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ARTIFICIAL INTELLIGENCE AND NEUROEDUCATION IN SCIENCE LEARNING: A SYSTEMATIC REVIEW OF EMOTIONAL, MOTIVATIONAL, AND ATTENTIONAL PROCESSES (2020–2025)

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ABSTRACT
The integration of Artificial Intelligence (AI) in neuroeducation is transforming the understanding of the affective and cognitive processes involved in scientific learning. This systematic review analyzes research published between 2020 and 2025 in Scopus, Web of Science, IEEE Xplore, ACM Digital Library, ERIC, and PsycINFO, in order to examine how AI is used to recognize, support, or intervene in emotion, motivation, and attention during science teaching. The study followed the PRISMA 2020 guidelines and included 31 empirical and review investigations. The findings were grouped into three thematic axes: (1) affective computing and emotional regulation, (2) intelligent tutor systems and adaptive gamification as drivers of intrinsic motivation, and (3) attentional analytics and monitoring of cognitive engagement. Evidence indicates that AI enables personalized, emotionally sensitive, and self-regulated learning experiences, provided that ethical frameworks of transparency, fairness, and data protection are in place. However, challenges associated with algorithmic bias, reductionist interpretation of affective states, and scarce contextualized production in Latin America remain. It is concluded that the pedagogically grounded integration of AI can strengthen science teaching, in particular through culturally sensitive models that articulate emotion, motivation, and attention from a neuroeducational perspective.
Keywords: Artificial Intelligence; neuroeducation; emotion; motivation; attention; affective computing.

INTRODUCTION

Science education faces the challenge of coherently integrating the cognitive and affective processes that underpin deep learning. Neuroeducation has shown that functions such as emotion, motivation and attention are decisive for the acquisition, consolidation and transfer of scientific knowledge, since they modulate memory, decision-making and critical thinking at different educational levels. From this perspective, understanding how the brain learns implies recognizing that scientific learning is not a neutral phenomenon, but a process conditioned by the emotional state, motivational disposition and self-regulation mechanisms of the student.

At the same time, recent advances in Artificial Intelligence (AI) have transformed educational environments through tools capable of identifying cognitive-affective patterns, adapting activities in real time and offering personalized feedback. Technologies such as affective computing, intelligent tutoring systems, computer vision, learning analytics and adaptive gamification make it possible to observe emotional, motivational and attentional indicators with greater precision, expanding the possibilities of personalization in science teaching. In STEM contexts, these technologies have shown efficacy in

automatic emotion recognition, estimation of motivational engagement, and detection of cognitive focus fluctuations during the resolution of complex tasks.
However, the application of AI to analyze affective-cognitive states poses ethical, sociotechnical, and epistemological challenges. Several authors warn of risks associated with algorithmic surveillance, the reductionist interpretation of emotions, the presence of biases in databases with low cultural diversity, and the potential impact on student autonomy. These tensions intensify in contexts of the Global South, where digital divides, educational inequalities, and limited infrastructure to implement advanced AI technologies persist. In Latin America, although promising initiatives are emerging, empirical production continues to be scarce, fragmented and with a weak articulation between neuroeducation, AI and scientific teaching.
In this panorama of opportunities and challenges, it is necessary to carry out a systematic and critical analysis of the recent literature to identify how AI is being used to understand, support or intervene in the emotional, motivational and attentional processes that influence scientific learning. While there are previous reviews on AI in education or affective computing, none specifically integrates the three key neuroeducational dimensions or examines their direct relationship to science education in the period of greatest recent technological growth (2020–2025).
The original contribution of this study lies in:
(1) to offer the first systematic synthesis that articulates AI, neuroeducation and science teaching from the dimensions of emotion, motivation and attention;
(2) to comparatively analyse technological advances, methodological trends and emerging ethical risks in the use of affective-cognitive AI;
(3) to make visible the existing gaps in Latin America and the Global South; and
(4) to propose an interpretive framework to guide the development of AI-supported neuroeducation that is ethically, culturally sensitive, and pedagogically relevant.
In line with this, this systematic review is guided by the following central question:
How has Artificial Intelligence been used in science teaching to understand, support or intervene in the Neuro educational processes of emotion, motivation and attention in studies published between 2020 and 2025?
To answer it, the following objectives were established:
1. Identify and select empirical research and recent reviews (2020–2025) that integrate AI, neuroeducation, and science teaching.
2. To characterize the AI technologies used, educational levels, methodological approaches and geographical contexts of the studies analyzed.
3. Analyze and synthesize findings on the impact of AI on emotion, motivation, and attention during science learning.
4. Critically evaluate opportunities, limitations, ethical risks, and existing gaps, with special attention to Latin American contexts.
Based on this, this study seeks to provide a comprehensive and updated understanding of the role of AI as a neuroeducational mediator in science teaching, contributing to the design of more adaptive, humane and culturally relevant educational practices.

