AI-SUPPORTED BRAIN-BASED LEARNING MODELS: INTEGRATING NEUROPLASTICITY AND ADAPTIVE INTELLIGENCE IN EDUCATION

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Review Article

ABSTRACT

Artificial intelligence (AI) has emerged as a disruptive force in education, allowing for personalised, data-driven, and adaptable learning experiences. Brain-Based Learning (BBL), which is based on neuroscience, emphasises that learning is optimised when instructional approaches fit with the brain's natural processes, particularly neuroplasticity. This research provides an integrated model of AI-Supported Brain-Based Learning (AI-BBL) that combines neuroplasticity principles with adaptive intelligence to improve overall learner development.

The paradigm is especially relevant for the foundational and early learning periods, when neuroplasticity is at its peak, and personalised scaffolding is essential. AI-BBL settings promote attention management, memory consolidation, executive functioning, and socio-emotional development while decreasing cognitive overload. From a pedagogical standpoint, instructors are repositioned as neuro-facilitators who use AI-generated insights to make informed teaching decisions.

The paper finds that combining AI with brain-based learning principles provides a scientifically sound path for future-ready education. It emphasizes the implications for curriculum design, teacher professional development, and inclusive practices, as well as the need for empirical validation of AI-BBL models across a variety of educational contexts.

KEYWORDS: AI-Supported Brain-Based Learning, Neuroplasticity, Adaptive Intelligence, Artificial Intelligence in Education (AIEd), Neuroeducation, Personalised Learning, Cognitive Neuroscience, Learning Analytics, Multisensory Instruction, Emotion-Centred Learning, Executive Functions, Holistic Development, Foundational Stage Education, Inclusive Education, Educational Technology Innovation

1. INTRODUCTION

The rapid growth of artificial intelligence (AI) has profoundly revolutionised educational methods, resulting in creative learning models that are more learner-centred, data-driven, and adaptable. Among these new techniques, AI-powered brain-based learning models provide a potent combination of neuroscience and education technology. These models are based on the principles of neuroplasticity—the brain's ability to rebuild and strengthen neural connections via experience—and adaptive intelligence, which allows learning systems to adjust dynamically to individual learner requirements.

Brain-based learning emphasises instructional practices that are consistent with how the human brain naturally learns, analyses information, and retains knowledge. Neuroscience research has shown that meaningful learning happens when cognitive, emotional, and sensorimotor experiences are actively engaged, especially in the early and foundational phases of development. Neuroplasticity is critical in this process because repeated, enriched, and emotionally supportive learning experiences stimulate the establishment of robust neural pathways that support overall development.

The incorporation of AI into brain-based learning models improves the process by creating personalised, responsive, and adaptable learning environments. AI systems can analyse learners' performance patterns, attention levels, and progress in real time, allowing instructional content, tempo, and feedback to be altered accordingly. Such adaptable intelligence promotes diversified learning, strengthens brain connections through timely repetition and diversity, and accommodates a wide range of learning styles and skills.

In educational settings, particularly at the basic level, AI-supported brain-based learning models have the potential to promote cognitive growth, emotional control, and psychomotor development. By merging neuroplasticity concepts with intelligent technological tools, these models provide engaging, inclusive, and developmentally appropriate learning experiences. As education becomes increasingly individualised and evidence-based, the integration of AI, neuroplasticity, and adaptive intelligence emerges as a promising avenue for improving learning outcomes and preparing students for the challenges of the twenty-first century.

Neuroplasticity is essential for learning: repetitive stimulation of neuronal circuits improves memory, understanding, and skill acquisition. This biological premise supports brain-based learning models that prioritize emotionally supportive, immersive, and contextually rich educational contexts. AI improves these models by allowing for fine-grained analysis of learner interactions, delivering adaptive feedback, and producing tailored learning paths. Integrating adaptive intelligence allows systems to evolve alongside learners, resulting in bespoke routes that take into account individual differences in cognition, motivation, and pace.

This study investigates the theoretical basis of AI-supported brain-based learning, assesses evidence of effectiveness, examines practical and ethical issues, and suggests future research and practice paths.

2. THEORETICAL BACKGROUND

2.1 Brain-based learning and neuroplasticity

Brain-based learning is founded on the premise that educational techniques should mirror how the brain functions. Neuroplasticity is the brain's ability to change its shape and function in response to experience and stimuli. The key principles include:

Learning causes neuronal connections to change based on experience.

