby impacting core cognitive processes such as attention, motivation, and memory. This theoretical model

continues to serve as a foundational framework for contemporary research on affective learning across diverse educational contexts, including human-computer interaction systems (Flores & Luna, 2024), Yin et al., 2024; Namaziandost & Rezai, 2024; Yuvaraj et al., 2025).

A prominent line of empirical research in this domain involves the application of Intelligent Tutoring Systems (ITS) that adapt instructional strategies based on learners' emotional states (Lin et al., 2023). Systems such as *AutoTutor* and *Affective AutoTutor* incorporate multimodal emotion detection technologies through the analysis of facial expressions, linguistic features, and interaction patterns (Fernández-Herrero, 2024; Khediri et al., 2024; Sirisha et al., 2025). These interventions have demonstrated substantial effects, with effect sizes reaching $d \approx 0.8$, which is equivalent to an improvement of nearly one letter grade compared to traditional instructional methods (Chen et al., 2025).

Technical approaches in this domain often integrate computer vision, voice analysis, and physiological sensors (Al-Saadawi et al., 2024; Flores & Luna, 2024), facilitating the advancement of Affective Learning Analytics (Arockia et al., 2025). These tools enable real-time monitoring of fluctuations in learner engagement and emotional states (Aly, 2024), thereby providing educational institutions with additional actionable insights to inform instructional practices.

However, these technological advances come with significant challenges. Emotion recognition models are particularly susceptible to dataset bias, especially when trained on homogeneous populations, which results in inaccurate or unfair predictions in diverse educational settings (Mattioli & Cabitza, 2024; Shah & Sureja, 2025). Moreover, the black box nature of AI systems raises concerns regarding transparency and trustworthiness; when adaptive decisions lack clear explanations, educators often express skepticism about integrating such technologies into real-world educational contexts (Flores, 2023; Salloum, 2024; Chaudhary, 2024; Marey et al., 2024).

Furthermore, a longitudinal study researching similar technological systems mentioned previously was conducted over a period of 2 last decades. In this kind of system, the teaching method changes based on the stimulus found on users adjusting lessons, offering support when they detect frustration or speeding up the pace when they identify boredom (Schmitz-Hübsch, et al, 2022). This adaptive capacity has been shown to significantly improve student comprehension and engagement across different utilization of digital system across in educational settings. This finding is crucial as it demonstrates that the relationship between emotion and performance is highly individual. However, according to Schmitz-Hübsch, et al, (2022) states that not all students learn best under the same emotional conditions, so affective tutoring systems must be able to adapt to individual differences and not respond in a standardized way to frustration,

boredom, or satisfaction. According to Chaudhary et al. (2024), personalizing tutoring based on emotional profile can improve learning effectiveness and help students develop stronger coping strategies.

This correlates with the study by Le et al. (2024) as it provides empirical evidence on the importance of emotional intelligence as a protective factor against academic burnout and as a driver of motivation and subjective well-being. Students with high EI are not only better able to regulate their emotions, but also report greater satisfaction with their academic life and a lower predisposition to emotional exhaustion additionally aligned with the framework for emotional target done by Flores & Luna (2024).

Thus, this study is structured around four key objectives:

1. To identify how emotional intelligence is being used as a predictive or modulating variable in technology-mediated educational environments.
2. To analyze affective educational systems and emotional detection frameworks that integrate psychophysiological and behavioral signals.
3. To explore the relationship between emotions, motivation, academic burnout, and subjective well-being, with an emphasis on university settings.
4. To reflect on the ethical and socio technical risks involved in incorporating emotion-sensitive technologies into teaching and learning processes.

2. METHODOLOGY

2.1 *Scoping literature review*

In the methodology of this study, an in-depth literature search will be positioned as the core strategy of this methodology (Arksey & O'Malley, 2005). This aims at achieving the goal of critically compiling, examining and interpreting the existing information within the academic arena concerning the interrelation between the emotional intelligence, the technologies involved and wellbeing which these would be capable of creating within a setting of education. Thus, according to this way, not only the patterns of evidence can be found but also possible gaps and ethical dilemmas.