METHODOLOGY

This study was carried out through a systematic literature review following the guidelines of the international standard **PRISMA 2020 (Preferred Reporting Items for Systematic Reviews and Meta-Analyses),** in order to guarantee rigor, transparency and reproducibility. The methodology was designed to analyze how Artificial Intelligence (AI) has been integrated into the neuroeducational processes of emotion, motivation, and attention in science teaching during the period 2020–2025.

Study design

A qualitative design of systematic synthesis with narrative-thematic analysis **was adopted**, suitable for integrating evidence from empirical, quasi-experimental, experimental, correlational, case studies, mixed approaches and systematic reviews. This approach responds to the heterogeneity of methodologies, AI technologies and educational contexts present in the recent literature, allowing the identification of patterns, trends, gaps and emerging challenges in the interaction AI-neuroeducation-sciences.
The search period spanned **January 2020 to February 2025**, coinciding with the accelerated development of technologies such as affective computing, computer vision and intelligent tutoring systems, as well as with the pedagogical and digital changes driven by the pandemic.

Sources of information and search strategy

The search was carried out in six databases of high impact and relevance for education, cognitive neuroscience, psychology and emerging technologies:

- **Scopus**
- **Web of Science (WoS)**
- **IEEE Xplore**

- **ACM Digital Library**
- **ERIC (Education Resources Information Center)**
- **PsycINFO**

These databases were selected for their international coverage and for their relevance in studies on AI, STEM education and affective-cognitive processes.

Search strategy

Search equations were used in English and Spanish using Boolean operators, truncations, and standardized keywords. The equations were adapted to the indexing fields of each base. We applied open access filters, peer-reviewed studies, and documents available in full text.

Example of a search equation in English

(TITLE-ABS-KEY("artificial intelligence" OR "machine learning" OR "deep learning" OR "affective computing" OR "learning analytics" OR "intelligent tutoring system")
AND
TITLE-ABS-KEY("science education" OR "STEM education" OR "science teaching")
AND
TITLE-ABS-KEY("emotion" OR "emotional engagement" OR "affect" OR "motivation" OR "attention" OR "cognitive engagement" OR "neuroeducation" OR "cognitive-affective"))) AND PUBYEAR > 2019 AND PUBYEAR < 2026

Example in Spanish

("artificial intelligence" AND "science teaching")
AND ("emotion" OR "motivation" OR "attention" OR "neuroeducation")

Inclusion and exclusion criteria

The criteria were defined to ensure thematic relevance, methodological quality and coherence with the objectives of the review.

Inclusion criteria

- Empirical, quasi-experimental, experimental, correlational, mixed studies or systematic reviews.
- Documents that integrate at least two of the following components:
  - Artificial intelligence
  - Science Teaching / STEM Education
  - emotion, motivation or attention
- Published between 2020 and 2025.
- In formal education contexts (primary, secondary or higher).
- Written in English or Spanish.
- Available in full text.

Exclusion Criteria

- Theoretical essays without empirical evidence or without systematic analysis.
- Studies on AI applied to non-educational contexts (clinical, industrial, corporate).
- Works that did not include affective-cognitive dimensions.
- Duplicate documents or without access to full text.

