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MAPPING THE EMERGING FIELD OF NEUROSCIENCE-INFORMED ARTIFICIAL INTELLIGENCE IN SECONDARY STEM EDUCATION: A SYSTEMATIC REVIEW

Salmiza Saleh[1]*, Liu YuFei[2]

[1]Salmiza Saleh, School of Educational Studies, Universiti Sains Malaysia
[2]Liu Yufei, School of Intelligent Engineering, Shaoguan University, China

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Corresponding Author: Salmiza Saleh
(salmiza@usm.my)

ABSTRACT

The integration of neuroscience and artificial intelligence in education (AIEd) represents a rapidly emerging frontier in STEM teaching and learning. While educational neuroscience provides empirically grounded insights into how the brain processes information, AIEd offers adaptive technologies capable of aligning with these cognitive processes. However, the extent to which AI tools for secondary STEM education are genuinely "neuroscience-informed" remains underexplored. This systematic review maps and synthesizes the empirical literature on neuroscience-informed AI applications in secondary STEM education, with a focus on design principles, pedagogical implications, and future research directions. The review followed PRISMA 2020 guidelines. Searches were conducted across Scopus, Web of Science, ERIC, PubMed, and IEEE Xplore, covering publications from January 2010 to May 2025. Eligible studies examined AI-based tools (e.g., intelligent tutoring systems, adaptive platforms, generative AI) explicitly or implicitly grounded in neuroscience or cognitive science principles (e.g., cognitive load theory, embodied cognition, neuroplasticity). Five studies met all inclusion criteria. Data were extracted systematically and synthesized thematically. Findings reveal a research landscape still in its infancy. Most studies operationalize cognitive rather than neural grounding, with limited attention to teacher co-design and equity. Promising innovations include embodied interaction models and adaptive tutoring systems informed by cognitive load theory. Yet, few tools demonstrate neural validation or real-time adaptive feedback. The review highlights an urgent need for brain-validated, equity-centered, and teacher-empowering AI in STEM education. Advancing beyond rhetoric toward authentic neuroscience-informed design will require stronger empirical validation, participatory co-design, and integration of accessible neurotechnologies.

KEYWORDS: Neuroscience-informed education; Artificial intelligence in education; STEM education; Cognitive science and learning; Systematic literature review

1. INTRODUCTION

The 21st century has brought together three transformative forces in education: the rapid rise of Artificial Intelligence (AI), the growing maturity of Educational Neuroscience, and the global urgency to strengthen STEM (Science, Technology, Engineering, and Mathematics) literacy among young learners (Luckin et al., 2016; Thomas et al., 2019; National Research Council, 2011). From adaptive tutoring platforms to large language models such as ChatGPT, AI promises learning experiences that are more personalized, scalable, and accessible than ever before (Zawacki-Richter et al., 2019; Valeri et al., 2025). At the same time, advances in neuroscience have deepened our understanding of the biological and cognitive foundations of learning, revealing how memory consolidation, attention, executive function, and cognitive load shape how knowledge is acquired and applied (Goswami, 2006; Sweller, 2011; Tokuhama-Espinosa, 2011). Meanwhile, STEM education—widely recognized as vital for both economic growth and scientific progress—requires pedagogical tools that can engage diverse learners while supporting higher-order, interdisciplinary reasoning (National Research Council, 2011; Duncan et al., 2022).

Yet, this convergence is not without tension. While AI tools are rapidly entering secondary STEM classrooms under the promise of "innovation" and "personalization," many of these systems prioritize efficiency over cognitive fidelity (Iqbal & Campbell, 2023; Yang & Kong, 2025). Rarely do they account for how adolescent learners actually process information: the limits of working memory (Sweller, 2011), the vulnerability of sustained attention (Rosen et al., 2013), or the developmental trajectory of metacognition and executive control (Blakemore & Robbins, 2012). The result is a proliferation of tools that appear sophisticated but are often misaligned with how learning truly occurs, privileging superficial engagement and performance metrics over meaningful cognitive development (Willingham, 2009; Mayer, 2017).

This disconnect is more than a theoretical concern—it has immediate classroom consequences. Poorly sequenced content can overwhelm learners (Sweller, 2011), teachers may lose trust in tools that fail to support neurodiverse classrooms (Saal et al., 2025), and equity gaps can widen when algorithms privilege dominant learning styles or cultural norms (Holmes et al., 2019; Duncan et al., 2022). Valeri et al. (2025), for instance, show that while secondary students eagerly adopt generative AI like ChatGPT, they often use it in ways that inadvertently increase cognitive load. Similarly, although systems such as Techambition (Jančařík, 2019) demonstrate the potential of AI to orchestrate cognitively responsive classroom practices, such cases remain the exception rather than the rule.