2.2 *Search Queries*

The review followed a systematic search protocol across academic databases including ERIC, Scopus, and IEEE:

- "emotion recognition" AND "education" AND "subjective well-being"
- "affective computing" AND "learning"
- "emotion-aware tutoring systems" OR "affective feedback" AND "student engagement"

Inclusion criteria limited studies to those published in the last decade written in English, peer-reviewed, and explicitly addressing emotion recognition in K–12, higher education, or digital learning contexts.

Studies in English and Spanish were included if they met the following conditions:

- Described or evaluated AI systems designed to detect or respond to learner emotion.
- Reported educational applications (e.g., tutoring, learning analytics, classroom tools).
- Provided empirical or validated evidence, either quantitative or qualitative.

Excluded were:

- Studies in therapeutic or clinical psychology unrelated to learning.
- Purely conceptual or editorial articles lacking methodology.
- Applications in entertainment, gaming, or unrelated sectors.

2.3 Data selection

After deduplication in Endnote, data screening and extraction focused on the following elements:

- Type of AI/affective technology used.
- Context of implementation (e.g., online, face-to-face, hybrid).
- Sample demographics, if reported.

2.4 Data analysis

The final review included 21 papers after applying the aforementioned inclusion and exclusion criteria. Thematic analysis was used to derive inductively emerging themes which are reported in the next section.

3. RESULTS

3.1 *Technological Approaches to Emotion Detection in Education*

In this paper the research has shown that correlation between emotion and academic performance is very complicated and largely dependent on individuals than initially thought. The most widely used theoretical perspective is the control-value theory by Pekrun (2024), which sets out that the student perceives the perceived control and value of a task identifies which emotions crop up during learning, which influence the most important cognitive mechanisms of attention, memory, as well as motivation.

Moreover, human centered technologies targeted to emotions such as the previously mentioned *AutoTutor* and *Affective AutoTutor*, have had the capacity to change their teaching methods according to the emotional state the user is being perceive by the system, producing significant increases in understanding and performance of students (Chen et al., 2025; Lin et al., 2023). Multimodal technologies (consist of computer vision, voice analysis, physiological sensors) allow the real-time identification of the changes in the emotional state of students, giving teachers more data to instantaneously modify teaching (Al-Saadawi et al., 2024; Flores & Luna, 2024; Arockia et al., 2025).

However, it is worth mentioning that the collective research suggests that there is an increasing evidence on the effectiveness of affective interventions in user centered educational designs as the aggregate results demonstrate that the effect sizes as the longitudinal studied shown an increase of roughly 2 points, which is the same as an increase of an entire grade improvement as compared to conventional approaches The study conducted by Schmitz-Hübsch et al. (2022) that shows students have better understanding and interest in what they learn with the possibilities of adjusting to their emotional status in the digital systems, whether it is providing assistance in cases of frustration detection or speeding up the lessons in case they become bored.

Additionally, as per usual with emotion detection systems, this requires data to be gathered and in most cases the data collected is live (in the moment the user engages with the system). There's, also worth mentioning that the reliability of the system varies so these systems are not totally independent regardless of their automation, many still have a generalization that could potentially affect certain individuals. For example, when used with culturally diverse communities, training biases in emotion recognition models can lead to erroneous or unjust forecasts (Mattioli & Cabitza, 2024; Shah & Sureja, 2025). The system would require proper iteration therefore the intervention of human computer interaction in which the user center cycle will adapt accordingly through the

variations, eliminating the issue with the black box model, and strengthening the trust among users as teaching staff require clear feedback from the system to justify and adapt their pedagogical adaptations and models (Flores, 2023; Salloum, 2024; Chaudhary, 2024).

Nevertheless, it is required to mention that the discussed systems in this research are declared to be working with focused groups and that not every student learns better when he/she is in the same emotional state. There are types of people who are more likely to be positively affected by the pressure-thriving environments or negative emotions, whereas others have to be placed in weaker positions of emotional charge to work the best. These are also consistent with Chaudhary et al. (2024), who argue that the personalization of learning according to individual emotional profile is instrumental in ensuring the optimal learning process. Affective systems are not supposed to provide pre-designed reactions but acknowledge individualistic emotional pathways of students and respond to them.