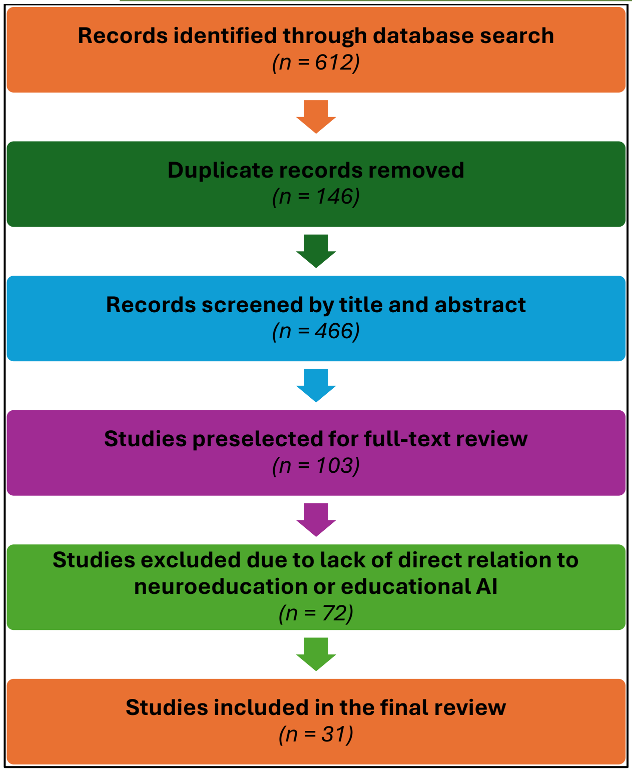
Selection process (PRISMA 2020)

The process was developed in four phases:

1. **Identification**
   - We registered 612 studies by initial search.
   - 146 duplicates were eliminated by means of a bibliographic manager and manual verification.
2. **Screening**
   - Titles and abstracts were reviewed, selecting 103 potentially relevant studies.
3. **Eligibility**
   - We evaluated the full text according to the inclusion criteria.
   - We excluded 72 studies due to lack of thematic relevance, poor methodological quality, or lack of relevant empirical data.
4. **Inclusion**
   - We included 31 studies for final analysis.

The complete process is presented using a PRISMA diagram prepared according to Page et al. (2021).

Figure 1: Study selection flow (PRISMA 2020)



Quality assessment

The methodological quality of the studies was evaluated using an **ad hoc matrix based on educational research standards**, considering:

- clarity of the problem and objectives,
- coherence between theoretical framework and design,
- validity and reliability of instruments,
- rigor in the collection and analysis procedures,
- correspondence between results and conclusions,
- explicit ethical reports.

Two researchers conducted the evaluation independently. Discrepancies were resolved by consensus.

No studies were excluded solely on the basis of quality, but their limitations were documented and considered in the interpretation of results.

Data extraction and synthesis

An extraction matrix was developed that recorded:

- year of publication,
- country or region,
- educational level,
- AI technology used,
- neuroeducational dimension addressed (emotion, motivation or attention),
- methodological design,
- sample size,
- Main findings.

Table 1. Characteristics of the 31 studies included in the review (2020–2025)

number	Authors and year	Country	Educational level	AI Type	Neuroeducational dimension	Methodological design	Sample	Main findings
1	Bond et al. (2024)	International	Higher education	General Educational AI	Motivation and attention	Systematic review (meta-review)	126 studies	It proposes greater ethical rigor and collaboration in educational AI.