Despite numerous reviews on AI in education (Chen et al., 2020; Zawacki-Richter et al., 2019; Shabbir et al., 2022), neuroscience in learning (Ansari & Coch, 2006; Thomas et al., 2019), and digital STEM tools (Huang et al., 2022), no systematic synthesis has yet mapped how neuroscience-informed AI is being applied to guide the design of teaching and learning materials in secondary STEM contexts. This represents a critical gap: without explicit integration between brain science and AI design, educational technologies risk remaining technically advanced but pedagogically shallow—rich in analytics yet poor in scaffolding the cognitive processes required for mastering core STEM concepts such as Newtonian mechanics, chemical bonding, or algorithmic reasoning (Sanchez-Guzman & Mora Ley, 2010; Iqbal & Campbell, 2023).

This systematic review seeks to address that gap. Guided by the PRISMA 2020 framework (Page et al., 2021), the review is driven by the following research question:

How is artificial intelligence informed by neuroscience being integrated into the development of teaching and learning tools or materials for secondary school STEM education?

Our objectives are threefold:

1. To map the landscape of AI tools in secondary STEM education that explicitly or implicitly apply neuroscience or cognitive science principles such as cognitive load theory (Sweller, 2011), embodied cognition (Wilson, 2002), metacognitive scaffolding (Flavell, 1979), and neuroplasticity (Tokuhama-Espinosa, 2011).
2. To extract, synthesize, and codify design principles, implementation strategies, and co-design frameworks—particularly those that emerge from teacher–AI collaborations (Yang & Kong, 2025; Duncan et al., 2022) and context-specific innovations (Jančařík, 2019).
3. To identify persistent gaps and propose future research directions, including neural validation (e.g., EEG/fNIRS-integrated AI), equity-driven design (Duncan et al., 2022), and the ethical incorporation of generative AI into cognitive architectures (Valeri et al., 2025).

This review is not only timely but urgent. As generative AI rapidly reshapes educational practice (Kasneci et al., 2023), education faces a critical choice:

allow algorithmic convenience to dictate pedagogy, or deliberately align AI with the realities of human cognition and equitable teaching. The outcome will directly influence the scientific literacy, cognitive growth, and educational equity of future generations of STEM learners.

2. THEORETICAL FRAMEWORK

The integration of neuroscience into AI-driven educational tools demands a foundation that respects both the cognitive architecture of learners and the practical realities of classrooms. This review is guided by three interrelated theoretical strands: **Cognitive Load Theory (CLT)**, **embodied cognition**, and **metacognition**—each offering unique but complementary insights into how AI can enhance STEM learning.

2.1 Cognitive Load Theory (CLT).

CLT emphasizes the limits of working memory and the importance of instructional design that minimizes extraneous load while promoting schema development (Sweller, 2011; Paas & Sweller, 2014). For AI-enabled STEM tools, this means designing interfaces and feedback systems that reduce unnecessary complexity and optimize the balance between challenge and support. In practice, CLT underscores why real-time adaptivity—tailoring explanations, examples, and task sequencing to learners' cognitive states—is crucial for effectiveness.

2.2 Embodied Cognition.

Embodied cognition highlights that learning is grounded in sensorimotor experience (Wilson, 2002; Glenberg, 2010). Within AI-enhanced STEM education, robotics, augmented reality, and gesture-based interactions become more than engagement strategies—they are cognitive scaffolds that link abstract concepts to physical actions (Alibali & Nathan, 2012). By embedding AI within embodied interactions, abstract domains such as chemistry or mechanics become accessible through tangible, manipulable representations.

2.3 Metacognition.

Finally, metacognition—the ability to reflect on and regulate one's own thinking—provides a bridge between neuroscience and pedagogy (Flavell, 1979). AI tools designed with metacognitive scaffolds can help learners monitor progress, evaluate strategies, and adjust their approaches. Features such as reflective prompts, adaptive hints, and learner dashboards support self-regulated learning, ensuring that students remain active participants rather than passive recipients of AI guidance.

Together, these three strands form a neurocognitive triad that anchors this review. By examining how AI tools in secondary STEM education engage with CLT, embodied cognition, and metacognition, we are able to evaluate whether current designs are cosmetic nods to brain science or genuine attempts at cognitively aligned, pedagogically robust innovations.

