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Research Article

Designing AI-Based Adaptive Learning Architectures for Inclusive and Culturally Responsive STEM Education

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ABSTRACT: The utilization of Artificial Intelligence (AI) is progressively revolutionizing pedagogical methodologies by providing adaptive, individualized, and easily accessible learning prospects for a wide range of learners. Nonetheless, numerous AI-driven educational frameworks persist in adhering to standardized methodologies that inadequately cater to issues of cultural diversity, fairness, and inclusivity. This article delves into the potential of AI-facilitated education in fostering the establishment of culturally sustaining and inclusive learning environments that bolster fair participation and meaningful learning encounters for all students. By drawing upon theories of inclusive education, culturally sustaining pedagogy, and technology-enhanced learning, this theoretical exposition advocates for a model that integrates AI technologies with culturally responsive and inclusive teaching strategies. The model accentuates features such as accessibility, provision of multilingual support, adaptive scaffolding, recognition of learner diversity, and student-centric engagement to preserve learners' cultural identities while advancing academic success and self-regulated learning. Moreover, the article delves into the functionalities of AI tools like intelligent tutoring systems, personalized feedback mechanisms, learning analytics, and speech recognition technologies in supporting students with varied linguistic, cultural, and educational requisites within inclusive educational settings. Furthermore, the research scrutinizes obstacles linked with the implementation of AI, encompassing issues of algorithmic partiality, digital disparity, ethical quandaries, and educator preparedness. It posits that efficacious AI-driven education necessitates cooperative efforts among educators, policymakers, communities, and technology innovators to ensure equitable and culturally responsive learning milieus. By proffering a culturally sustaining viewpoint on the amalgamation of AI and offering guidance for crafting future-proof inclusive educational frameworks rooted in diversity, accessibility, and social equity, this article enriches ongoing dialogues on inclusive and fair education.

Keywords: Artificial intelligence, Inclusive education, Culturally sustaining pedagogy, Educational equity, Educational Ecosystems.

INTRODUCTION

The notion of learning ecosystems offers a valuable perspective for comprehending how AI can be integrated into STEM education in a more holistic fashion. Learning ecosystems denote interconnected systems comprising learners, educators, technologies, and sociocultural contexts that collectively shape educational experiences. Within such ecosystems, AI can function not merely as a tool but as an adaptive agent that mediates learning interactions and supports decision-making processes. Downes (2012) argue that digital learning environments should be viewed as complex adaptive systems where knowledge is dispersed across networks rather than confined to individual learners. Recent studies further extend this perspective by emphasizing that AI-enabled

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learning ecosystems must integrate human-centred design principles to ensure meaningful pedagogical alignment and ethical use of learner data (Luckin *et al*., 2016; Amin *et al*., 2025). Moreover, AI-driven educational environments are increasingly conceptualized as socio-technical systems where learning outcomes emerge from continuous interactions between learners, algorithms, and instructional contexts rather than from isolated instructional inputs (Williamson & Eynon, 2020; Zawacki-Richter *et al*., 2019). An unequal approach to AI-enabled learning environments has a risk of AI being used inadvertently as a tool to promote and enhance inequities in schooling. If this happens, learners from marginalized backgrounds will disproportionately feel the effects of having limited access to high-quality learning experiences and individualized educational support. In STEM education specifically, research highlights that adaptive digital ecosystems can significantly enhance conceptual understanding when they incorporate real-time analytics, scaffolding mechanisms, and feedback loops tailored to learner diversity (Roll & Wylie, 2016). However, scholars also caution that without culturally responsive design principles, such ecosystems risk reinforcing existing inequities by embedding bias into algorithmic decision-making structures (Noble, 2018; Mehrabi *et al*., 2022). Therefore, contemporary research increasingly advocates for AI systems that integrate cultural intelligence, fairness-aware modelling, and explainable AI mechanisms to ensure equitable participation across diverse learner populations (Baker & Hawn, 2022; Mejeh & Rehm, 2024). Building on this perspective, learning ecosystems in STEM education must be reconceptualized as inclusive and adaptive environments where AI supports—not replaces—human pedagogical agency while ensuring that cultural diversity is treated as a core design variable rather than an external constraint.

LITERATURE REVIEW

The integration of Artificial Intelligence (AI) in the field of education has brought about significant transformations, facilitating the creation of intelligent systems that facilitate personalized and data-driven learning experiences (Wang *et al*., 2025). The domain of AI in education (AIED) encompasses a variety of technologies, including machine learning, natural language processing, and recommender systems, which are specifically designed to improve teaching and learning processes (Mejeh & Rehm, 2024). A key application of AI in education is adaptive learning, which involves systems that dynamically modify instructional content, pace, and feedback based on individual learner requirements and performance data (Holmes *et al*., 2023; Luo *et al*., 2025).

The proposed framework, as delineated in Figure **1**, elucidates AI-based adaptive learning systems as the foundational technology underpinning culturally

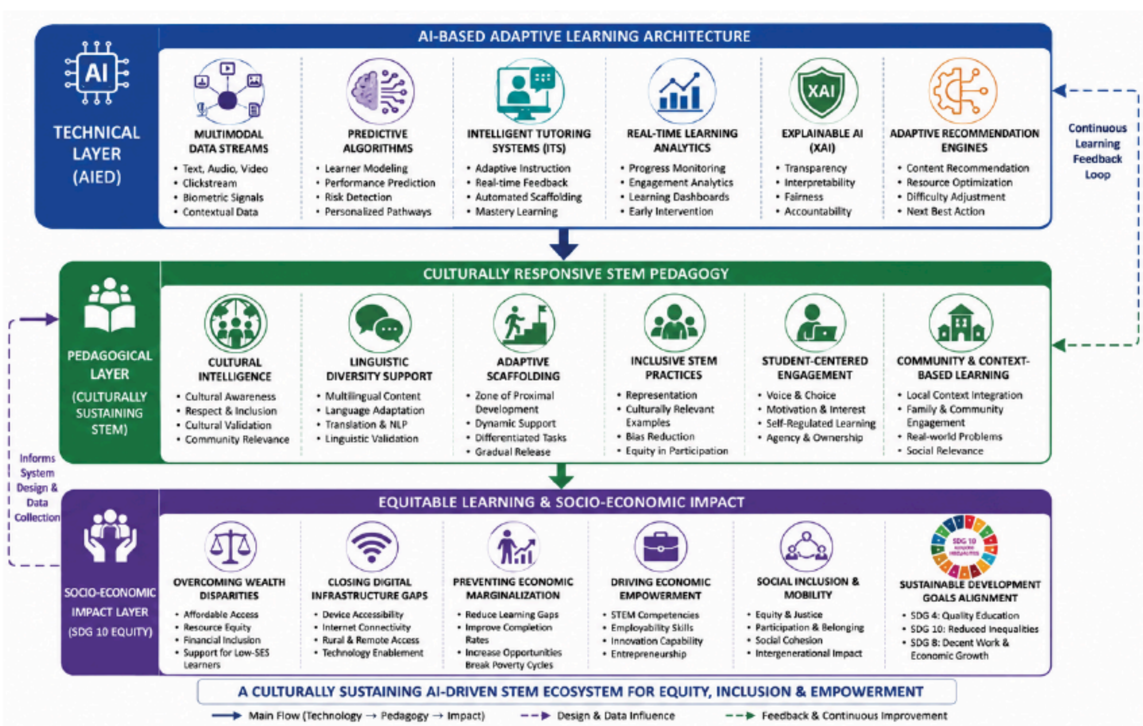

Figure 1: Conceptual Framework of Culturally Sustaining AI-Driven STEM Ecosystems.