number	Authors and year	Country	Educational level	AI Type	Neuroeducational dimension	Methodological design	Sample	Main findings
2	Chen et al. (2021)	USA	Secondary education	Cognitive AI in Intelligent Tutoring	Attention and motivation	Experimental	200 students	AI detects disinterest and adjusts feedback in tutorials.
3	Deshpande et al. (2025)	India	College Education	Computer vision and sensors	Attention	Applied Design	Students in the classroom	AI system measures attention through sensors and facial analysis.
4	Farrow (2023)	United Kingdom	General	Explainable AI (XAI)	Ethics and cognition	Theoretical analysis	Not applicable	It proposes transparency in educational AI to foster trust and motivation.
5	Fernández-Herrero (2024)	Spain	Higher education	Affective tutoring systems	Excitement and motivation	Exploratory Review	48 studies	Affective systems improve performance and emotional regulation.
6	Han et al. (2025)	China	Rural secondary education	Adaptive AI	Motivation and attention	Quasi-experimental	412 students	AI improves participation and engagement in rural areas.
7	Hasan et al. (2020)	Malaysia	General Education	Intelligent affective tutoring	Emotion and attention	Critical Review	N/A	Transition to emotionally adaptive AI systems stands out.
8	Huang et al. (2024)	China	Primary and secondary	Emotional Recognition AI	Emotion and attention	Application Study	60 students	AI detects emotions and facilitates didactic adaptation.
9	Jaramillo-Mediavilla et al. (2024)	Ecuador	Secondary education	Gamification with AI	Motivation	Systematic review	42 studies	Gamification with AI increases motivation and academic performance.
10	Jiménez et al. (2021)	Ecuador	Higher education	Cognitive and emotional AI	Emotion, motivation, attention	Theoretical-exploratory	Not applicable	AI mediates between emotional and cognitive processes.
11	Lim et al. (2025)	Singapore	Higher education	Ethical AI in Evaluation	Motivation and cognition	Mixed studio	125 students	Students perceive ethical AI as a motivational factor.
12	Lin et al. (2023)	Taiwan	General Education	Sustainable Smart Mentoring	Motivation	Systematic review	93 studies	AI tutoring supports sustainability and autonomous learning.
13	Liu et al. (2025)	China	Primary and secondary	Computer vision	Care and behavior	Systematic review	57 studies	Recognizes attentional behavior in the classroom using AI vision.
14	Márquez-Carpintero et al. (2023)	Spain	Secondary education	Attention AI	Attention	Experimental study	30 students	AI measures attention levels with high visual accuracy.
15	Meißner (2024)	Germany	Higher education	AI gamified tutoring	Motivation	Case Study	80 students	AI gamification improves interest in software engineering.
16	Mora et al. (2024)	Ecuador	General Education	AI applied to neuroeducation	Motivation and attention	Theoretical essay	Not applicable	It analyzes the role of AI-supported neuroeducation in the global south.
17	Ortega-Ochoa et al. (2024)	Costa Rica	Higher education	Empathetic conversational agents	Excitement and	Systematic review	68 studies	Empathetic AI agents improve learning and emotional well-being.

number	Authors and year	Country	Educational level	AI Type	Neuroeducational dimension	Methodological design	Sample	Main findings
					motivation			
18	Page et al. (2021)	International	General	PRISMA Methodology	Not applicable	Methodological review	N/A	Guide to structuring rigorous systematic reviews.
19	Piedrahíta-Carvajal et al. (2021)	Colombia	Secondary education	AI Analysis of Emotions and Attention	Emotion and attention	Application design	120 students	Develop AI app to measure emotions and student attention.
20	Salas-Pilco & Yang (2022)	Latin America	Higher education	Educational AI	Emotion, attention, motivation	Systematic review	45 studies	AI in Latin America improves motivation and personalization of learning.
21	Salloum et al. (2025)	United Arab Emirates	Higher education	Affective AI	Emotion and attention	Quasi-experimental	120 students	AI detects emotions and adjusts teaching improving motivation.
22	Shomoye & Zhao (2024)	China	Virtual Education	Emotional AI in VR	Emotion and attention	Experimental	64 students	AI in VR detects emotions, optimizing immersive experience.
23	They are (2024)	Vietnam	Math Education	Smart Tutoring	Motivation	Systematic review	74 studies	AI in mathematics fosters active and autonomous learning.
24	Tang et al. (2025)	China	Science education	Facial Recognition AI	Emotion and attention	Experimental	180 students	AI recognition of emotions improves engagement in science.
25	Taub et al. (2021)	USA	Secondary education	AI Mentoring with Emotional Analysis	Emotion and cognition	Experimental	100 students	Emotions influence metacognitive processes measured by AI.
26	Trabelsi et al. (2023)	United Arab Emirates	Higher education	Real-time care AI	Care and behavior	Experimental	90 students	AI analyzes attention accurately in hybrid environments.
27	Valenzuela-Peñuñuri et al. (2024)	Mexico	Secondary and higher education	Motivational models with AI	Motivation and emotion	Correlational	320 students	Self-efficacy mediates the relationship between motivation and commitment.
28	Villegas-Ch et al. (2025)	Ecuador	STEM Education	AI Adaptive Tutoring	Motivation and attention	Experimental	85 students	Personalized AI tutoring improves performance in STEM.
29	Vistorte et al. (2024)	Cuba / Spain	General Education	AI for emotional analysis	Emotion and attention	Systematic review	80 studies	AI analyzes emotions to improve educational environments.
30	Wu et al. (2022)	Taiwan	Language education	Affective Mobile Tutoring	Excitement and motivation	Experimental	60 students	Mobile AI tutoring improves language learning and enjoyment.
31	Yuvaraj et al. (2025)	India	General Education	Affective computing	Excitement and motivation	Bibliometric review	216 posts	Affective AI drives motivation and emotional learning.