3.3. Protective Factor of Emotional Intelligence

The latter study by Le et al. (2024) supplements these findings by introducing the evidence about higher emotional intelligence (EI) control rates of the students and lower burnout risks and more positive emotions about the university experience. EI is a shield against academic stress and a stimulus to long-term motivation and well-being. These findings underline a need to pay attention not only to the real-time tracking of other emotions but also to the deliberate acquisition of socio-emotional skills. Moreover, this solution correlates with the findings of Flores & Luna (2024), who state that developing affective systems has to be incorporated into the ethical and emotionally accountable pedagogical practices, and the emotional control of students in those systems is a clear goal of the learning process, rather than one of the inputs in the technology setting.

3.4. Derived conclusive research points

The combined analysis of the reviewed studies suggests that the effectiveness of affective tutoring systems depends on three key elements:

- Accurate and multimodal detection of emotions in specific scenarios where motivators can be boosted
- The capacity for a personalized education system based on individual differences.
- The integration of emotional development strategies, that aid emotional intelligence, strengthen student autonomy and resilience.

These elements not only optimize adaptive learning but also contribute to the construction of more inclusive, ethical, and emotionally sustainable educational environment.

4. CONCLUSION

This integrated review demonstrates that both emotional intelligence (EI) and affective technologies in education share a central objective: to improve the learning experience from a comprehensive approach that recognizes emotion as an essential component of the educational process. The findings show that students with high levels of EI not only exhibit greater motivation and subjective well-being, but also manage to cushion the effects of academic burnout, thereby improving their performance and satisfaction in the university context.

For their part, emotional detection technologies such as intelligent tutoring systems and affective analysis platforms contribute to personalizing teaching, adapting in real time to students' emotional needs. However, their positive impact is only sustainable if they are integrated into pedagogical models that promote self-regulation, active participation, and student autonomy.

This study confirms that the combination of emotional intelligence, intrinsic motivation, and emotionally responsive technology can enhance not only learning but also students' psychological well-being. However, it cautions that this integration must be carried out critically, responsibly, and with solid ethical principles that guarantee privacy protection and algorithmic transparency.

4.1. Recommendations

This scoping review shows that 2 performative factors: emotional intelligence and affective technologies in learning can be used to have a common objective of enhancing the learning experiences. The results indicate that high-EI students do not only have a high level of motivation and subjective well-being, but also succeed in offsetting academic burnout, which in turn means that these skill sets allows them to perform better and be more satisfied in the university environment. On their part, the emotional recognition tools like the intelligent tutoring systems and affective analysis platforms are also helping in the personalization of teaching, adapting based on real-time emotional requirements of the students.

Nonetheless, their positive effects are only feasible under strict controlled conditions in which they should be incorporated into pedagogical models by the educator that encourage self-regulation, active involvement, and student independence. This research provides a point into supporting the individual's emotional intelligence through the use of technology that can not only improve the learning outcomes but the psychological state of students, as well. However,

it is worth mentioning that such integration should be done in a critical, responsible and strong ethical framework especially in regards to technological use, ensuring that the users involved are aware of which data and performance targets are being used for sustaining the system.

6. CONFLICT OF INTEREST STATEMENT

The author declares no conflicts of interest. No funding or support was received from any organization or entity that could influence the content of this work.

7. AUTHOR'S CONTRIBUTION

Author Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Resources, Software, Validation, Visualization, Writing – original draft, Writing – review & editing