responsive STEM learning environments. By utilizing multimodal analytics, intelligent tutoring systems, explainable artificial intelligence, and adaptive recommendation mechanisms, individual learner data is converted into customized instructional assistance. These technological functionalities are influenced by culturally responsive pedagogical strategies, encompassing cultural intelligence, linguistic inclusivity, adaptive scaffolding, and learner-centered engagement. The synergy between these technological and pedagogical aspects fosters impartial learning results by advancing educational accessibility, digital inclusivity, STEM involvement, and socio-economic empowerment. Aligned with Sustainable Development Goal 10 (Reduced Inequalities), the framework presents AI not solely as a tool for personalization but as a socio-technical apparatus capable of bolstering inclusive and culturally nurturing STEM environments.

Adaptive learning systems are rooted in learner modelling, where algorithms driven by data continuously analyse learner interactions to anticipate knowledge gaps and propose customized learning paths (Li & Lu, 2025). Corbett & Anderson (1995) underscores the capacity of intelligent tutoring systems to replicate elements of human instruction by providing immediate feedback and personalized assistance. These systems have shown positive effects on learner attainment, engagement, and motivation, particularly in disciplines like STEM that demand tailored support due to the conceptual intricacies involved (Hariyanto *et al*., 2025). Nonetheless, most adaptive systems predominantly concentrate on cognitive performance metrics, often overlooking affective, cultural, and contextual facets of learning (Li & Lu, 2025). Inadequate consideration of socio-cultural and contextual factors when creating adaptive learning models can worsen existing inequalities in education and socio-economic status for marginalized individuals. Without these considerations, AI systems will be less likely to produce equal learning opportunities for diverse groups of students.

Recent advancements in AI-based adaptive learning systems underscore the growing significance of multimodal learning analytics and real-time data processing in enhancing personalization (Ouhaichi *et al*., 2024). Contemporary adaptive platforms are no longer confined to monitoring basic interaction data; instead, they increasingly integrate complex data streams such as eye-tracking, learning behaviour patterns, emotional states, and engagement indicators (Lal *et al*., 2024). These developments enable systems to formulate more detailed learner profiles that better capture student interactions within digital learning environments. However, despite these technological strides, the educational interpretation of such data remains restricted, particularly in STEM educational settings where learning processes entail abstract reasoning, experimentation, and iterative problem-solving. Moreover, the indiscriminate implementation of data-centric technologies, without mitigating fundamental structural disparities, may perpetuate systemic obstacles associated with inequity, economic gaps, and wider socio-economic disparities. Hence, there exists a pressing need to amalgamate educational theory with computational modelling to ensure that adaptive systems are not solely data-driven but also hold pedagogical significance (Anwar *et al*., 2023).

Furthermore, the scalability of adaptive learning systems in diverse educational settings poses a notable challenge. Many AI-powered platforms are formulated and trailed in controlled environments, frequently with homogeneous learner cohorts, thereby diminishing their efficacy when implemented in culturally and linguistically diverse classrooms (Wu *et al*., 2023). This issue raises apprehensions regarding generalizability and equity, especially in global STEM education settings where learners exhibit diverse educational backgrounds and epistemic traditions (Alkabbany *et al*., 2023). Without meticulous consideration of cultural and contextual elements, adaptive systems risk perpetuating standardized learning pathways that fail to cater to the array of learner necessities (Ma *et al*., 2023). The advancement of adaptive learning technologies necessitates a more interdisciplinary approach that fuses artificial intelligence, learning sciences, and culturally responsive pedagogy. This amalgamation is crucial for crafting systems that are not just technically adaptive but also attuned to the broader educational, cultural, and ethical dimensions of learning within STEM environments (Ouhaichi *et al*., 2023).

- **Culturally Responsive and Inclusive STEM Education**

Culturally responsive pedagogy serves as a foundational framework aimed at addressing issues of educational equity and inclusivity within academic settings. According to Gay (2018), this educational approach involves the incorporation of students' cultural backgrounds, experiences, and knowledge systems into instructional strategies to enhance the relevance and effectiveness of learning experiences. Ladson-Billings (1995) underscores culturally relevant pedagogy as a mechanism for fostering academic achievement, cultural proficiency, and critical awareness among students (Aguayo *et al*., 2023).

In the realm of STEM (Science, Technology, Engineering, and Mathematics) education, the adoption of culturally responsive methodologies becomes particularly crucial due to the persistent disparities observed in the participation and attainment levels of students hailing from diverse cultural and linguistic backgrounds (King *et al*., 2023). Scholarly investigations indicate that conventional STEM teaching practices often reflect predominant epistemological viewpoints, potentially marginalizing alternate modes of understanding and impeding student involvement (Nasir *et al*., 2014). As a result, culturally responsive STEM education endeavours to reframe students' identities and experiences as valuable assets in the learning process, thereby fostering enhanced motivation, identity formation, and sustained engagement in STEM disciplines (King *et al*., 2023).

Moreover, the implementation of culturally responsive and inclusive practices in STEM education extends beyond mere content adaptation to encompass the transformation of classroom dynamics, evaluation methodologies, and learning environments (Xie & Ferguson, 2022). It underscores the significance of viewing students not solely as knowledge recipients but as active participants who bring forth invaluable cultural and experiential insights into STEM learning. This perspective challenges the conventional notion of STEM as culturally impartial, shedding light on its socially constructed essence (Xie & Ferguson, 2022). According to Lee (2017), effective STEM instruction necessitates recognition of the diverse ways in which learners construe scientific and mathematical concepts based on their cultural and linguistic contexts. Furthermore, inclusive STEM education mandates attention to systemic impediments that influence student engagement, encompassing unequal resource access, underrepresentation in STEM domains, and limited exposure to culturally relevant role models. These barriers often contribute to diminished self-assurance and diminished interest in STEM vocations among underrepresented groups. Research conducted by Nasir *et al*. (2014) indicates that linking STEM content with learners' everyday experiences and cultural identities significantly enhances their engagement and conceptual comprehension, underscoring the importance of crafting learning environments that support identity development alongside scholastic accomplishments.