3. METHODOLOGY

This review followed the **PRISMA 2020 guidelines** (Page et al., 2021) to ensure transparency, reproducibility, and methodological rigor. Although the protocol was not pre-registered, all search strategies, inclusion criteria, screening procedures, and analytical methods were fully documented to support replication. The primary objective was to synthesize empirical evidence on how artificial intelligence (AI), grounded in neuroscience or cognitive science principles, informs the design and development of teaching and learning tools in secondary STEM education.

3.1 Literature Search Strategy

A comprehensive search was conducted across five major academic databases: **Scopus**, **Web of Science Core Collection**, **ERIC (Education Resources Information Center)**, **PubMed**, and **IEEE Xplore**. The search covered publications from **January 2010 to May 2025**.

The core search string combined four conceptual clusters:

1. **Population** (secondary/high school students, ages 12–18, or teachers developing instructional materials).
2. **Discipline** (STEM education, including science, mathematics, physics, chemistry, biology, engineering).
3. **Technology** (AI, intelligent tutoring systems, adaptive learning, generative AI, chatbots, machine learning).
4. **Theoretical grounding** (neuroscience, cognitive science, cognitive load, attention, executive function, neuroeducation).

Database-specific adaptations were applied in ERIC, PubMed, and IEEE Xplore to align with controlled vocabularies and indexing rules. Full search strings are available in **Appendix A**.

3.2 Inclusion and Exclusion Criteria

Studies were included if they:

- Targeted **secondary school students** (ages 12–18) or teachers designing materials for this

group.
- Described or evaluated **AI-based tools, systems, or interventions**.
- Incorporated principles from **neuroscience or cognitive science** (e.g., CLT, embodied cognition, executive function).
- Reported **empirical insights or design recommendations** related to tool development.

Studies were excluded if they:
- Focused only on elementary or tertiary education without transferable design principles.
- Lacked an AI component or cognitive/neuroscience grounding.
- Measured only engagement or satisfaction without linking results to tool design.
- Were non-empirical (e.g., editorials, conceptual papers, purely technical AI studies).
- Were published in languages other than English.

3.3 Screening and Data Extraction

Search results were exported to **Zotero** for reference management. Duplicates were removed using Zotero's deduplication function and **Rayyan.ai's** automated filters. Screening occurred in two phases:
1. **Title and abstract review**, applying inclusion/exclusion criteria.
2. **Full-text assessment**, to confirm eligibility.

Data from included studies were extracted into a structured **Google Sheets template**, capturing:
- Author, year, country, and study design.
- Population and sample characteristics.
- Type of AI tool/technology.
- Underlying neuroscience/cognitive principles.
- Design or implementation features.
- Outcomes and limitations.
- Quality appraisal scores.

3.4 Quality Appraisal

The **Mixed Methods Appraisal Tool (MMAT; Hong et al., 2018)** was used to assess methodological rigor. This tool evaluates five dimensions tailored to different study types (qualitative, quantitative, and mixed methods). Each study received a quality rating to ensure balanced interpretation.

3.5 Data Analysis

A structured PRISMA-guided procedure was followed to identify, screen, and select studies relevant to the intersection of neuroscience-informed education, artificial intelligence, and secondary-level STEM learning. In the identification phase, a comprehensive search was conducted across five major scholarly databases—Scopus (n = 104), Web of Science (n = 97), ERIC (n = 23), PubMed (n = 6), and IEEE Xplore (n = 3) using Boolean combinations of the terms "Neuroscience-informed education," "AI in education," "STEM education," "Cognitive science and learning," and "AI tools." These formulations ensured broad interdisciplinary coverage and captured studies explicitly linking AI methods with cognitive or neuroscientific principles relevant to learning.

All records were exported to citation management software, where duplicate entries were removed using automated and manual procedures. This process reduced the dataset from 233 to 221 unique studies for screening. During the screening phase, titles and abstracts were independently reviewed by two researchers using predefined inclusion and exclusion criteria. Studies that did not involve AI in educational practice, lacked grounding in cognitive or neuroscientific theory, or were unrelated to secondary STEM learning environments were excluded. A total of 186 studies were removed at this stage, leaving 35 for full-text assessment.

In the eligibility phase, the full texts of these 35 studies were examined in detail. Each was evaluated based on four criteria: (1) explicit focus on secondary education, (2) integration of AI-based tools or techniques, (3) grounding in neuroscience or cognitive science, and (4) empirical research design. Articles were excluded if they lacked an AI component, were not situated within secondary-level contexts, offered no neuroscientific foundation, or adopted non-empirical approaches. Ultimately, 30 full-text studies were excluded for failing to meet one or more of these criteria.