Reinforcement improves distributed neural networks through repetition and practice.

Emotional and social context: Engagement and motivation improve retention.

Developmental sensitivity: Synaptogenesis and pruning are most active throughout early development.

Applying neuroplasticity to education implies that courses should be adaptive, multimodal, and responsive to learners' developmental requirements.

Brain-based learning is an educational strategy based on the idea that effective teaching and learning should be consistent with the brain's natural structure, functions, and developmental processes. Brain-based learning, which builds on discoveries in neuroscience, cognitive psychology, and educational research, focuses on how the brain encodes, organises, stores, and retrieves information. Rather than viewing learning as a merely behavioural or instructional consequence, this approach sees it as a biological process influenced by neuronal activity, experience, emotion, and surroundings.

At the heart of brain-based learning is the idea of neuroplasticity, which refers to the brain's natural ability to modify its structure and functional organization in response to learning, experience, and environmental stimuli. Neuroplasticity allows for the development of new brain connections (synaptogenesis), the reinforcement of existing routes, and the removal of unused connections. These dynamic alterations provide the neural foundation for learning, memory, skill development, and behavioral adaptation.

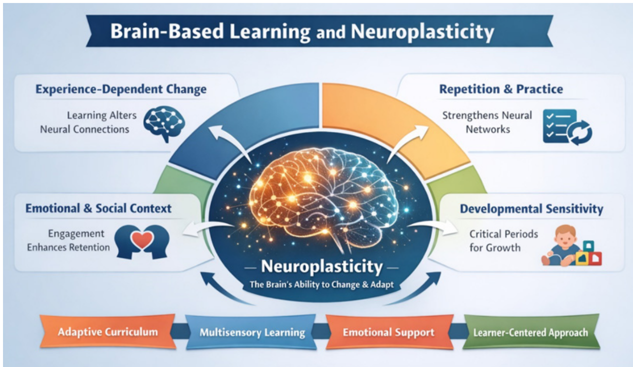
One of the basic principles of neuroplasticity is experience-dependent change. Learning experiences, particularly those that are meaningful, engaging, and context-rich, engage certain neural networks in the brain. Repeated activation of these networks builds synaptic connections, increasing information processing efficiency and retrieval reliability. This principle emphasizes the significance of active learning tactics, hands-on experiences, and practical applications, as passive exposure alone is insufficient to generate long-term brain change.

Repetition and practice are crucial for neuronal consolidation. Neuroscientific research implies that frequent practice improves myelination and synapse efficiency, resulting in faster and more accurate neural transmission. As a result, brain-based learning focuses on instructional tactics such as spaced repetition, rehearsal, revision through variation, and practice in diverse situations. These tactics help to spread learning over time, reducing cognitive overload and encouraging long-term retention rather than short-term memorisation.

The emotional and social environment of learning is another important factor influencing neuroplastic development. Emotional processes are inextricably related to cognitive functioning, as structures like the amygdala and hippocampus play important roles in attention, memory formation, and motivation. Positive emotional experiences, such as curiosity, happiness, safety, and a sense of belonging, increase brain receptivity and aid learning. Chronic stress, worry, or anxiety, on the other hand, can impede neuroplastic processes by slowing memory consolidation and limiting cognitive flexibility. As a result, brain-based learning promotes emotionally supportive, socially interactive, and psychologically safe learning settings that foster motivation, engagement, and self-regulation.

Neuroplasticity is also developmentally sensitive, with some stages of life characterised by increased brain flexibility. Early childhood, in particular, is a vital period marked by rapid brain development, substantial synaptogenesis, and selective synaptic pruning. During this time, the brain is particularly sensitive to environmental stimuli, making early learning experiences extremely impactful. Rich, multisensory, and developmentally appropriate activities—such as movement, play, music, language exposure, and social interaction—can profoundly influence brain architecture and provide the framework for subsequent cognitive, emotional, and motor competencies.

Fig. 1: Educational techniques that promote Brain-Based Learning



The application of neuroplasticity concepts to education suggests that curricula and instructional approaches should be adaptable, multimodal, learner-centred, and developmentally responsive. Brain-based learning allows the integration of visual, aural, kinesthetics, and tactile inputs to activate multiple brain regions simultaneously, strengthening neural networks. It also emphasises pacing, differentiation, and instructional strategies that are adaptable to individual learning styles, skills, and developmental trajectories.