Nevertheless, the widespread implementation of culturally responsive STEM education encounters challenges attributable to inflexible curricular structures, standardized assessment frameworks, and inadequate educator training in culturally sustaining pedagogies (Casto, 2022). These obstacles underscore the necessity for innovative strategies capable of assisting instructors in translating inclusivity into tangible practices. In this context, emergent technologies like Artificial Intelligence present promising avenues for facilitating culturally responsive instruction by facilitating adaptable, personalized, and contextually aware learning encounters that respond to learner diversity in real-time (Smith *et al*., 2022)

- **Integration of AI and Culturally Responsive Learning Systems**

Despite the proliferation of Artificial Intelligence (AI) in the field of education, the incorporation of culturally responsive pedagogy into AI-driven adaptive systems is currently constrained (Casto, 2022). Existing systems predominantly prioritize algorithmic efficiency and the optimization of academic performance, often neglecting considerations for cultural diversity and epistemic variance. Consequently, a substantial disparity exists between the technological capabilities of these systems and their pedagogical inclusivity (Xie & Ferguson, 2022).

Recent scholarly investigations have underscored apprehensions regarding algorithmic bias within educational AI platforms, wherein the training data and model architecture may inadvertently perpetuate existing inequities. As Baker and Hawn (2022) said, predictive learning mechanisms might misconstrue linguistic variations or culturally specific learning behaviours as indications of inferior ability, rather than recognizing them as distinctions in modes of expression or cognitive processes. Algorithmic bias has consequences beyond incorrect performance predictions. These prejudices in adaptive learning systems have potential negative effects on learners from underrepresented cultural and linguistic backgrounds. This can result in unequal recommendations and learning opportunities, and restricts equitable access to STEM education. Addressing these issues is crucial to ensure that education is fair, inclusive and accessible to all**.** To mitigate such biases in AI systems, scholars such as Mehrabi *et al*. (2022) advocate for the implementation of fairness-aware machine learning techniques. In line with the prevailing tendencies observed in technical literature at the regional level, scholars are engaging in the development of tailored computational hybrids. These hybrids, which integrate machine learning with fuzzy logic systems, aim to provide a more adaptable modelling approach for capturing intricate learner characteristics, thereby contributing to the advancement of educational equity (Mohammad *et al*., 2025). Hence, the integration of culturally sustaining principles into AI-driven adaptive learning frameworks is imperative to ensure that technological advancements uphold educational equity rather than undermining it.

Furthermore, the fusion of culturally responsive pedagogy with AI-based adaptive learning systems necessitates a paradigm shift in the conceptualization and utilization of learner data (Williamson & Eynon, 2020; Baker & Hawn, 2022). Instead of perceiving data solely as quantitative metrics of performance, there is a burgeoning necessity to interpret educational data through cultural, linguistic, and contextual lenses (Mehrabi *et al*., 2022). This transformation entails the infusion of cultural intelligence into algorithmic design, enabling AI systems to validate diverse patterns of learning expression as legitimate rather than deficient. This approach aligns with the tenets of human-centred AI, which underscore the importance of fairness, accountability, transparency, and inclusivity in the design of systems (Mehrabi *et al*., 2022).

Moreover, the development of culturally sustaining AI systems demands interdisciplinary collaboration among computer scientists, educators, cognitive scientists, and sociocultural theorists (Williamson & Eynon, 2023). Without such collaborative efforts, there is a risk that AI systems will persist in reflecting narrow technical objectives that inadequately capture the intricacies of human learning within diverse educational settings (Baker & Hawn, 2022). Particularly in the realm of STEM education, this limitation becomes more pronounced as learners grapple with abstract concepts often mediated through language, cultural metaphors, and prior experiential knowledge (Xie & Ferguson, 2022). Furthermore, emerging methodologies like explainable AI (XAI) and fairness-aware machine learning present promising avenues for addressing these challenges. These methodologies aim to enhance the transparency and interpretability of algorithmic decision-making, enabling educators to comprehend the underlying mechanisms driving adaptive recommendations (Ali *et al*., 2023). Such transparency is pivotal for cultivating trust in AI systems and ensuring that pedagogical decisions remain aligned with inclusive teaching practices. Ultimately, the successful amalgamation of AI and culturally responsive pedagogy hinges on the development of adaptive learning systems that are not only technically proficient but also ethically grounded and culturally cognizant (Rachha & Seyam, 2023).

- **Learning Ecosystems and AI-Based Educational Architectures**

The theoretical framework of learning ecosystems offers a valuable perspective for comprehending the integration of artificial intelligence (AI) within intricate educational settings. These ecosystems consist of interconnected components such as learners, educators, technologies, and socio-cultural contexts that collectively mold learning encounters. Downes (2012) portray learning in the digital era as decentralized across networks, where knowledge emerges through interactive processes rather than being conveyed in a linear manner.

Within this framework, AI-driven adaptive learning systems can be perceived as socio-technical structures that facilitate interactions between learners and educational content (Williamson & Eynon, 2023). Nonetheless, to promote inclusivity and cultural responsiveness, these structures need to progress beyond purely cognitive frameworks and incorporate socio-cultural intelligence layers. Luckin *et al*. (2016) advocate for AI in education to complement human teaching rather than supplant educators, underscoring the significance of human-centred AI design in creating inclusive STEM learning environments.

Moreover, within the context of AI-based educational structures, learning ecosystems underscore the dynamic and adaptable relationships between technological systems and human participants in educational settings (Downes, 2012; Holmes *et al*., 2023). These ecosystems are not static entities but rather continuously evolving networks influenced by feedback mechanisms, contextual variations, and learner engagements (Williamson & Eynon, 2023; Luckin *et al*., 2016). In such systems, AI serves not only as a tool for customization but also as an interactive mediator that influences how knowledge is accessed, interpreted, and applied. Consequently, AI is considered an indispensable element of the learning ecosystem rather than an external support tool (Cress & Kimmerle, 2023).

The effectiveness of AI-based learning ecosystems relies on the integration of cognitive, pedagogical and cultural intelligence. Cognitive intelligence helps to analyse the data-driven analysis to identify the needs of the learners. Pedagogical intelligence translates these insights into instructional strategies that are consistent with the objectives of the curriculum (Luckin *et al*., 2016; Holmes *et al*., 2023). Cultural intelligence makes sure that learning experiences are flexible to learners' cultural orientations, linguistic diversity, and modes of cognition, these intelligences promote a more flexible and inclusive STEM learning environment. The incorporation of cultural intelligence into AI frameworks is imperative for ensuring the genuine inclusivity and equity of learning ecosystems (Samuel *et al*., 2023).

Additionally, the design of AI-driven educational structures must address the ethical and societal implications of automated decision-making in education. As AI systems exert growing influence over learning trajectories, assessment results, and instructional suggestions, concerns regarding accountability, transparency, and fairness become pivotal (Baker & Hawn, 2022; Holmes *et al*., 2019). This underscores the necessity of human-in-the-loop systems where educators retain decision-making authority while utilizing AI-generated insights to enhance instructional quality. Consequently, learning ecosystems should be perceived as collaborative arenas where human and artificial intelligence collaborate to facilitate meaningful and culturally responsive STEM learning encounters (Zawacki-Richter *et al*., 2019; Holmes *et al*., 2023).