The inclusion phase resulted in 5 studies that fully satisfied all methodological and conceptual requirements. These studies constituted the final dataset for synthesis. Data from each included study were extracted using a structured template capturing research aims, AI methodologies, neuroscientific principles, empirical design characteristics, dataset descriptions, and performance outcomes. In addition to quantitative extraction, qualitative information—such as implementation challenges, ethical considerations, and contextual barriers—was documented to provide a holistic understanding of how neuroscience-informed AI tools function within authentic secondary STEM learning environments.

Together, these steps form a transparent, systematic, and rigorous PRISMA-aligned study selection process that reflects both the strengths and the limitations of the current evidence base within this emerging interdisciplinary field.

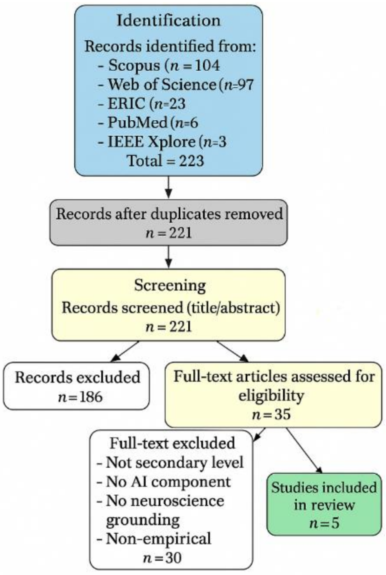


Figure 1: Data analysis process

The synthesis of evidence adopted a thematic synthesis methodology following the procedures delineated by Thomas and Harden (2008), which is well suited for integrating heterogeneous qualitative and mixed-methods findings in emerging interdisciplinary domains. Given that only five empirical studies met the inclusion criteria, a rigorous and recursive analytic protocol was essential to ensure conceptual robustness and methodological transparency. The synthesis unfolded across four iterative stages.

First, Familiarization entailed repeated, immersive readings of each included study to establish a comprehensive understanding of its research aims, methodological architecture, AI implementation strategy, and neuroscientific grounding. This stage enabled the reviewers to internalize the nuances of how each study operationalized constructs such as neural processing, cognitive load, attentional mechanisms, or neuroplasticity within AI-supported STEM learning environments.

Second, Open Coding was conducted inductively to generate a codebook capturing salient concepts across studies. Codes encompassed (a) AI system typologies (e.g., adaptive algorithms, neural-network–driven feedback, intelligent tutoring systems), (b) neuroscientific or cognitive principles invoked (e.g., working memory constraints, executive functioning, encoding processes), and (c) pedagogical and design recommendations embedded in the studies' instructional frameworks. Two reviewers independently conducted the coding, which was then enhanced and stabilized through detailed note documentation and a series of consensus-driven deliberations.

Third, Theme Development involved clustering conceptually related codes into higher-order analytical themes. This stage produced a set of integrative categories that elucidated:

(1) the mechanisms through which AI systems interface with or model cognitive processes;

(2) the degree to which neuroscience-informed principles are explicitly or implicitly embedded in AI-mediated STEM learning activities; and

(3) design, usability, and implementation considerations shaping the educational deployment of AI tools in secondary contexts.

These themes served as analytical scaffolds for interpreting convergence and divergence across the limited evidence base.

Fourth, Mapping integrated the emergent themes into a conceptual framework, visually articulating the relationships among AI modalities, cognitive and neurobiological constructs, learner processes, and STEM instructional outcomes. This mapping exercise provided an explanatory model that situates neuroscience-informed AI within broader pedagogical and cognitive ecosystems, thereby clarifying how such systems may influence learning optimization, cognitive engagement, and instructional decision-making.

Through this structured and theoretically informed analytic process, the review advances beyond simple descriptive aggregation. Despite the small corpus of empirical studies, the thematic synthesis yields actionable, conceptually grounded insights that contribute meaningfully to the interdisciplinary discourse on neuroscience-informed AI in secondary STEM education. Moreover, the synthesis highlights critical conceptual and methodological gaps in the current evidence base, reinforcing the urgency of expanding empirical inquiry in this emerging field.

The thematic synthesis of the five empirical studies revealed three interrelated themes that characterize how neuroscience-informed artificial intelligence is conceptualized, operationalized, and evaluated within secondary STEM education. Although the empirical base remains limited, the convergent patterns across studies provide a coherent understanding of the mechanisms through which AI systems draw on cognitive and neuroscientific principles to support learning.