8. REFERENCES

- Alenezi, A. (2024). The effect of emotional intelligence on higher education: A pilot study on the interplay between artificial intelligence, emotional intelligence, and e-learning. *Multidisciplinary Journal for Education, Social and Technological Sciences*, 11(2), 51-77. <https://doi.org/10.4995/muse.2024.21367>
- Al-Saadawi, H. F. T., Das, B., & Das, R. (2024). A systematic review of trimodal affective computing approaches: Text, audio, and visual integration in emotion recognition and sentiment analysis. *Expert Systems with Applications*, 124852. <https://doi.org/10.1016/j.eswa.2024.124852>
- Aly, M. (2024). Revolutionizing online education: Advanced facial expression recognition for real-time student progress tracking via deep learning model. *Multimedia Tools and Applications*, 1-40. <https://doi.org/10.1007/s11042-024-19392-5>
- Arksey, H., & O'Malley, L. (2005). Scoping studies: towards a methodological framework. *International Journal of Social Research Methodology*, 8(1), 19-32. <https://doi.org/10.1080/1364557032000119616>
- Arockia, V. J., Vettriselvan, R., Rajesh, D., Velmurugan, P. R. R., & Cheelo, C. (2025). Leveraging AI and Learning Analytics for Enhanced Distance Learning: Transformation in Education. In *AI and Learning Analytics in Distance Learning* (pp. 179-206). IGI Global Scientific Publishing. <https://doi.org/10.4018/979-8-3693-7195-4.ch008>
- Bazurto Palma, C. J., & Ocaña Garzón, M. (2023). The use of a virtual environment to improve students' Listening skills: a learning analytics approach. *Ciencia Latina Revista Científica Multidisciplinar*, 7(2), 2937-2953. https://doi.org/10.37811/cl_rcm.v7i2.5537
- Chaudhary, G. (2024). Unveiling the black box: Bringing algorithmic transparency to AI. *Masaryk University Journal of Law and Technology*, 18(1), 93-122.
- Chen, J., Mokmin, N. A. M., & Qi, S. (2025). Generative AI-powered arts-based learning in middle school history: Impact on achievement, motivation, and cognitive load. *The Journal of Educational Research*, 1-13. <https://doi.org/10.1080/00220671.2025.2510395>

- Chen, S., Cheng, H., & Huang, Y. (2024). Emotion Recognition in Self-Regulated Learning: Advancing Metacognition through AI-Assisted Reflections. In *Trust and Inclusion in AI-Mediated Education: Where Human Learning Meets Learning Machines* (pp. 185-212). Cham: Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-64487-0_9
- Ding, L., & Zou, D. (2024). Automated writing evaluation systems: A systematic review of Grammarly, Pigai, and Criterion with a perspective on future directions in the age of generative artificial intelligence. *Education and Information Technologies*, 29(11), 14151-14203. <https://doi.org/10.1007/s10639-023-12402-3>
- Fernández-Herrero, J. (2024). Evaluating recent advances in affective intelligent tutoring systems: A scoping review of educational impacts and future prospects. <https://doi.org/10.3390/educsci14080839>
- Flores, H. I. O. (2023). Human computer interaction's insights into the recognition of love: a comprehensive framework. *Tierra Infinita*, 9(1), 228-245. <https://doi.org/10.32645/26028131.1254>
- Flores, H. I. O. (2025). Creating an Adaptive Voice and Language Model Capable of Emotional Response and Self-Profiling to Emulate User Personality. *Ciencia Latina Revista Científica Multidisciplinar*, 9(1), 3454-3471. https://doi.org/10.37811/cl_rcm.v9i1.16093
- Flores, H. I. O., & Luna, A. (2024). AI for Psychological Profiles: Advances, Challenges, and Future Directions. *Ciencia Latina Revista Científica Multidisciplinar*, 8(3), 10592-10609. https://doi.org/10.37811/cl_rcm.v8i3.12221
- Glickman, M., & Sharot, T. (2025). How human-AI feedback loops alter human perceptual, emotional and social judgements. *Nature Human Behaviour*, 9(2), 345-359. <https://doi.org/10.1038/s41562-024-02077-2>
- Guallichico, G., Ocaña, M., Tejada, C., Bautista, C. (2023). Assessing Digital Competence Through Teacher Training in Early Education Teachers. In: Botto-Tobar, M., Zambrano Vizúete, M., Montes León, S., Torres-Carrión, P., Durakovic, B. (eds) *Applied Technologies. ICAT 2022. Communications in Computer and Information Science*, vol 1757. Springer, Cham. https://doi.org/10.1007/978-3-031-24978-5_6
- Härting, R. C., Schmidt, S., & Krum, D. (2021). Potentials of Emotionally Sensitive Applications Using Machine Learning. In *Human Centred Intelligent Systems: Proceedings of KES-HCIS 2020 Conference* (pp. 207-219). Springer Singapore. https://doi.org/10.1007/978-981-15-5784-2_17
- Kaklauskas, A., Abraham, A., Ubarte, I., Kliukas, R., Luksaite, V., Binkyte-Veliene, A., ... & Kaklauskienė, L. (2022). A review of AI cloud and edge sensors, methods, and applications for the recognition of emotional, affective and physiological states. *Sensors*, 22(20), 7824-7824. <https://doi.org/10.3390/s22207824>
- Khediri, N., Ben Ammar, M., & Kherallah, M. (2024). A Real-time Multimodal Intelligent Tutoring Emotion Recognition System (MITERS). *Multimedia Tools and Applications*, 83(19), 57759-57783. <https://doi.org/10.1007/s11042-023-16424-4>
- Kim, J., Yang, K., Min, J., & White, B. (2022). Hope, fear, and consumer behavioral change amid COVID-19: Application of protection motivation theory. *International Journal of Consumer Studies*, 46(2), 558-574. <https://doi.org/10.1111/ijcs.12700>
- Kivijärvi, H., & Pärnänen, K. (2023). Instrumental usability and effective user experience: Interwoven drivers and outcomes of Human-Computer interaction. *International Journal of Human-Computer Interaction*, 39(1), 34-51. <https://doi.org/10.1080/10447318.2021.2016236>