Despite the notable progress in the implementation of Artificial Intelligence (AI) in educational settings, there remain critical gaps in research on the design and utilization of AI-driven adaptive learning systems, particularly within STEM education (Holmes *et al*., 2023; Williamson & Eynon, 2020). While existing studies have extensively explored AI-powered personalization and adaptive learning mechanisms, the dominant focus has largely been on cognitive and performance-oriented enhancements, such as predicting learner outcomes, recommending content, and providing automated feedback (Khosravi *et al*., 2022; Zawacki-Richter *et al*., 2019). This narrow emphasis often overlooks broader socio-cultural dimensions of learning, including learners' cultural identities, linguistic diversity, and epistemological perspectives (Baker & Hawn, 2022; Williamson & Eynon, 2020). As a result, many current adaptive learning systems remain limited in their capacity to fully support diverse learners within inclusive and culturally responsive STEM education environments (Holmes *et al*., 2019; Baker & Hawn, 2022).

Additionally, there exists a significant gap in incorporating culturally responsive pedagogy into AI-based learning architectures (Gay, 2018; Ladson-Billings, 1995; Williamon & Eynon, 2020). Despite the well-established nature of culturally responsive teaching in educational theory, its integration into computational models, adaptive learning systems, and algorithmic decision-making remains limited and underexplored (Holmes *et al*., 2023; Luckin *et al*., 2016). Most AI systems in education primarily rely on behavioural, cognitive, and performance data, often failing to incorporate cultural intelligence or socio-cultural learner variables in their decision-making processes (Baker & Hawn, 2022; Williamson & Eynon, 2020). As a result, such systems may inadvertently reinforce dominant cultural norms embedded in training data and algorithmic design, potentially marginalizing underrepresented learners and compromising equity and inclusivity in AI-driven educational environments (Baker & Hawn, 2022).

Furthermore, the transparency and interpretability of existing adaptive learning systems are often limited, particularly in the generation of recommendations and personalized learning pathways (Khosravi *et al*., 2022; Holmes *et al*., 2019). The opacity of many machine learning and deep learning models restricts educators' capacity to comprehend, validate, and trust the decisions produced by AI systems, especially in data-driven educational environments (Zawacki-Richter *et al*., 2019; Baker & Hawn, 2022). This issue becomes particularly critical in STEM education, where instructional decisions require high levels of accuracy, contextual sensitivity, and pedagogical justification (Holmes *et al*., 2023). The absence of explainable AI mechanisms in many educational platforms widens the gap between technological capability and pedagogical applicability, limiting effective human–AI collaboration in learning design and assessment (Khosravi *et al*., 2022; Williamson & Eynon, 2020).

Moreover, there is a dearth of research on the development of comprehensive AI-based learning architectures that amalgamate various forms of intelligence, including cognitive, pedagogical, and cultural intelligence (Holmes *et al*., 2023). Many existing frameworks treat AI as an isolated tool rather than as an integral part of a broader socio-technical learning ecosystem (Williamson & Eynon, 2020). Consequently, there is a deficiency in unified conceptual models elucidating how adaptive learning systems can concurrently facilitate personalization, equity, and cultural responsiveness within STEM education (Baker & Hawn, 2022). Studies on AI in education have predominantly been conducted in technologically advanced or homogenous educational contexts, neglecting diverse and multicultural learning environments (Zawacki-Richter *et al*., 2019). Consequently, concerns arise regarding the generalizability and scalability of current AI-based learning models across varied cultural and educational settings, particularly in supporting learners from linguistically and culturally diverse backgrounds in STEM disciplines (Holmes *et al*., 2023).

In conclusion, there is a pressing necessity to align AI-based educational innovations with global sustainability agendas, notably the Sustainable Development Goals (SDGs) (United Nations, 2015; Holmes *et al*., 2023). While discussions surrounding AI in education often emphasize efficiency and innovation, fewer studies explicitly link adaptive learning systems to broader objectives such as educational equity, inclusion, and lifelong learning (Williamson & Eynon, 2020; Baker & Hawn, 2022). To address these gaps, this study proposes the development of an AI-based adaptive learning architecture that incorporates culturally responsive pedagogy, socio-technical system design, and inclusive STEM education principles (Holmes *et al*., 2023; Luckin *et al*., 2016). This approach seeks to bridge the gap between technological progress and educational equity by embedding cultural intelligence within adaptive learning systems, thus contributing to more inclusive, ethical, and sustainable STEM learning environments (Baker & Hawn, 2022).

CONCEPTUAL FRAMEWORK

This research introduces an extensive theoretical framework for an AI-based adaptive learning structure aimed at fostering inclusive and culturally sensitive STEM education (Wang *et al*., 2025; Mejeh & Rehm, 2024). The framework is a response to the increasing demand for intelligent educational systems that go beyond conventional personalization approaches to incorporate socio-cultural, pedagogical, and ethical aspects of learning (Chen & Jia, 2025). While current adaptive learning systems concentrate mainly on optimizing cognitive performance, this framework portrays AI as a socio-technical system integrated within a wider learning environment that considers learner diversity, cultural identity, and educational fairness (Baker & Hawn, 2022; Wang *et al*., 2025). The suggested architecture is rooted in interdisciplinary principles, drawing from Artificial Intelligence in Education (AIED), adaptive learning theory, culturally sustaining pedagogy, and learning ecosystem theory (Gay, 2018; Ladson-Billings, 1995; Mejeh & Rehm, 2024). It is tailored to address persistent deficiencies in existing AI systems, particularly their limited ability to acknowledge cultural differences and their excessive reliance on standardized performance measures (Williamson & Eynon, 2020; Chen & Jia, 2025). By fusing cognitive intelligence with cultural intelligence and pedagogical intelligence, the framework aims to establish a more holistic and equitable model for STEM learning settings (Holmes *et al*., 2019; Wang *et al*., 2025).

The theoretical basis of this framework is influenced by adaptive learning theory, which underscores the significance of data-driven customization in enhancing learner outcomes through the dynamic adaptation of content and instructional pathways (Gay, 2018). It is also underpinned by culturally responsive pedagogy, which underscores the necessity of integrating learners' cultural backgrounds, experiences, and knowledge frameworks into educational methods to boost relevance and engagement (Gay, 2018; Ladson-Billings, 1995). Furthermore, learning ecosystem theory conceptualizes learning as a dispersed and interconnected process involving continual interactions among learners, educators, technologies, and socio-cultural contexts (Downes, 2012). Collectively, these theories offer a multidimensional basis for designing AI systems that are not only adaptive but also inclusive and contextually responsive.