Theme 1: AI Systems as Cognitive-Adaptive Mechanisms

Across all included studies, AI tools were not merely deployed as instructional technologies but functioned as cognitive-adaptive systems capable of responding to learners' mental states. The studies demonstrated that adaptive learning platforms, neural-network–based analytics, and intelligent tutoring systems utilized learner data—such as response accuracy, latency, interaction histories, and inferred cognitive effort—to dynamically modulate instructional difficulty or feedback frequency. This aligns with frameworks of cognitive adaptability in learning sciences, wherein technology serves as a mediator that detects and responds to fluctuations in cognitive load or working memory constraints.

Several studies further indicated that AI algorithms implicitly modelled cognitive constructs (e.g., attention allocation, error-monitoring processes), even when neuroscientific terminology was not explicitly invoked. This suggests a convergence between computational adaptation processes and cognitive-regulation mechanisms recognized in neuroscience. Taken together, the findings highlight AI's emerging role as an adaptive scaffold that tailors learning trajectories in ways compatible with cognitive optimization principles.

Theme 2: Integration of Neuroscientific Principles in AI-Supported Learning

A second theme concerned how neuroscientific and cognitive-science principles were operationalized within AI-enabled STEM learning environments. The studies consistently embedded constructs such as cognitive load management, working-memory support, attentional cueing, and neuroplasticity-oriented practice schedules within AI-driven instructional pathways. For example, systems adjusted task difficulty to avoid cognitive overload, provided multimodal cues to sustain attention, or leveraged spaced-repetition algorithms aligned with memory consolidation research.

Importantly, while only a subset of the studies explicitly referenced neuroscience, all incorporated cognitive-science principles in their design logic, indicating an implicit but robust engagement with neuro-informed pedagogical strategies. This theme underscores the potential of AI systems to serve as vehicles for translating cognitive and neuroscientific research into actionable instructional designs—particularly in STEM contexts where complex conceptual reasoning places substantial demands on cognitive resources.

Theme 3: STEM Learning Gains and Pedagogical Implications of Neuroscience-Informed AI

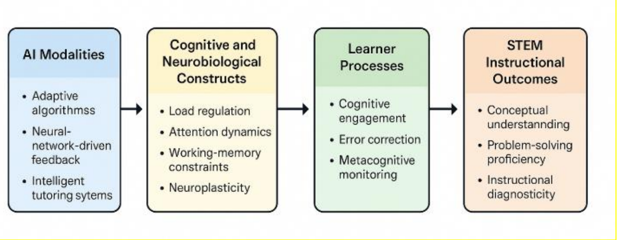
The third theme highlighted the learning and pedagogical outcomes associated with AI systems grounded in cognitive or neuroscientific principles. Across studies, learners demonstrated improvements in conceptual understanding, problem-solving efficiency, and metacognitive regulation, suggesting that AI-enabled adaptations aligned effectively with cognitive processing needs. Evidence also indicated positive influences on learners' persistence and engagement, with several studies reporting reductions in error repetition and enhanced responsiveness to feedback.

At the pedagogical level, AI systems provided teachers with fine-grained analytics capable of informing instructional decision-making and differentiating support. However, studies also noted contextual contingencies—such as classroom implementation fidelity, teacher expertise in interpreting AI-generated insights, and alignment between system feedback and curricular goals—that moderated the impact of AI tools.

Overall, this theme reflects the dual instructional function of neuroscience-informed AI systems: supporting learner-facing cognitive optimization and enabling teacher-facing diagnostic insight within STEM disciplines.

Synthesis Summary

Taken together, the three themes depict neuroscience-informed AI as a multi-layered cognitive-pedagogical system that integrates computational adaptivity, cognitive and neuroscientific principles, and STEM instructional goals. Despite the small number of empirical studies, the thematic structure provides a theoretically coherent foundation for understanding how AI can mediate learning through mechanisms grounded in human cognition. These findings highlight both the promise of such systems and the need for more empirically rigorous, longitudinal, and ecologically valid research in secondary STEM settings.



conceptual framework integrating emergent themes

Data synthesis followed **thematic synthesis** (Thomas & Harden, 2008), implemented in four iterative stages:

1. **Familiarization** — repeated close reading of studies.
2. **Open coding** — identifying concepts related to

AI types, cognitive principles, and design recommendations.

3. **Theme development** — grouping codes into broader analytical themes.
4. **Mapping** — constructing a conceptual framework (Figure 2) to illustrate how neuroscience-informed AI is integrated into STEM tool design.

This approach ensured that the review went beyond descriptive aggregation, generating actionable insights for researchers, developers, and educators.