- Le, U. P. N., Nguyen, A. T. T., Van Nguyen, A., Huynh, V. K., Le Bui, C. T., & Nguyen, A. L. T. (2024, August). How Do Emotional Support and Emotional Exhaustion Affect the Relationship Between Incivility and Students' Subjective Well-Being?. In *Disruptive Technology and Business Continuity: Proceedings of The 5th International Conference on Business (ICB 2023)* (pp. 237-248). Singapore: Springer Nature Singapore.
- Lee, Y. F., Hwang, G. J., & Chen, P. Y. (2022). Impacts of an AI-based chatbot on college students' after-class review, academic performance, self-efficacy, learning attitude, and motivation. *Educational technology research and development*, 70(5), 1843-1865. <https://doi.org/10.1007/s11423-022-10142-8>
- Lin, C. C., Huang, A. Y., & Lu, O. H. (2023). Artificial intelligence in intelligent tutoring systems toward sustainable education: a systematic review. *Smart Learning Environments*, 10(1), 1-22. <https://doi.org/10.1186/s40561-023-00260-y>
- Liu, C. Y., & fShi, B. (2024). Affective foundations in AI-human interactions: Insights from evolutionary continuity and interspecies communications. *Computers in Human Behavior*, 161, 108406. <https://doi.org/10.1016/j.chb.2024.108406>
- Luna, A., Ocaña, M., Rodríguez-Moreno, J., & Ortiz-Colón, A. M. (2025). Establishing the foundation for technology adoption: profiles of military students in the digital age. *Frontiers in Psychology*, 16, 1593326. <https://doi.org/10.3389/fpsyg.2025.1593326>
- Marey, A., Arjmand, P., Alerab, A. D. S., Eslami, M. J., Saad, A. M., Sanchez, N., & Umair, M. (2024). Explainability, transparency and black box challenges of AI in radiology: Impact on patient care in cardiovascular radiology. *Egyptian Journal of Radiology and Nuclear Medicine*, 55(1), 183. <https://doi.org/10.1186/s43055-024-01356-2>
- Mattioli, M., & Cabitza, F. (2024). Not in my face: Challenges and ethical considerations in automatic face emotion recognition technology. *Machine Learning and Knowledge Extraction*, 6(4), 2201-2231. <https://doi.org/10.3390/make6040109>
- McStay, A. (2020). Emotional AI, soft biometrics and the surveillance of emotional life: An unusual consensus on privacy. *Big Data & Society*, 7(1), 2053951720904386. <https://doi.org/10.1177/2053951720904386>
- Namaziandost, E., & Rezai, A. (2024). Interplay of academic emotion regulation, academic mindfulness, L2 learning experience, academic motivation, and learner autonomy in intelligent computer-assisted language learning: A study of EFL learners. *System*, 125, 103419. <https://doi.org/10.1016/j.system.2024.103419>
- Ngo, D., Nguyen, A., Dang, B., & Ngo, H. (2024). Facial expression recognition for examining emotional regulation in synchronous online collaborative learning. *International Journal of Artificial Intelligence in Education*, 34(3), 650-669. <https://doi.org/10.1007/s40593-023-00378-7>
- Nicolescu, L., & Tudorache, M. T. (2022). Human-computer interaction in customer service: the experience with AI chatbots—a systematic literature review. *Electronics*, 11(10), 1579. <https://doi.org/10.3390/electronics11101579>
- Ocaña, M., García-Cañarte, A., & Rosales, M. (2024). Enhancing EFL Vocabulary Through Short Stories: Insights from Learning Analytics. In *International Conference on Intelligent Information Technology* (pp. 438-449). Cham: Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-87701-8_32
- Ocaña, M., Almeida, E., Albán, S. (2022). How Did Children Learn in an Online Course During Lockdown?: A Piagetian Approximation. In: Botto-Tobar, M., Cruz, H., Díaz Cadena, A., Durakovic, B. (eds) *Emerging Research in Intelligent Systems. CIT 2021. Lecture Notes in*