To summarise, brain-based learning, guided by neuroplasticity principles, provides a scientifically grounded foundation for creating effective educational experiences. Recognising learning as a dynamic brain process driven by experience, repetition, emotion, and development allows educators to design learning environments that promote greater comprehension, retention, and holistic development. This theoretical foundation serves as a solid platform for incorporating new technologies, such as AI-supported adaptive learning systems, to further customise instruction and promote neuroplastic growth in a variety of educational scenarios.

2.2 Using Adaptive Intelligence and AI in Education

Adaptive intelligence in educational AI refers to systems that can modify instructional content and pace based on ongoing assessments of student performance. The core capabilities include:

Real-time data analytics involves tracking accuracy, response times, and engagement metrics.

Personalised content sequencing involves delivering resources based on the learner's preparedness.

Predictive modelling involves anticipating misconceptions and giving targeted corrections.

Feedback and scaffolding provide instant corrective and motivational support. AI thus acts as a bridge between learner cognition and instructional method.

In the context of educational artificial intelligence, adaptive intelligence refers to intelligent systems' ability to continually adjust instructional content, learning paths, and pedagogical tactics in response to real-time learner data analysis. Adaptive AI systems, unlike standard digital learning aids that give homogeneous content, are intended to adjust dynamically to individual variances in learners' cognitive skills, learning pace, engagement levels, and performance patterns. This responsiveness establishes AI as an effective facilitator of tailored and brain-aligned learning experiences.

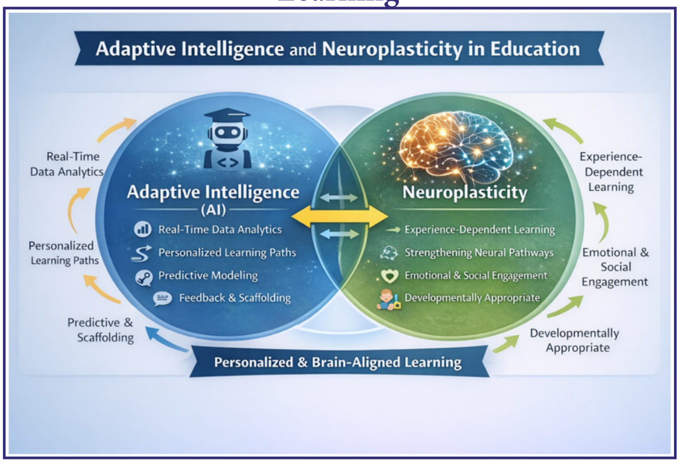
Real-time data analytics are a key component of adaptive intelligence. AI-driven learning platforms capture and evaluate a variety of learner data, such as response accuracy, task completion time, error frequency, interaction patterns, and engagement indicators. These systems provide detailed learner profiles based on continuous monitoring, reflecting current understanding and learning needs. Such real-time assessment allows for fast instructional modifications, which supports timely reinforcement and reduces learning gaps.

Personalized content sequencing is another key adaptive intelligence skill. Based on ongoing assessment, AI systems may evaluate learners' preparation levels and change the difficulty, complexity, and sequence of instructional materials accordingly. Learners who demonstrate mastery may be assigned advanced tasks, whilst those who struggle may be given more practice, different explanations, or scaffolded support. This personalized sequencing is consistent with neuroplasticity concepts, as learning is most effective when assignments are properly difficult and fall within the learner's zone of proximal development.

Predictive modelling boosts AI's adaptive potential in education. By analysing trends and patterns in student behaviour and performance, AI systems can detect possible misconceptions or areas of trouble before they become persistent. Predictive algorithms allow for proactive interventions such as focused remediation, revision exercises, or conceptual reinforcement. This anticipatory strategy not only increases learning efficiency but also decreases irritation and cognitive stress, promoting long-term engagement.

Feedback and scaffolding are another important aspect of adaptive intelligence. AI-powered solutions deliver rapid, detailed, and actionable feedback to help learners identify mistakes and improve their thinking. In addition to corrective feedback, adaptive systems include motivational cues, encouragement, and progress indicators to boost self-esteem and perseverance. As learners achieve competency, scaffolding tactics such as hints, prompts, and guided practice are gradually phased out, promoting autonomy and self-regulation.