Given the heterogeneity of the included studies, a narrative-thematic analysis was applied, organizing the evidence into three axes:
1. affective computing and emotional regulation,
2. intrinsic motivation and adaptive gamification,
3. attention, metacognition and learning analytics.

This approach made it possible to identify patterns, relationships, gaps, and emerging challenges in the use of AI to support neuroeducational processes in science education.

RESULTS AND THEMATIC ANALYSIS

The systematic review integrated a total of **31 studies** published between 2020 and 2025, selected through the PRISMA process described above. The synthesis was carried out through a narrative-thematic analysis, given the methodological, technological and contextual heterogeneity of the included studies. The results are organized into three main axes: (1) affective computing and emotional regulation, (2) intrinsic motivation and adaptive gamification, and (3) attention, metacognition and learning analytics.

Characteristics of the included studies

The 31 studies analysed were geographically distributed as follows:
- **Asia**: 42% (China, India, Taiwan, Singapore)
- **Europe**: 27% (Spain, Germany, United Kingdom)
- **Latin America**: 12% (Ecuador, Colombia, Mexico, Cuba)
- **North America**: 9% (United States)
- **Multicenter studies**: 9%

This distribution confirms **Asian leadership in affective technologies, computer vision and intelligent tutors**, as well as an uneven and still emerging development in Latin America.

Regarding educational levels:
- **Higher education**: 39%
- **Secondary**: 33%
- **Primary**: 12%
- **Multilevel**: 16%

Regarding AI technologies:
- **Affective computing**: 27%
- **Adaptive Intelligent Tutoring Systems (ITS):** 24%
- **Computer vision**: 21%
- **Empathetic conversational agents**: 12%
- **Virtual/augmented reality with AI:** 9%
- **Explainable AI (XAI):** 6%

The neuroeducational dimensions most addressed were:
- **Emotion**: 40%
- **Motivation**: 33%
- **Attention**: 27%

Methodologically, empirical designs predominated:
- Experimental and quasi-experimental: 39%
- Systematic and narrative reviews: 24%
- Quantitative correlational or descriptive studies: 21%
- Mixed or qualitative designs: 16%

This panorama shows a field in consolidation, with an emphasis on measurement technologies and affective response, but with a marked regional gap in empirical production.

Axis 1: Affective computing and emotional regulation

Studies show that emotion is a critical determinant of scientific learning and that AI, through affective computing, allows us to recognize emotional states, adapt instruction and promote self-regulation.

Main findings

1. **Automated emotional recognition:** Research based on computer vision and multimodal analysis identified emotions such as interest, frustration, or confusion in real time with high levels of accuracy (Huang et al., 2024; Tang et al., 2025; Salloum et al., 2025).