Within this framework, the AI-based adaptive learning architecture is envisioned as a multi-layered system comprising interconnected components that collaborate to provide personalized and culturally responsive STEM learning experiences (Holmes *et al*., 2019; Wang *et al*., 2025). The initial layer is the learner data and interaction layer, which gathers multifaceted data encompassing academic performance, behavioural patterns, engagement levels, language usage, and interaction with digital learning tools (Khosravi *et al*., 2022). In contrast to traditional systems reliant heavily on test scores and performance metrics, this framework broadens data collection to incorporate cultural and contextual cues reflecting learners' identities and real-life experiences (Williamson & Eynon, 2020; Baker & Hawn, 2022). This facilitates a more comprehensive grasp of learner requirements and supports the formulation of adaptive pathways that are sensitive to diversity and inclusion in STEM education (Mejeh & Rehm, 2024; Holmes *et al*., 2019). Cognitive intelligence measures learners' academic achievement, knowledge levels, problem-solving skills, and engagement patterns (Corbett & Anderson, 1995; Wang *et al*., 2025). These data provide a comprehensive understanding of the learners' learning progress, strengths, and weaknesses (Khosravi *et al*., 2022). These insights then inform pedagogical intelligence that determines the most appropriate instructional interventions, such as feedback, content sequencing, scaffolding, and assessment strategies (Luckin *et al*., 2016; Mejeh & Rehm, 2024). These functions are enriched by cultural intelligence, which interprets learner behaviour in relevant cultural contexts, such as language, beliefs, educational experiences, and cultural values (Gay, 2018; Ladson-Billings, 1995; Samuel *et al*., 2023). Together, these three intelligences create STEM learning experiences that are culturally responsive, adaptive, and inclusive (Holmes *et al*., 2023; Williamson & Eynon, 2020).

The next layer in the framework is the Learner Modelling and Intelligence Layer, which applies machine learning algorithms to analyze learner information in order to construct a dynamic profile of the learner. (Khosravi *et al*., 2022; Wang *et al*., 2025). These profiles encompass cognitive, behavioural, emotional, and socio-cultural attributes, facilitating the discernment of individual learner requisites and the provision of tailored instructional assistance (Holmes *et al*., 2019; Mejeh & Rehm, 2024). Situated within the Learner Modelling and Intelligence Layer are three distinct forms of intelligence, namely cognitive intelligence, pedagogical intelligence, and cultural intelligence, operating synergistically to guide decisions related to adaptive learning processes (Williamson & Eynon, 2020; Baker & Hawn, 2022). The proposed adaptive learning architecture is based on the interaction of cognitive, pedagogical and cultural intelligence. Cognitive intelligence can determine the educational needs and learner characteristics. Pedagogical intelligence takes this knowledge and decides how best to respond. Cultural intelligence helps ensure that educational materials and teaching methods are culturally sensitive and inclusive. The combination of these components can help the system provide personalized, equitable, and effective STEM learning experiences. They can also reduce algorithmic bias and inappropriate recommendations (Lata, 2024). Through synergistic engagement within the adaptive learning infrastructure, cognitive intelligence discerns the individualized requisites of learners, pedagogical intelligence strategizes the requisite interventions, and cultural intelligence ensures the appropriateness, inclusivity, and cultural sensitivity of instructional modalities (Chen & Jia, 2025). This amalgamation culminates in an adaptive learning schema that furnishes learners with an efficacious, pedagogically robust, and culturally equitable academic journey. Consequently, the prevalence of algorithmic partiality, misclassifications, and unsuitable suggestions is mitigated, thereby fostering a fair and inclusive educational milieu for all learners (Baker & Hawn, 2022; Chen & Jia, 2025).

The third layer is the adaptive decision-making engine, serving as the central intelligence of the system (Villegas-Ch *et al*., 2025). This engine translates learner models into personalized learning pathways, instructional sequences, support strategies, and feedback mechanisms through explainable and adaptive AI processes (Chen & Jia, 2025). It continually adjusts based on real-time learner interactions to guarantee that learning experiences remain responsive, efficient, and context-sensitive within dynamic STEM environments (Wang *et al*., 2025). Notably, this layer integrates pedagogical constraints defined by educators, ensuring that AI-driven decisions align with curriculum standards and culturally responsive teaching practices (Zhang, 2025). This underscores the role of teachers as active decision-makers and co-designers in the learning process rather than passive recipients of algorithmic recommendations, reinforcing human-in-the-loop governance in AI-enhanced education systems (Prentzas & Binopoulou, 2025).

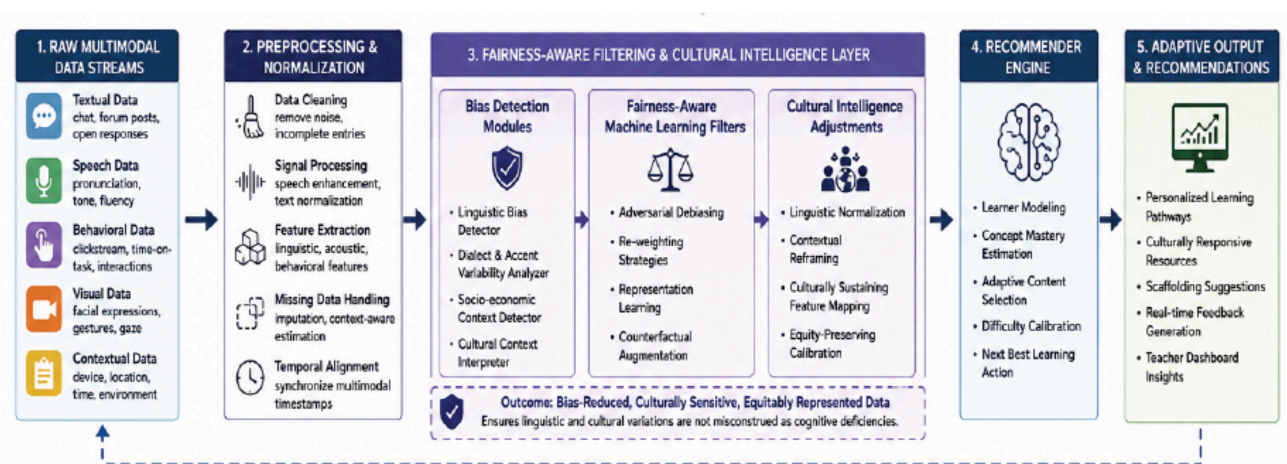

Figure 2: The algorithmic processing pipeline illustrates the incorporation of fairness-aware machine learning filters into the multimodal data stream to address socio-economic bias.

The fourth layer is the instructional delivery and feedback layer, which furnishes learners with personalized STEM learning experiences through intelligent tutoring systems, simulations, interactive platforms, and multimodal content delivery (Wang *et al*., 2025). This layer facilitates continuous feedback loops among learners, educators, and the AI system, enabling iterative enhancement of learning pathways (Chen & Jia, 2025). It also guarantees accessibility and inclusivity by supporting multilingual content delivery and diverse representation of STEM concepts (Mejeh & Rehm, 2024). Encompassing these core layers is a pervasive cultural intelligence and ethics layer, ensuring that equity, transparency, accountability, and inclusivity are ingrained throughout the system. This layer is responsible for identifying and mitigating algorithmic bias, ensuring ethical utilization of learner data, and enabling explicable AI mechanisms that allow educators and learners to comprehend decision-making processes (Prentzas & Binopoulou, 2025). It also ensures that cultural diversity is not viewed as extraneous within data systems but as a meaningful aspect of learning that enriches customization and fairness (Baker & Hawn, 2022).

In this architecture, AI is portrayed not merely as a technological instrument but as an essential component of a broader learning ecosystem (Holmes *et al*., 2023). In this ecosystem, learners, educators, digital technologies, and socio-cultural contexts engage dynamically to collaboratively construct knowledge. This outlook aligns with network-based learning theories, which emphasize that knowledge is disseminated across systems rather than confined to individual learners (Downes, 2012). Consequently, AI acts as a mediator that supports interaction, adaptation, and knowledge circulation throughout the ecosystem (Luckin *et al*., 2016).