Fig. 2: Conceptual Framework Linking Adaptive Intelligence and Neuroplasticity in Brain-Based Learning



Collectively, these capabilities establish AI as a link between learner cognition and instructional method. Adaptive AI systems bridge the gap between how students learn and how teachers give teaching by continuously evaluating learner data and changing pedagogical responses. When combined with brain-based learning principles, adaptive intelligence promotes experience-dependent neuronal plasticity, optimizes cognitive load, and reinforces learning via timely practice and feedback. As a result, AI-driven adaptive learning models have the potential to significantly improve educational effectiveness, inclusivity, and customisation across a variety of learning environments.

3. AI-SUPPORTED BRAIN-BASED LEARNING MODELS.

3.1 Core Components. AI-enabled brain-based models often integrate:

Learner profiling uses dynamic models of cognitive strengths, deficits, and preferences.

Neuroadaptive pathways are instructional paths altered by performance and engagement.

Contextualized feedback loops are iterative loops of assessment and targeted training.

Embodied learning environments use multimodal inputs (visual, aural, and interactive) to match how the brain processes information.

AI-supported brain-based learning models are intended to connect instructional techniques with the biological and cognitive processes of the human brain, while also utilizing artificial intelligence's adaptive capabilities. These methods combine several interconnected components to offer individualized, responsive, and developmentally appropriate learning experiences. Learner profiling, neuroadaptive learning pathways, contextualized feedback loops, and embodied learning environments are all important components.

Learner profiling is the core component of AI-powered brain-based learning models. AI systems create dynamic learner profiles by collecting and analyzing data on a continuous basis, capturing individual variances in cognitive ability, prior knowledge, learning pace, engagement habits, and preferences. These profiles do not remain static; rather, they change over time as students interact with educational content. AI systems can adjust educational tactics that respect individual heterogeneity and foster optimal learning circumstances by keeping up with current representations of learners' strengths and areas of need.

Neuroadaptive learning pathways are instructional paths that are constantly modified based on students' performance, engagement, and responsiveness. These pathways, which are based on neuroplasticity principles, ensure that learning experiences are difficult enough and structured correctly to reinforce brain connections. Learners who exhibit mastery may progress to progressively challenging tasks, while those who struggle receive further scaffolding, different explanations, or diversified practice. Such adaptability promotes experience-dependent brain development and keeps learners in their optimal zone of cognitive engagement.

Contextualized feedback loops are crucial for reinforcing learning and driving progress. AI-powered systems use iterative cycles of assessment, feedback, and instructional adjustment to offer learners with relevant, actionable information. Immediate feedback helps to rectify misconceptions before they become established, whereas positive reinforcement increases drive and persistence. These feedback loops also influence the AI system's adaptive decisions, resulting in an ongoing cycle of data-driven refinement that promotes both cognitive growth and self-regulated learning.

Embodied learning environments are another important component of AI-powered brain-based models. These environments use multimodal inputs, including as visual, aural, kinesthetic, and interactive aspects, to align education with the way the brain naturally receives information. Embodied learning experiences stimulate distributed brain networks by engaging numerous sensory pathways at the same time, which strengthens memory formation and conceptual understanding. Interactive simulations, movement-based activities, and multimedia tools all help to increase engagement and promote holistic development, especially in the early and foundational phases of learning.

These essential components allow AI-supported brain-based learning models to work as integrated systems that dynamically respond to learners' cognitive and developmental needs. By merging learner-centered data analytics with neuroplastic concepts, such models provide a solid foundation for creating individualized, engaging, and neurologically matched educational experiences.

3.2 Mechanisms for Integration

AI-supported brain-based learning models use special techniques that combine adaptive intelligence and neuroplasticity principles. These systems make personalization, cognitive efficiency, and emotional engagement possible, guaranteeing that instructional experiences are neurologically appropriate and pedagogically effective. The key mechanisms include personalized learning paths, cognitive load management, and engagement and motivation.

3.2.1 Personalized Learning Paths

Personalized learning routes are instructional trajectories built by AI systems based on ongoing monitoring of learner data, such as performance accuracy, learning pace, engagement levels, and reaction patterns. Unlike fixed curriculum, these adaptive paths evolve dynamically as students grow, ensuring that training is tailored to their specific needs.