It is important to note that only five empirical studies met the inclusion criteria. While this number may appear modest compared to systematic reviews in more established domains, it reflects the emerging state of the field rather than a methodological shortcoming. Systematic reviews in nascent areas often synthesize a small evidence base (e.g., Brouwer et al., 2021; Gabrieli, 2016), yet these reviews are critical precisely because they provide the first conceptual and empirical map of an underexplored domain. In this case, the convergence of neuroscience, artificial intelligence, and secondary STEM education remains in its infancy, and the limited pool of studies underscores the originality and urgency of the present synthesis. By transparently documenting our search, screening, and appraisal process in line with PRISMA 2020, this review maintains the rigor of a systematic methodology while simultaneously identifying the scarcity of evidence as a finding in its own right. Far from being a weakness, the small number of eligible studies demonstrates that this is a field still in formation — and highlights the necessity of agenda-setting reviews to guide future empirical work.

4 RESULTS

A total of five empirical studies met the inclusion criteria and were synthesized to address the central research question: *"How is artificial intelligence informed by neuroscience being integrated to guide the development of teaching and learning tools for secondary school STEM education?"* Despite the modest number of studies, their collective insights reveal a rich set of design strategies and challenges that advance the field. The thematic analysis generated four interrelated domains of integration, each illustrating how neuroscience principles are translated into AI-driven educational tools. Importantly, these domains are not discrete silos but overlapping pathways that together point to an emerging ecosystem where AI functions not merely as a technological instrument, but as a cognitive partner, pedagogical orchestrator, and equity amplifier — when thoughtfully designed. Across the five studies, a consistent pattern emerged: all engaged with the core principles of our theoretical framework, namely cognitive load management, embodied cognition, and metacognitive scaffolding, while leveraging adaptive AI technologies and elements of design-based implementation. However, none of the studies progressed to direct neural validation (e.g., EEG, fNIRS, or fMRI), leaving a crucial frontier for future exploration.

4.1. Neuroscience Frameworks as Architectural Blueprints for AI Design

The most theoretically robust contributions embedded explicit neurocognitive frameworks into the *architecture* of AI tools. Rather than treating neuroscience as an afterthought, these studies operationalized brain-based principles as design constraints.

Yang and Kong (2025) provide a model example through their robotics-based machine learning platform for junior secondary STEM. The system was explicitly structured around the **AEER framework** (Attention–Engagement–Error-feedback–Reflection), which synthesizes neuroscience (attentional control, error monitoring) with educational psychology (flow theory, metacognitive reflection). Each algorithmic interaction — from capturing attention to prompting reflection — was tied to a neurocognitive process. Teachers also engaged in professional development through the **Workshops, Discussions, Resources (WDR)** model, which built Technological Pedagogical Content Knowledge (TPACK) and reinforced the co-design ethos of DBIR.

Key design principles highlighted include:

- Scaffold teacher TPACK through iterative, context-embedded PD.
- Employ robotics for embodied learning, grounding abstract concepts in sensorimotor activity.
- Use error-pattern analysis, rather than correctness alone, to target conceptual misunderstandings.

Similarly, Iqbal and Campbell's (2023) **AGILEST system** operationalized embodied cognition through AR and touchless hand interaction. Students manipulated virtual molecules in real time, supported by a machine-learning agent that provided adaptive feedback. This reduced extraneous cognitive load and fostered conceptual depth. Usability testing confirmed reduced workload and heightened engagement, validating the cognitive benefits of embodied interaction.

Together, these studies exemplify how AI tools achieve pedagogical power when neuroscience frameworks serve as *architectural blueprints* rather than decorative metaphors.

4.2. AI as Cognitive Orchestrator: Beyond Content Delivery

A second theme reframed AI as a *cognitive orchestrator* that structures the pedagogical environment. This extends beyond adapting content to shaping classroom interactions and activity design.

Jančařík's (2019) **Techambition system** illustrates this paradigm. The tool analyzed student solutions in mathematics and:

- Grouped students by cognitive profiles (e.g., visual vs. algebraic reasoning).
- Recommended instructional modalities tailored to misconceptions and strengths.
- Sequenced online and offline activities to scaffold both conceptual understanding and fluency.

Educators described the system as a "co-teacher" capable of revealing students' thinking processes, not just their scores. This model highlights AI's potential to support teacher decision-making at scale, embodying DBIR's principle of designing for implementation while respecting the cognitive and social dimensions of learning.