The interaction among the five architectural layers is characterized by an iterative process rather than a linear one (Holmes *et al*., 2023; Luckin *et al*., 2016). Data gathered by the Learner Data Layer undergoes transformation into a learner profile within the Learner Modelling Layer (Corbett & Anderson, 1995; Li & Lu, 2025). Subsequently, a comprehensive analysis of this data occurs, drawing from cognitive, pedagogical, and cultural perspectives before being processed by the Adaptive Decision Engine (Khosravi *et al*., 2022; Mejeh & Rehm, 2024). Following the generation of recommendations, these suggestions are then presented to the learner via the Instructional Delivery Layer. This presentation allows learners to engage with personalized STEM (science, technology, engineering, mathematics) materials, thereby generating additional learning data about themselves (Hariyanto *et al*., 2025; Wang *et al*., 2025). Simultaneously, the Cultural Intelligence and Ethics Layer persistently ensures the integration of fairness, inclusivity, transparency, and bias mitigation within the system (Baker & Hawn, 2022; Holmes *et al*., 2023). This layer also ensures the system's rapid adaptation to diverse learner needs while maintaining educational integrity, cultural responsiveness, and ethical accountability (Gay, 2018; Samuel *et al*., 2023).

A multicultural secondary school with a STEM focus using Algebra as part of their curriculum provides a practical illustration of the application of the model. Cognitive intelligence (CI) recognizes that many of its students are experiencing difficulty with complex abstract/symbolic reasoning (Corbett & Anderson, 1995; Wang *et al*., 2025). Pedagogical intelligence (PI) provides scaffolding, visual representations, and differentiated practice exercises to support them in developing their ability to resolve algebraic equations (Luckin *et al*., 2016; Mejeh & Rehm, 2024). Cultural intelligence (CI) continues developing the same students through culturally

Table 1: AI-Based Adaptive Learning Architecture

Layer	Function	AI Techniques	Educational Purpose
Learner Data Layer	Gathers data on behaviour, cognition, and context.	Educational data analysis, extracting insights	Constructs comprehensive student profiles.
Learner Modelling Layer	Creates personalized learner profiles	Artificial intelligence algorithms, forecasting algorithms	Individualizes educational trajectories
Adaptive Decision Engine	Produces educational material and responses	Systems for suggesting items, reinforcement techniques	Enhances pedagogy and support
Instructional Delivery Layer	Delivers STEM learning content	Intelligent tutoring systems, NLP	Enhances understanding and engagement
Cultural Intelligence & Ethics Layer	Ensures fairness, inclusivity, transparency	Explainable AI, fairness-aware ML	Prevents bias and ensures equity

responsive instructional strategies, such as using examples from the students' own communities, languages, and life experiences, when contextualizing math problems (Gay, 2018; Ladson-Billings, 1995; Smith *et al*., 2022). For example, one might use local businesses as part of the mathematics problem-solving process; while students will be very familiar with their own nearby businesses, they are likely to find math problems much easier to solve as they relate well to real scenarios in their own lives (Gay, 2018; Xie & Ferguson, 2022). As students interact with the adaptive platform in this example, the platform continually refines the provision of instructional recommendations to the teacher based on students' performance, engagement, and cultural alignment over time (Khosravi *et al*., 2022; Wang *et al*., 2025). This indicates how the proposed model can support culturally responsive and inclusive STEM learning experiences for all learners in quality, authentic educational settings (Holmes *et al*., 2023; Casto, 2022).

Moreover, the outlined framework demonstrates a strong correlation with international educational and sustainability objectives, specifically Sustainable Development Goal 4 (Quality Education), Sustainable Development Goal 9 (Industry, Innovation, and Infrastructure), and Sustainable Development Goal 10 (Reduced Inequalities) (United Nations, 2015; Holmes *et al*., 2023). These connections underscore the significance of AI-driven adaptive learning platforms in fostering comprehensive, fair, and high-calibre STEM education, while also propelling advancements in educational infrastructure innovation and diminishing gaps among varied learner demographics (Williamson & Eynon, 2020; Baker & Hawn, 2022). By virtue of this alignment, the framework contributes to the worldwide endeavour to ensure that technological progress in education adheres to ethical standards and sustainability principles. To sum up, the suggested AI-based adaptive learning structure presents a comprehensive and ethically driven blueprint for reshaping STEM education. By amalgamating cognitive, cultural, and pedagogical intelligences within an integrated system, it tackles critical constraints of current adaptive learning methodologies and bolsters the establishment of inclusive, fair, and forward-looking educational settings (Luckin *et al*., 2016). Ultimately, this framework positions AI as a revolutionary facilitator of culturally nurturing STEM education in the contemporary era.

DISCUSSION

The outcomes of this theoretical study position AI-based adaptive learning architectures as transformative mechanisms capable of reshaping STEM education by integrating cognitive, cultural, and pedagogical intelligence (Holmes *et al*., 2023; Luckin *et al*., 2016). In contrast to conventional adaptive learning systems focusing primarily on performance enhancement and content customization, the proposed framework introduces a multidimensional approach that encompasses cultural responsiveness and ethical considerations as fundamental system elements (Baker & Hawn, 2022; Williamson & Eynon, 2020). This marks a substantial conceptual transformation within the domain of Artificial Intelligence in Education (AIED), where technological progress has frequently advanced autonomously from considerations of educational equity (Zawacki-Richter *et al*., 2019).

A primary theoretical contribution of this study lies in its reinterpretation of adaptive learning systems as socio-technical ecosystems rather than stand-alone computational tools (Holmes *et al*., 2023). In traditional models, AI systems are typically structured to enhance learning efficiency through the analysis of learner interactions and the prediction of performance outcomes (Khosravi *et al*., 2022). The suggested framework challenges this constraint by embedding AI within a broader learning ecosystem that includes learners, educators, digital technologies, institutional frameworks, and cultural milieus (Zawacki-Richter *et al*., 2019). This ecosystem perspective resonates with connectivism learning theory and networked knowledge systems (Downes, 2012), underscoring that learning arises through distributed interactions rather than the linear dissemination of knowledge. The iterative interaction among the learner, the adaptive decision-making system, and the educational environment is graphically represented as a cyclical feedback loop in Figure **3**, illustrating a dynamic process.