From a neuroplasticity approach, personalized learning paths stimulate brain circuits through spaced repetition and varied practice. AI systems deliberately reintroduce concepts at appropriate intervals, allowing brain connections to be strengthened over time rather than overburdened by mass repetition. This treatment increases long-term memory while reducing forgetting.AI-driven adaptation also allows for the adjustment of task complexity to keep learners in their zone of proximal development, where learning is most effective. Too easy tasks do not foster brain growth, and overly complicated tasks might cause cognitive overload and disengagement. By adjusting difficulty levels, AI systems encourage persistent cognitive effort, facilitating experience-dependent brain plasticity.

Furthermore, individualized learning routes aid in the transfer of knowledge by presenting concepts across numerous settings and modalities. This diversity promotes the building of adaptable brain representations, allowing learners to use their knowledge and skills in new settings. As a result, AI-driven customisation improves immediate performance while also contributing to long-term and transferable learning results.

One significant method used by AI systems is content segmentation, which divides educational material into small, logically ordered, and sequential parts. This method is consistent with the brain's limited working memory capacity and allows students to assimilate material in manageable chunks. By providing content sequentially, AI systems promote gradual knowledge development and prevent cognitive overload, allowing learners to better integrate new information with existing neural networks.

Another significant strategy for cognitive load control is the minimization of unnecessary processing. AI technologies improve instructional design by removing extraneous material, streamlining visual and textual layouts, and presenting content in ways that adhere to cognitive processing principles. Eliminating extraneous distractions and redundancies allows learners to dedicate more mental resources to critical processing, improving understanding and recall. Furthermore, AI-driven adaptive pacing enables students to move through content at a pace that is suited for their specific learning needs. Learners who require more time have the opportunity to practice more, while those who have mastered the material can go on without delay. This adaptability reduces cognitive fatigue and promotes long-term interest.

Overall, AI-supported brain-based learning models generate cognitively efficient learning environments by segmenting content, offering adaptive scaffolding, decreasing unnecessary load, and regulating instructional tempo. These tactics promote effective neural encoding, memory consolidation, and accurate retrieval, hence improving learning outcomes and cognitive development.

3.2.3 Engagement and Motivation.

Engagement and motivation are essential for efficient learning because affective and emotional states have a direct influence on attention, memory formation, and neuroplastic change. According to neuroscientific studies, pleasant emotional experiences increase neuronal receptivity, but stress, boredom, and anxiety can impair learning by disrupting cognitive processes. AI-supported brain-based learning models contain targeted mechanisms to promote long-term engagement and intrinsic motivation, resulting in optimal conditions for neuroplastic maturation.

Gamification is a popular method for increasing learner engagement in AI-supported learning settings. Points, levels, badges, challenges, and progress indicators provide rapid feedback and a sense of accomplishment. These characteristics trigger reward-related brain pathways involved in dopamine release, which is linked to motivation and learning preparedness. When gamification is linked with educational goals, it enhances persistence, stimulates repeated practice, and helps to develop neural connections through continuous engagement.

Adaptive pacing increases student motivation by allowing instruction to progress at a rate that is appropriate for individual talents and learning preparedness. AI algorithms continuously analyze student performance and alter the rate of content delivery accordingly. Learners are not pushed through complex content or limited by strict deadlines, which lowers frustration and fosters a sense of autonomy and competence. Such learner-controlled pacing promotes sustained attention and confidence, both of which are required for optimal neuroplastic adaptation.

Furthermore, real-time feedback and rewards are important in keeping students engaged and reinforcing learning practices. AI-powered systems deliver fast, detailed feedback that assists learners in recognizing errors, tracking progress, and celebrating success. Positive reinforcement, such as verbal praise, visual cues, or digital prizes, boosts self-efficacy and promotes perseverance, especially during difficult activities. These emotionally supportive interactions generate a good learning environment, which boosts motivation and encourages continual brain engagement. Gamification, adaptive pacing, and real-time incentives work together to provide emotionally gratifying and cognitively effective learning experiences. AI-supported brain-based learning models promote experience-dependent neural plasticity by maintaining motivation, attention, and positive affect, resulting in deeper, more persistent learning outcomes.