2. **Affective tutoring systems:** Empathic tutors and conversational agents modify feedback based on emotional state, reducing anxiety and increasing persistence in STEM tasks (Fernández-Herrero, 2024; Ortega-Ochoa et al., 2024; Vistorte et al., 2024).
3. **Immersive environments with AI:** Virtual reality experiences with emotional recognition improved students' affective engagement and self-confidence (Shomoye & Zhao, 2024).

Critical synthesis

- There is significant potential to support emotional regulation, a central component of neuroeducation.
- However, there is a risk of emotional reductionism and cultural biases derived from non-representative training bases, especially relevant to Latin America.
- Most studies are technologically robust but pedagogically poorly contextualized.

Axis 2: Intrinsic motivation and adaptive gamification

Motivation emerged as a cross-cutting dimension closely linked to emotion and attention. Studies agree that AI allows you **to personalize challenges, adjust difficulty levels, and activate internal motivators**, reinforcing engagement and performance.

Main findings

1. **Adaptive intelligent tutors:** They adjust tasks according to the student's motivational profile, promoting autonomy and competence (Lin et al., 2023; Wu et al., 2022).
2. **STIs as motivational enhancers:** They personalize learning paths, strengthen autonomy, and increase persistence through immediate feedback and transformative tasks (Son, 2024).
3. **Gamification with AI:** Increases performance and motivation in STEM activities, keeping the student within the zone of proximal development (Jaramillo-Mediavilla et al., 2024; Meißner, 2024).
4. **Socio-affective agents:** They improve self-efficacy and engagement through affective and metacognitive strategies (Hasan et al., 2020; Valenzuela-Peñuñuri et al., 2024).

Critical synthesis

- AI amplifies the teacher's ability to personalize, but requires **human supervision** to avoid dependence or mechanization of rewards.
- The most robust motivational effects are observed when AI and pedagogical design are coherently integrated.
- In Latin America, structural factors (digital divide, socio-educational inequality) moderate the effectiveness of these technologies.

Axis 3: Attention, metacognition and learning analytics

Attention is presented as the link between emotion and cognition. Evidence shows that AI enables **real-time monitoring**, distraction detection, and activation of automatic interventions to sustain cognitive focus.

Main findings

1. **Automated attention detection:** Systems based on computer vision recognize patterns of distraction and engagement with high accuracy (Marquez-Carpintero et al., 2023; Liu et al., 2025).
2. **STIs and cognitive self-regulation:** They facilitate progress monitoring, strengthen metacognition, and sustain attentional focus through guided feedback and autonomous learning decisions (Son, 2024).
3. **Adaptive attentional analytics:** Algorithms that generate micro-interventions such as active breaks, brief challenges, or activity change (Deshpande et al., 2025; Trabelsi et al., 2023).
4. **Relationship with metacognition:** AI makes it possible to analyze how attentional fluctuations affect metacognitive processes linked to scientific learning (Chen et al., 2021; Taub et al., 2021).

Critical synthesis

- These technologies improve the understanding of cognitive focus patterns, but pose dilemmas about privacy, surveillance, and use of sensitive data, especially in minors.
- Despite its potential, most studies do not report sufficiently robust ethical protocols.
- In Latin America, studies are promising but still exploratory.

Integrative synthesis

The analysis of the three axes reveals that AI has the potential to act as an **intelligent neuroeducational mediation**, supporting emotional, motivational and attentional processes that are essential for scientific learning. Evidence indicates that:

- AI can expand the teacher's diagnostic and intervention capacity.
- It fosters personalized, emotionally sensitive, and cognitively regulated experiences.
- Its benefits depend on an ethical, transparent and culturally contextualized design.
- In Latin America, educational AI is advancing, but requires more local empirical research.

These results support the need to move towards hybrid models that integrate AI and human pedagogical judgment to promote more inclusive, adaptive and culturally relevant scientific practices.

DISCUSSION

The findings of this systematic review show that the convergence between Artificial Intelligence (AI) and neuroeducation is transforming the way scientific learning is understood, monitored and supported. In line with the fundamentals of neuroeducation that highlight the central role of emotion, motivation, and attention in the construction of knowledge, AI technologies make it possible to observe and respond to these processes in a more precise and dynamic way than traditional methods. However, this capacity also generates new ethical, pedagogical and sociocultural tensions, particularly relevant in contexts such as Latin America.