Table 2: Alignment with Sustainable Development Goals

SDG Goal	Focus Area	Contribution of Study
SDG 4: Quality Education	Inclusive education	Enhances equitable STEM learning through adaptive AI systems
SDG 9: Industry, Innovation and Infrastructure	Educational innovation	Develops AI-based intelligent learning architecture
SDG 10: Reduced Inequalities	Equity	Reduces cultural and learning disparities in STEM education

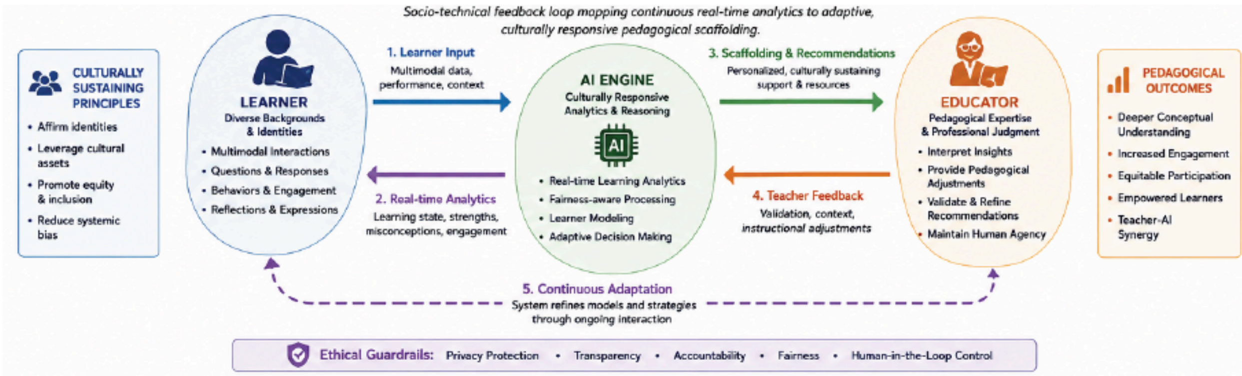

Figure 3: Mapping real-time analytics to culturally responsive teaching for adaptive pedagogical support in a feedback loop.

The inclusion of cultural intelligence into adaptive learning systems signifies another significant advancement in this study. Existing AI-powered educational technologies frequently draw upon standardized datasets reflecting predominant cultural norms, leading to algorithmic biases and restricted generalizability across diverse learner cohorts (Zawacki-Richter *et al*., 2019). As previous research has underscored, such systems may inadvertently misinterpret linguistic variations, culturally specific reasoning patterns, or alternative problem-solving strategies as indicators of subpar performance (Williamson & Eynon, 2020; Noble, 2018). The proposed framework tackles this challenge by incorporating cultural intelligence as an integral element of the learning architecture (Gay, 2018; Ladson-Billings, 1995). This enables the system to interpret learner behaviour within culturally relevant contexts rather than relying solely on detached performance metrics (Khosravi *et al*., 2022).

Moreover, the study accentuates the significance of fairness-aware machine learning in mitigating systemic biases within AI-driven educational systems. Algorithmic bias remains a critical issue in the integration of AI in education, particularly in crucial domains like STEM learning (Zawacki-Richter *et al*., 2019). When adaptive systems are trained on incomplete or unrepresentative datasets, they risk perpetuating existing inequities instead of alleviating them (Williamson & Eynon, 2020). The suggested architecture integrates bias detection and mitigation mechanisms within the learner modelling layer, guaranteeing that adaptive decisions are not only precise but also equitable (Holmes *et al*., 2023). This contributes to the growing dialogue on ethical AI design and responsible innovation in education.

Another crucial aspect of this discourse is the role of educators within AI-enhanced learning environments. In contrast to concerns that AI might supplant teachers, this study reinforces the notion that teachers continue to play a central role in the learning process (Holmes *et al*., 2023). The proposed framework portrays educators as interpretive agents who contextualize AI-generated insights and formulate pedagogical decisions based on cultural, emotional, and situational factors that AI systems cannot entirely grasp (Luckin *et al*., 2016). This aligns with human-centred AI principles, which emphasize the augmentation rather than the replacement of human expertise (Zhang, 2025). In STEM education, where comprehensive understanding often necessitates explanation, experimentation, and contextual interpretation, the involvement of teachers remains indispensable (Gay, 2018). The study also underscores the limitations of current adaptive learning systems in capturing the full complexity of learner cognition. Most systems rely on quantifiable indicators such as test scores, clickstream data, and response accuracy (Zawacki-Richter *et al*., 2019). While these metrics offer valuable insights into learner performance, they fail to encompass deeper cognitive processes like conceptual change, metacognitive regulation, and epistemic reasoning (Wang *et al*., 2025). The proposed framework addresses this limitation by integrating multidimensional learner modelling, which encompasses behavioural, cognitive, emotional, and cultural data (Khosravi *et al*., 2022). This facilitates a more holistic portrayal of the learner and supports more precise adaptive decision-making. Additionally, the discussion underscores the significance of transparency and explainability in AI-based educational systems (Khosravi *et al*., 2022). One of the primary criticisms of machine learning models is their opaque nature, which hampers interpretability and diminishes trust among educators and learners (Williamson & Eynon, 2020). In educational contexts, transparency is especially crucial as instructional decisions directly influence learner trajectories (Holmes *et al*., 2023). The proposed framework incorporates explainable AI (XAI) mechanisms that enable educators to comprehend how recommendations are generated and how learner data is interpreted (Chen & Jia, 2025). This enhances accountability and fosters informed pedagogical decision-making.

Furthermore, the framework contributes to ongoing dialogues on equity in STEM education. Despite global endeavours to boost participation in STEM fields, substantial disparities persist across gender, socioeconomic status, and cultural heritage (Zawacki-Richter *et al*., 2019). These disparities are frequently perpetuated by educational systems that neglect diverse learning identities and experiences (Williamson & Eynon, 2020). By embedding cultural responsiveness into AI-based adaptive systems, the suggested model promotes more inclusive STEM learning environments (Gay, 2018). This has the potential to enhance learner engagement, strengthen STEM identity development, and support long-term engagement in STEM professions (Holmes *et al*., 2023). Another critical point of discussion is the scalability of AI-based adaptive learning architectures (Wang *et al*., 2025). While the proposed framework presents a comprehensive conceptual model, its implementation in real-world educational settings poses notable challenges.

The implementation of AI-Based Adaptive Learning Architectures, despite all their potential benefits, presents practical challenges for educators. The key obstacle to implementing AI-based adaptive learning systems is the readiness of teachers. In order for AI technologies to be well-integrated into the classroom, teachers need to be technically proficient, pedagogically knowledgeable, and equipped with data interpretation skills, knowledge of ethical AI, and culturally-aware pedagogical practices in order for them to intelligently scrutinize and make appropriate use of AI-driven findings in varying STEM learning contexts (Ayanwale *et al*., 2025; Ren & Wu, 2025). Without sufficient professional development, teachers may struggle to understand, implement, and adapt AI-based suggestions, support, and advice in their own classrooms. The sustained investment in teacher capacity, for example in the development of AI literacy, data driven instruction, ethical AI, and culturally responsible pedagogies, therefore, becomes crucial for effective deployment of AI-based adaptive learning systems (Ren & Wu, 2025; Shi, 2025). A second challenge relates to institutional barriers affecting the adoption of AI-based adaptive learning systems. The financial burden is still among the main hurdles because the adoption of AI-based adaptive learning systems might fail to progress on the level of digital infrastructure, AI acquisition, and technical support (Hughes *et al*., 2025). Additionally, resistance to organizational change could present a challenge to institutional adoption and learner data privacy and security issues as well as ethical implications could result in lack of stakeholder buy-in and trust (Zhu *et al*., 2025).