4. EVIDENCE OF EFFECTIVENESS.

4.1 Research findings

An increasing corpus of empirical research reveals that AI-mediated adaptive learning systems improve educational outcomes across a wide range of learner demographics and topic domains. Studies in mathematics, language learning, and science education repeatedly show that using AI-supported adaptive training leads to considerable increases in academic achievement. These advantages are ascribed to the alignment of instructional content with individual learner needs, which allows for efficient brain encoding and the strengthening of key cognitive pathways via customised practice.

Furthermore, research findings show that adaptive learning environments help to improve information retention and transfer. AI-driven systems help to consolidate learning in long-term memory by utilizing neuroplasticity concepts such as spaced repetition, multimodal engagement, and constant feedback. Learners who have been exposed to adaptive sequencing demonstrate a stronger capacity to apply learned knowledge in unfamiliar circumstances, indicating deeper conceptual understanding rather than surface-level memory.

In addition to cognitive outcomes, research shows significant gains in learner engagement and self-regulated learning practices. AI-powered platforms encourage active engagement through interactive tasks, real-time feedback, and goal-oriented advancement. These elements allow students to evaluate their own performance, set attainable objectives, and persevere in difficult activities. Enhanced self-regulation promotes sustained attention and motivation, which are required for experience-dependent brain plasticity. Evidence also suggests that tailored feedback from AI systems promotes learning more efficiently than traditional static training. Real-time diagnostic feedback enables learners to quickly rectify misconceptions, avoiding the reinforcement of incorrect brain patterns. According to comparative research, learners who receive adaptive feedback make faster learning gains and achieve higher levels of mastery than counterparts who receive uniform teaching.

Importantly, research in early childhood and foundational stage settings has shown that age-appropriate adaptive devices can effectively assist nascent literacy and numeracy skills. When combined with active teacher facilitation, AI-based tools improve phonemic awareness, numerical sense, and fundamental problem-solving skills. Such integrated techniques ensure that technology enhances, rather than replaces, social interaction and guided instruction, both of which are essential for healthy cognitive and emotional development during the early learning phases. Overall, empirical data supports the conclusion that AI-mediated adaptive learning, founded on brain-based concepts and neuroplasticity, provides a potent foundation for boosting educational efficacy at all developmental levels.

4.2 Case Examples

Practical applications of AI-powered brain-based learning models demonstrate how adaptive intelligence improves learning results. Several case studies demonstrate the effectiveness of these approaches in various educational settings. One noteworthy example is the employment of artificial intelligence tutoring systems that modify education based on learners' mistake patterns. These intelligent tutors constantly examine learner replies for misconceptions, repeating errors, and areas of conceptual difficulty. Based on this analysis, the systems offer focused explanations, tailored practice exercises, and remedial feedback. Such tailored intervention promotes neuroplastic learning by rewarding optimal neural pathways and avoiding the persistence of faulty patterns. Empirical reviews of AI tutoring systems have shown that they improve mastery levels, accelerate learning progression, and increase student confidence when compared to traditional instructional techniques.

Another notable application involves intelligent practice platforms meant to maximize learning using principles such as spaced repetition and interleaving. These systems use AI algorithms to find appropriate intervals for revisiting subjects and deliberately blend similar topics during practice sessions. These systems improve memory consolidation and knowledge transfer by spreading learning over time and various practice situations. According to the research findings, learners who use AI-driven practice platforms have better long-term retention and problem-solving abilities than learners who engage in massed or repetitive practices.

Another example is the use of sensor-based engagement detection systems, which adjust content delivery in real time. AI systems can infer learners' involvement and attention levels by analyzing data from eye tracking, facial expressions, interaction patterns, and reaction latency. When disengagement or cognitive tiredness is recognized, educational content can be adjusted by altering the pace, incorporating interactive aspects, or offering motivational prompts. Such responsiveness promotes emotional regulation and sustained attention, both of which are required for successful neuroplastic adaptation. Studies show that in environments with sensor-based adaptive systems, engagement increases, dropout rates decrease, and learning results improve.

These case studies show that AI-supported brain-based learning interventions can lead to significant increases in academic performance, engagement, and learning efficiency. These AI-driven models demonstrate the practical potential of merging adaptive intelligence with neuroplastic principles in education by tailoring teaching tactics to learners' cognitive and emotional states.