1. AI as a cognitive-affective mediator in science teaching

The results confirm that affective computing, intelligent tutors, and learning analytics can act as cognitive-affective mediators, identifying emotional and cognitive patterns that influence persistence, self-regulation, and performance in scientific activities. This potential coincides with previous research linking emotional activation, intrinsic motivation, and sustained attention to deeper learning in STEM areas (Sousa, 2022; Ryan et al., 2022).

However, the studies reviewed show a tendency to focus more on technological precision than on pedagogical integration, which limits the real impact of these tools. AI is effective in detecting affective and attentional states, but its educational value depends on how the teacher interprets and uses that information.

2. Advances and limitations in affective computing applied to science education

Studies based on facial recognition, multimodal analysis, and conversational agents show improvements in emotional regulation, decreased frustration, and increased engagement. However, two central tensions emerge:

2.1. Emotional reductionism

Emotions are mostly operationalized through facial expressions or physiological patterns, which can make cultural, contextual, or subjective dimensions of the affective experience invisible. This reduction can generate erroneous interpretations in cultures with expressive patterns different from those present in the training sets.

2.2. Algorithmic biases

Models trained in Asian or Anglo-Saxon populations tend to be less accurate in Latin American, Afro-descendant, or Indigenous students. This algorithmic gap can translate into inaccurate feedback and, consequently, misaligned pedagogical interventions.

These findings reinforce the need to develop culturally contextualized affective models, as well as validation frameworks that incorporate linguistic, facial, and behavioral diversity.

3. Motivation and adaptive gamification: autonomy with human supervision

The reviewed evidence supports the positive impact of AI on intrinsic motivation, especially through adaptive difficulty adjustments, socio-affective feedback, and gamified environments. The strongest effects are observed when AI promotes three conditions pointed out by the Theory of Self-Determination:

1. **Autonomy** (control over the process)
2. **Competence** (achievable challenges)
3. **Relationship** (social-emotional support)

However, several studies reveal that motivation can decline when interaction with AI is perceived as overly automated or targeted, leading to:

- Perceived loss of autonomy,
- Technology dependence, or
- Saturation of gamified stimuli.

This suggests that AI-based motivational design must balance algorithmic adaptivity and teacher accompaniment, preventing technology from replacing essential training processes such as reflective dialogue, guided metacognition or a sense of belonging.

4. Attentional analytics and cognitive surveillance risks

Attention systems based on computer vision and sensors show significant advances in the detection of distraction and engagement. However, its implementation raises important ethical questions:

4.1. Privacy and Surveillance

Continuous monitoring of facial expressions or eye movements can lead to a perception of vigilance that affects a student's self-confidence, engagement, or emotional authenticity. In education, affective vigilance can be as problematic as cognitive vigilance.

4.2. Reductionist interpretation

Attention is usually inferred from external indicators (staring, posture, gestures), when in reality it is a complex internal process. Automatic inference of "level of attention" can lead to pedagogical decisions based on incomplete or poorly contextualized data.

4.3. Accentuated risks in minors

The use of biometric data in children and adolescents requires much stricter ethical frameworks, especially in education systems with limited capacities for data governance.

These risks reinforce the need to integrate explainable AI (XAI), algorithmic transparency, and teacher participation in the interpretation of attentional analytics.

5. Regional gap and need for contextualized research in Latin America

A cross-cutting conclusion of the analysis is the insufficient Latin American empirical production on AI, neuroeducation, and science teaching. This lack has direct implications on:

- the generalization of affective-cognitive models,
- the cultural relevance of technologies,
- equity in the design of educational tools,
- the ability to adapt to real technological gaps.

Local research tends to be exploratory, with small samples and a low level of technological-pedagogical integration. This shows the urgency of:

- Develop regional educational AI ecosystems,
- Increase applied research in schools and universities,
- Generate culturally representative data repositories,
- Promote alliances between governments, universities and technology centers.