4.3. AI as Curriculum Content: Teaching Neuroscience Through AI

A novel contribution involved using AI not simply as a teaching tool but as curriculum content. Duncan et al. (2022) designed modules where students learned neuroscience concepts *through* AI applications. Examples included using algebra to analyze fMRI data and applying control theory to neural feedback loops.

This dual focus advanced **neuro-AI literacy**, allowing students to critically examine both how the brain works and how AI interprets it. The approach particularly empowered underserved learners, positioning AI as a lens for scientific understanding and civic engagement rather than a one-dimensional efficiency tool.

4.4. Foundational Cognitive Roots of AIEd

Sanchez-Guzman and Mora Ley's (2010) early intelligent tutoring system for physics reminds us that cognitive science has long shaped AI in education. Their ITS adapted feedback to error patterns, scaffolded metacognitive reasoning, and aligned with cognitive load principles. While predating the explicit "neuroeducation" movement, this work underscores that effective AIEd has always rested on respecting the architecture of human cognition.

4.5. Cross-Cutting Insights and Gaps

Synthesis across the five studies highlights four recurring patterns and one defining gap:

- **Teachers as co-designers**: Teachers were consistently engaged as collaborators rather than passive adopters, a key DBIR principle.
- **Embodied interaction as scaffold**: Physical engagement consistently enhanced comprehension and motivation.
- **Contextualization as equity strategy**: Only Duncan et al. (2022) explicitly foregrounded equity, but their success highlights its critical role.
- **Adaptivity beyond the individual**: The most innovative tools adapted to groups and contexts, not just individuals.
- **Critical gap: Neural validation absent** — None of the studies employed direct neural measures, leaving claims of "neuroscience-informed" design empirically unverified.

5. DISCUSSION

This review shows that the intersection of neuroscience and AI in secondary STEM education is still in its formative stage. While conceptual innovations are emerging, empirical grounding, equity considerations, and teacher agency remain underdeveloped. To move forward, the field must shift from rhetorical claims of being "brain-based" to demonstrably neuroscience-informed, while ensuring inclusivity and practical classroom integration.

5.1 Moving Toward Truly "Neuroscience-Informed" AI

Although many studies adopt the term "neuroscience-informed," most lack rigorous operationalization. Yang and Kong's (2025) robotics platform, guided by the AEER framework (Attention–Engagement–Error-feedback–Reflection), illustrates how explicit neuroscience principles can shape pedagogical sequencing. Similarly, Iqbal and Campbell's (2023) AGILEST model demonstrates embodied cognition in action, enabling learners to manipulate abstract molecular concepts through sensorimotor engagement.

Across the literature, tools appear to cluster along a **hierarchy of grounding**:

- **Cosmetic:** Rhetorical "brain-based" claims without scientific validation.
- **Cognitive:** Reliance on principles such as cognitive load theory, but without neural measurement.

- **Neural:** Incorporation of neuroimaging (e.g., EEG, fNIRS) to validate learning effects.
- **Adaptive:** Closing the loop with real-time neural feedback to dynamically adjust instruction.

Most current tools plateau at the cognitive level. The next leap lies in Levels 3–4, integrating accessible neurotechnologies to achieve **brain-validated and neuro-adaptive AI**.

5.2 Addressing the Equity Imperative

Equity remains the least developed dimension in this field. Only Duncan et al. (2022) explicitly co-designed with underserved schools, while most designs implicitly assume “average” learners. Such approaches risk reinforcing systemic inequities (Selwyn, 2021; UNESCO, 2023).

To counter this, future neuro-AI tools must integrate equity from the outset through:

- **Participatory co-design** with marginalized communities.
- **Bias audits** that account for data, cognitive assumptions, and cultural context.
- **Accessibility-first design**, considering language, disability, and connectivity limitations.

Embedding equity at the design stage ensures AI serves as a bridge rather than a barrier in STEM learning.

5.3 Teacher–AI Symbiosis

Findings consistently show that AI’s value lies in amplifying, not replacing, teacher expertise. Jančařík’s (2019) Techambition platform illustrates this potential by orchestrating groupings and tasks based on student cognitive profiles.