Networks and Systems, vol 406. Springer, Cham. https://doi.org/10.1007/978-3-030-96046-9_20

Pacheco-Mendoza, S., Guevara, C., Mayorga-Albán, A., & Fernández-Escobar, J. (2023). Artificial intelligence in higher education: A predictive model for academic performance. *Education Sciences*, 13(10), 990. <https://doi.org/10.3390/educsci13100990>

Pekrun, R. (2024). Control-value theory: From achievement emotion to a general theory of human emotions. *Educational Psychology Review*, 36(3), 1-36. <https://doi.org/10.1007/s10648-024-09909-7>

Roemmich, K., & Andalibi, N. (2021). Data subjects' conceptualizations of and attitudes toward automatic emotion recognition-enabled wellbeing interventions on social media. *Proceedings of the ACM on Human-Computer Interaction*, 5(CSCW2), 1-34. <https://doi.org/10.1145/3476049>

Salloum, S. A. (2024). Trustworthiness of the AI. In *Artificial intelligence in education: The power and dangers of ChatGPT in the classroom* (pp. 643-650). Cham: Springer Nature Switzerland.

Sarnou, D., & Sarnou, H. (2023). Highlighting the Consequences of Ignoring Children's Emotions in Schools: Case of 30 pupils in 3 Algerian Primary Schools. *Academy Journal of Educational Sciences*, 6(1), 44-51. <https://doi.org/10.31805/acjes.1091001>

Schmitz-Hübsch, A., Stasch, S. M., Becker, R., Fuchs, S., & Wirzberger, M. (2022). Affective Response Categories-Toward Personalized Reactions in Affect-Adaptive Tutoring Systems. *Frontiers in artificial intelligence*, 5, 873056. <https://doi.org/10.3389/frai.2022.873056>

Shah, M., & Sureja, N. (2025). A comprehensive review of bias in deep learning models: Methods, impacts, and future directions. *Archives of Computational Methods in Engineering*, 32(1), 255-267. <https://doi.org/10.1007/s11831-024-10134-2>

Shi, L. (2025). The integration of advanced AI-enabled emotion detection and adaptive learning systems for improved emotional regulation. *Journal of Educational Computing Research*, 63(1), 173-201. <https://doi.org/10.1177/07356331241296890>

Sirisha, N., Mageswari, P., Raj, V. M., Kumar, S., Priya, R. V., & Ananthi, S. (2025, May). Emotion Centric Artificial Intelligence Driven Engagement Systems for Adaptive Learning Environments Personalized Knowledge Acquisition and Cognitive Skill Enhancement. In *International Conference on Sustainability Innovation in Computing and Engineering (ICSICE 2024)* (pp. 528-540). Atlantis Press. https://doi.org/10.2991/978-94-6463-718-2_46

Villamarín, A., Chumaña, J., Narváez, M., Guallichico, G., Ocaña, M., & Luna, A. (2023, November). Artificial Intelligence in the Detection of Autism Spectrum Disorders (ASD): a Systematic Review. In *International Conference on Intelligent Vision and Computing* (pp. 21-32). Cham: Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-71388-0_3

Yin, J., Goh, T. T., & Hu, Y. (2024). Interactions with educational chatbots: the impact of induced emotions and students' learning motivation. *International Journal of Educational Technology in Higher Education*, 21(1), 1-23. <https://doi.org/10.1186/s41239-024-00480-3>

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), 1-47. <https://doi.org/10.3390/educsci15010065>

Zhao, G., Li, Y., & Xu, Q. (2022). From emotion AI to cognitive AI. *International Journal of Network Dynamics and Intelligence*, 65-72. <https://doi.org/10.53941/ijndi0101006>