5. CHALLENGES AND ETHICAL CONSIDERATIONS

While AI-supported brain-based learning models have the potential to improve educational performance through personalisation and neuroplastic alignment, their application raises several obstacles and ethical considerations. Addressing these concerns is critical to ensuring responsible, egalitarian, and long-term usage of AI in education.

5.1 Data Protection and Security

One of the most pressing ethical concerns around AI-supported learning systems is the collection, storage, and use of learner data. Adaptive AI platforms rely on continuous data streams that include academic performance, behavioural patterns, engagement indicators, and, in certain circumstances, physiological or sensor-based data. Such data are quite sensitive, especially when the learners are children in the foundational period. Maintaining data privacy necessitates careful adherence to ethical data governance standards such as informed permission, data anonymisation, secure storage, and controlled access. Educational institutions must have transparent rules that outline how learner data is gathered, processed, and used. Failure to protect data may result in privacy violations, misuse of information, and a loss of trust among students, parents, and instructors.

5.2 Algorithmic Bias and Equity.

Another key concern is the possibility of algorithmic bias in AI-powered educational systems. AI models are trained using existing statistics that may reflect socioeconomic, cultural, or educational disparities. If not addressed, such biases can lead to unequal learning opportunities, erroneous learner profile, and reinforcement of existing achievement discrepancies. From an ethical standpoint, AI-powered brain-based learning models must promote inclusion and equity. This necessitates regular algorithm audits, the use of diverse and representative datasets, and ongoing monitoring of system outcomes across several learner groups. Ethical AI deployment requires that adaptive intelligence treat all learners similarly, regardless of background, skill, or socioeconomic standing.

5.3 Teacher Roles and Professional Autonomy.

The incorporation of AI into educational settings raises worries about the changing role of teachers. Excessive reliance on AI systems risks undermining educators' professional judgment, creativity, and relationship function. However, brain-based learning research highlights the value of human connection, emotional support, and social engagement, which AI cannot fully imitate. Ethically responsible deployment regards AI as a support tool rather than a replacement for teachers. Educators remain critical in interpreting AI-generated insights, contextualizing education, and creating emotionally responsive learning environments. Adequate professional development is required to provide teachers with the necessary abilities to effectively integrate AI tools while maintaining pedagogical autonomy.

5.4 Ethical use and accountability

The use of AI in education poses broader ethical concerns about transparency, accountability, and decision-making authority. Learners and educators should understand how AI systems generate instructional decisions and recommendations. Black-box algorithms with no explainability may weaken trust and hinder genuine human control. Clear accountability frameworks must be established to understand who is responsible for instructional decisions, system mistakes, or unexpected outcomes. Ethical governance mechanisms should keep AI systems in line with educational goals, human values, and learners' best interests.

6. CONCLUSION

The combination of artificial intelligence with brain-based learning concepts constitutes a substantial improvement in modern educational practice. AI-supported brain-based learning models, which are based on neuroplasticity science, provide a powerful framework for developing adaptive, individualised teaching environments that are consistent with how the brain learns naturally. These models go beyond standard one-size-fits-all approaches by dynamically reacting to learners' cognitive, emotional, and developmental needs, resulting in more effective and inclusive learning experiences.

This paper proved that adaptive intelligence is critical in implementing neuroplastic principles through processes such as individualized learning pathways, cognitive load management, and increased learner engagement. AI-powered systems promote experience-dependent brain plasticity by optimizing instructional tempo, reinforcing learning with spaced repetition, and giving timely feedback and scaffolding. Empirical research and case studies show that such treatments can enhance academic performance, retention, knowledge transfer, and self-regulated learning behaviours across subject areas and developmental stages.

Simultaneously, the successful application of AI-supported brain-based learning models necessitates careful attention to ethical, developmental, and pedagogical concerns. Data privacy, algorithmic bias, teacher autonomy, and learners' psychological well-being are all issues that underscore the importance of using AI in education responsibly and transparently. These problems highlight the necessity of presenting AI as a supporting tool that supplements rather than replaces human teaching, especially in early and fundamental learning environments where social contact and emotional support are critical.

In conclusion, AI-supported brain-based learning models hold substantial promise for transforming education by aligning instructional design with the principles of neuroplasticity and adaptive intelligence. These models, when implemented thoughtfully and ethically, can enhance learning outcomes, support holistic development, and contribute to more equitable and responsive educational systems. Future research and practice should continue to explore interdisciplinary approaches.

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