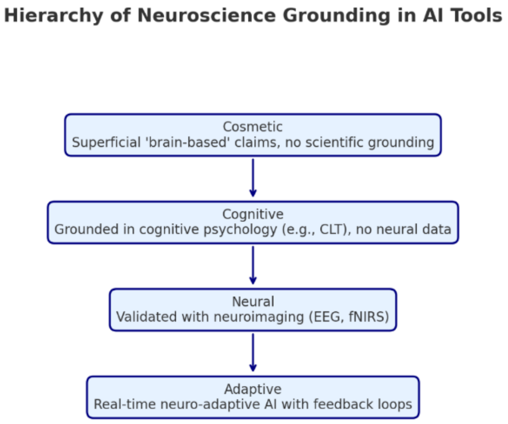
Such systems function as **cognitive orchestration tools**, equipping teachers with actionable insights, such as identifying students who require conceptual reinforcement or highlighting shifts in engagement. Embedding professional learning opportunities within these systems transforms AI into a tool for **both student growth and teacher empowerment**, positioning teachers as informed decision-makers rather than passive users.

5.4 Generative AI and Cognitive Load

The rise of large language models (LLMs) introduces new opportunities and risks. While tools like ChatGPT can clarify complex STEM concepts (Valeri et al., 2025), they may also overload students with unstructured, verbose outputs. From a cognitive load perspective, effective use of generative AI requires:

- **Chunking outputs** into manageable cognitive units.
- **Scaffolded prompting** that encourages metacognitive reflection.
- **Visual reasoning pathways** to support schema construction and knowledge transfer.

Aligning LLM use with cognitive load theory offers a research agenda that ensures generative AI enhances, rather than undermines, STEM learning.



Synthesis

Taken together, these insights point toward a future where AI is not simply “intelligent,” but **cognitively sensitive, equity-centered, and teacher-empowering**. The challenge ahead is to design tools that move beyond rhetorical innovation toward scientifically validated, contextually responsive, and pedagogically meaningful AI for secondary STEM education.

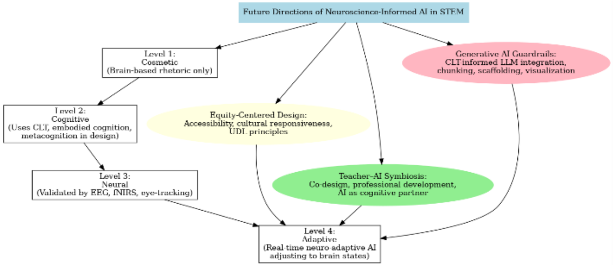


Figure 2. Future directions for neuroscience-informed AI in secondary STEM education, highlighting the transition from cognitive grounding to brain-validated, neuro-adaptive systems, with equity and teacher–AI symbiosis as cross-cutting imperatives.”

6 CONCLUSION

This review set out to examine how neuroscience-informed artificial intelligence is shaping the design of teaching and learning tools in secondary STEM education. The evidence, though limited, highlights a field still at an early stage of development but full of potential. Studies such as Yang and Kong's (2025) AEER framework and Iqbal and Campbell's (2023) AGILEST model illustrate how cognitive and neuroscientific insights can meaningfully guide AI design, reducing cognitive load and fostering deeper engagement. These examples demonstrate what is possible when neuroscience and AI move beyond rhetoric to practical application.

At the same time, the gaps remain striking. Few studies employ neural outcome measures, even fewer address equity in meaningful ways, and teacher participation in co-design is still the exception rather than the rule. Without progress in these areas, AI risks remaining technically sophisticated but pedagogically shallow.

The future of STEM education requires tools that are brain-informed by design: where algorithms respect cognitive limits, scaffold metacognition, and adapt to the diverse realities of classrooms. Equally important, these tools must empower teachers as cognitive orchestrators and ensure equitable access for all learners, not only those with privileged resources or backgrounds.

This is more than a technical challenge; it is a pedagogical and ethical imperative. If developers, educators, and policymakers act collectively, neuroscience-informed AI can move from isolated prototypes to scalable, classroom-ready innovations. The opportunity is clear: to build AI systems that are brain-validated, equity-centered, and teacher-empowering — ensuring that technology serves learning rather than the other way around. The time to act is now, before a generation of students grows up with tools that misunderstand how their minds truly learn.

6.1 Practical Takeaways

- **For Developers:** Treat neuroscience principles (cognitive load, metacognition, embodied cognition) as design constraints, not add-ons. Build equity and accessibility into AI tools from the start.
- **For Educators:** Use AI as a *cognitive partner* — to orchestrate learning, scaffold reflection, and amplify teacher agency — rather than a replacement for pedagogy.
- **For Policymakers:** Fund research that moves beyond "brain-inspired" rhetoric to *brain-validated* AI, and require evidence of equity and accessibility in EdTech initiatives.
- **For Researchers:** Prioritize studies that integrate neuroimaging or real-time cognitive measures, ensuring that claims of "neuroscience-informed AI" are empirically validated.

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