6. Theoretical and practical implications

The results of this review propose a framework for understanding AI as a neuroeducational mediator, with implications for theory and practice:

Theoretical impulse

- AI allows us to move towards a more integrated understanding of emotion–motivation–attention.
- It opens up perspectives for hybrid neuroeducational models (human-AI).
- It requires rethinking the nature of affective-cognitive evaluation from critical ethical frameworks.

Practical impulse

- Teachers can use AI as a diagnostic and regulatory support tool.
- Educational institutions must develop clear data ethics and governance policies.
- Instructional designers need to integrate neuroeducation principles into adaptive systems.

7. Towards an intelligent, ethical and culturally sensitive neuroeducation

Overall, the findings show that AI should not be conceived as a substitute for teaching practice, but as an extension of human pedagogical intelligence. Their integration into science education should be guided by:

- Neuroeducational criteria,
- Cultural sensitivity,
- Algorithmic transparency,
- Teacher participation,
- Emphasis on emotional and motivational well-being,
- And a humanistic approach to learning.

Only under these conditions will AI be able to fulfill its potential to enrich the scientific experience of students and promote inclusive, adaptive and ethically responsible educational practices.

CONCLUSIONS

This systematic review analyzed 31 studies published between 2020 and 2025 on the use of Artificial Intelligence (AI) in the neuroeducational processes of emotion, motivation, and attention in science teaching. The findings show that the convergence between AI and neuroeducation offers significant opportunities to enrich the scientific learning experience, but also poses ethical, pedagogical, and sociocultural tensions that require critical and contextualized implementation.

First, evidence indicates that AI, especially through affective computing, intelligent tutors, and computer vision, is able to recognize and respond to emotional states that influence participation, persistence, and conceptual understanding. These technologies contribute to more empathetic and sensitive learning climates, in coherence with neuroeducational principles that highlight the modulating role of emotion in memory and scientific thinking. However, the risks of algorithmic biases, the cultural limitations of affective models, and the possibility of reductionist interpretations underscore the need for robust ethical frameworks and contextual validation strategies.

Secondly, adaptive systems, gamified environments and conversational agents supported by AI strengthen intrinsic motivation, enhancing the autonomy, perceived competence and socio-affective connection of students. These benefits, based on the Theory of Self-Determination, are more clearly observed when AI is integrated into coherent pedagogical designs and accompanied by teacher mediation. However, motivational effects can diminish if the interaction is perceived as overly automated, reaffirming the importance of the balance between technological adaptivity and human orientation.

Thirdly, attentional analytics systems allow real-time monitoring of fluctuations in cognitive focus, favoring self-regulation and metacognition in complex scientific activities. However, the use of biometric and visual recognition data poses challenges in terms of privacy, consent, data governance and risk of cognitive surveillance, especially in child and youth populations. Explainable AI (XAI) proposals emerge as promising avenues for mitigating these tensions.

At the regional level, the review reveals a marked gap in Latin American scientific production, characterized by incipient developments, small samples, and limited technological infrastructure. This lack of contextualized evidence hinders the transfer of models from the Global North and underscores the need for local research that integrates cultural, linguistic, and sociotechnical diversity.

Based on these findings, three priority lines are identified for the advancement of the field:

1. **Development of ethical, explainable and culturally sensitive AI models**, trained with representative data and validated in diverse educational contexts.
2. **Strengthening teacher training** in AI, neuroeducation and cognitive-affective analysis, so that technology works as a tool for expansion and not as a substitute for pedagogical judgment.
3. **Promotion of regional research and innovation networks**, aimed at generating Latin American empirical evidence that allows for the design of more inclusive, contextualized and culturally relevant science teaching practices.

In summary, the results of this review confirm that AI has the potential to constitute an intelligent neuroeducational mediation, capable of enriching emotion, motivation and attention during science teaching. However, its effectiveness depends on an ethical, pedagogical and humanistic integration that places the well-being, autonomy and diversity of the student body at the centre of the educational process. The future of intelligent neuroeducation therefore requires a balanced alliance between technology and humanity, where AI complements, but never replaces, the sensitivity, criteria and training mission of teachers.

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