With regard to technology, most AI-based adaptive learning systems still have shortcomings within a variety of educational settings. The use of most AI-based adaptive learning systems relies on access to large and well-curated data sets as well as stable, high-speed Internet access, but these can often be unavailable in under supported and rural settings, and therefore affect the scalability of AI-supported learning environments (Mejeh & Rehm, 2024, Hughes *et al*., 2025). Institutional, technological and ethical issues need to be addressed for successful adoption of AI-based adaptive learning systems across settings.

IMPLICATIONS

The proposed AI-based adaptive learning architecture for inclusive and culturally responsive STEM education has significant implications across theoretical, pedagogical, technological, and policy domains (Holmes *et al*., 2023; Williamson & Eynon, 2020). As AI becomes increasingly embedded in education systems, it is essential to evaluate not only its technical effectiveness but also its ethical, cultural, and societal consequences (Zawacki-Richter *et al*., 2019). From a theoretical perspective, this study extends Artificial Intelligence in Education (AIED) by integrating socio-cultural and ethical dimensions into adaptive learning theory (Holmes *et al*., 2023). Traditional models emphasize performance-based metrics such as accuracy and completion rates, whereas the proposed framework introduces cultural intelligence as a core construct in learner modelling (Gay, 2018; Ladson-Billings, 1995). This shift repositions learning from a purely cognitive process to a socio-culturally embedded phenomenon, aligning with distributed and networked knowledge perspectives (Downes, 2012). The framework also reconceptualizes learning as a socio-technical ecosystem involving learners, educators, technologies, and cultural contexts (Holmes *et al*., 2023). This aligns with connectivism and distributed cognition theories, emphasizing that knowledge emerges through interaction across systems rather than within individuals alone (Gay, 2018). Pedagogically, the framework reinforces the central role of teachers as interpreters and co-designers of AI-supported learning rather than passive users of automated recommendations (Cukurova *et al*., 2020). It highlights the importance of culturally responsive teaching in STEM education and supports the development of teacher competencies in AI literacy and data-informed decision-making (Gay, 2018; Mejeh & Rehm, 2024). Technologically, the study calls for the development of fairness-aware, explainable, and culturally sensitive AI systems in education (Baker & Hawn, 2022; Khosravi *et al*., 2022). The framework provides educators with guidance to design personalised learning experiences grounded in STEM, which honour learner variability and honour academic rigour (Holmes *et al*., 2023; Mejeh & Rehm, 2024). Educators can leverage AI-driven insights to inform differentiated pedagogy, track learner engagement, and implement culturally relevant teaching approaches more effectively (Khosravi *et al*., 2022; Gay, 2018). The architecture presented could also support curriculum developers to design culturally responsive, accessible, and differentiated STEM curricula (Ladson-Billings, 1995; Smith *et al*., 2022). AI based learning tools that support diversity, inclusion and align with national and global standards need to be part of the future curriculum development efforts (Casto, 2022; Holmes *et al*., 2023). Additionally, the framework emphasizes on governance processes that support the ethical implementation of AI, privacy and security of the learner's data, algorithm transparency, and equal access to digital learning resources (Baker & Hawn, 2022; Prentzas & Binopoulou, 2025). Furthermore, policymakers should make investments in areas such as teacher professional development, digital infrastructure, and inclusive technology initiatives to ensure that students who benefit from AI-enhanced STEM education have access to similar opportunities (Williamson & Eynon, 2020; United Nations, 2015)This includes bias mitigation, transparent decision-making processes, and multimodal learner data integration, supported by explainable AI (XAI) techniques to enhance trust and accountability (Prentzas & Binopoulou, 2025). From a policy perspective, the findings highlight the need for regulatory frameworks ensuring equity, transparency, and accountability in AI-driven education systems. Strengthening digital infrastructure in underserved contexts is also essential to reduce educational inequality and ensure equitable access to AI-enhanced learning (Williamson & Eynon, 2020). These contributions align strongly with Sustainable Development Goal 4 (Quality Education) and broader global equity agendas (United Nations, 2015).

CONCLUSION

This study adds significantly to the area of AI in education through a comprehensive adaptive learning framework that integrates cognitive, pedagogical and cultural intelligences in a socio-technical paradigm (Holmes *et al*. 2023; Williamson & Eynon 2020). A novel contribution of this framework is that it emphasizes culturally responsive pedagogy, equity and ethical considerations as components of adaptive learning systems beyond traditional notions of performance optimization characteristic of existing adaptive learning approaches (Zawacki-Richter *et al*. 2019; Baker & Hawn 2022).

In this study, AI is not considered an add-on feature for personalization; it is regarded as a core part of the socio-technical learning system that consists of learners, teachers, technologies and socio-cultural context with which learners construct knowledge collaboratively (Downes, 2012). Incorporating cultural intelligence in an adaptive learning framework and an over-arching ethical design, adaptive learning systems are more equipped to understand and react to the variations in learner characteristics on equal and contextually responsive terms (Ladson-Billings, 1995; Williamson & Eynon 2020). This is a movement away from data-centric frameworks towards human-centered and culturally sustainable AI frameworks.

Moreover, this paper highlights the pivotal role of teachers in AI-driven learning environments for STEM contexts (Cukurova *et al*. 2020). Instead of replacing teachers, AI should assist teachers with the instructional decision-making by providing informative guidance for enabling differentiation and inclusiveness (Holmes *et al*. 2023). This framework underlines the need for transparency, fairness and explainability in AI systems to develop trustworthy, accountable and ethical artificial intelligence (Khosravi *et al*. 2022; Prentzas & Binopoulou 2025). Additionally, the presented framework aligns with the international call for sustainable learning by linking to sustainable development goals: SDG 4 (Quality Education), SDG 9 (Industry, Innovation and Infrastructure), and SDG 10 (Reduced Inequalities) (United Nations, 2015).

Despite its promising aspects, as an exploratory paper, the framework still needs empirical testing in a variety of learning environments to determine its effectiveness, feasibility and adaptability (Wang *et al*. 2025). Studies need to be designed in real STEM classrooms and with learners from varied cultural and linguistic backgrounds in order to see the impact on student performance and learning experiences and equity.

In summary, the proposed framework offers an innovative and visionary solution for developing AI-supported STEM learning environments that integrates the strengths of technological innovation with the principles of educational equity, cultural sustainability and human-centred design to inform the future of pedagogy, curriculum development, educational technology design, and policy reform (Gay, 2018; Holmes *et al*. 2023). Given the increasingly widespread application of artificial intelligence in education, this framework will inform and guide us towards a more effective, equitable, inclusive, and socio-responsive future of learning and educational innovation.

CONFLICT OF INTEREST STATEMENT

The authors declare that there is no potential conflict of interest concerning the publication of this article. The research was carried out without any commercial or financial ties that might be perceived as a conflict of interest.

AUTHOR'S CONTRIBUTION STATEMENT

The author takes complete responsibility for the various elements of the manuscript, such as the conceptualization of the study, literature review, development of the proposed framework, interpretation of findings, preparation of the manuscript, and its final approval for submission to a journal for publication.

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