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Putting AI in Fair: A Framework for Equity in AI-driven Learner Models and Inclusive Assessments

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Abstract

This paper delves into the critical role of learner models in educational assessment and includes a systematic review of recent literature on AI and K-12 education. This review brings to light gaps and opportunities in current practices and serves as a foundation for the Fair AI Framework, which centers on fairness and transformative justice, and aspires to influence AI applications to ensure they are inclusive of diverse learners. This paper concludes with a recommended path forward that underscores the critical importance of learner models in accessible, inclusive, equitable, and valid assessment for all learners.

Keywords: *artificial intelligence, K-12 education, assessment, validity, framework, equity, social justice, accessiblity, inclusion, students with disabilities, cultural diversity, linguistic diversity, English learners, policy, research, ethics*

Introduction

The field of educational measurement is experiencing significant advancements in methods and technologies, particularly through the integration of innovative tools that incorporate Artificial Intelligence (AI). These developments aim to create more efficient, personalized, and accurate evaluations of learning. This paper explores the implications of such advancements, focusing on AI-driven learner models and their potential to transform educational assessment practices within the U.S. Kindergarten through Grade 12 (K-12) assessment context. More specifically, this paper introduces a validity framework that centers fairness and transformative justice, addressing the critical need for equitable AI applications that are inclusive of students with disabilities, culturally and linguistically diverse students, and other currently and historically systemically marginalized and underserved student groups. The authors assert that learner models are fundamental to educational assessment and require meticulous consideration to ensure inclusivity and equity. Learner models reflect our understanding of learner characteristics in terms of how learners represent information and develop competence, and these models shape our definition of what is measured (constructs) as well as the criteria for evaluating demonstrations of knowledge, skills, and abilities (Mislevy, 2004; Pellegrino et al., 2001; Sato, 2024).

The first part of this paper delves into the critical role of learner models in educational assessment and includes a review of recent literature on AI and K-12 education. This review brings to light gaps and opportunities in current practices and serves as a foundation for the framework proposed in the second part of this paper, which centers on fairness and transformative justice. The framework aspires to influence AI applications to ensure they are inclusive of students with disabilities, culturally and linguistically diverse students, and other currently and historically systemically marginalized and underserved student groups. This paper concludes with a recommended path forward that underscores

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the critical importance of learner models in accessible, inclusive, equitable, and valid assessment for all learners.

The Essential Role of Learner Models in Valid Educational Assessment

An assessment cannot be designed and implemented and will not yield valid interpretations of student knowledge without appropriate and adequate consideration of a learner model reflective of a student's unique capabilities and needs (Marion & Pellegrino, 2006; Michel & Shyyan, 2024; Mislevy, 2004; Pellegrino, 2003; Pellegrino et al., 2001; Sato, 2024; Shyyan & Christensen, 2018). Without such a model, assessment results will not yield valid interpretations of what students know and can do.

The centrality of learner models for valid assessment is depicted in the assessment triangle (see Figure 1) which is a useful heuristic for examining the qualities and influence of learner models vis-a-vis assessment tasks and evaluative criteria. Learner models, assessment tasks, and evaluative criteria must be in congruence to yield a valid assessment (Marion & Pellegrino, 2006). The components of the assessment triangle heuristic are as follows (Mislevy, 2004; Pellegrino et al., 2001; Sato, 2024):

• Cognition: How information is represented, and competence is developed, including the learning theory and articulation of the knowledge being measured (learner model).

• Observation: How information is elicited, and the types of tasks that would best elicit demonstrations of understanding and knowledge (task model, assessment methods).

• Interpretation: How information is understood, including tools and methods for making sense of observed behaviors/responses (inferences, evaluative criteria).

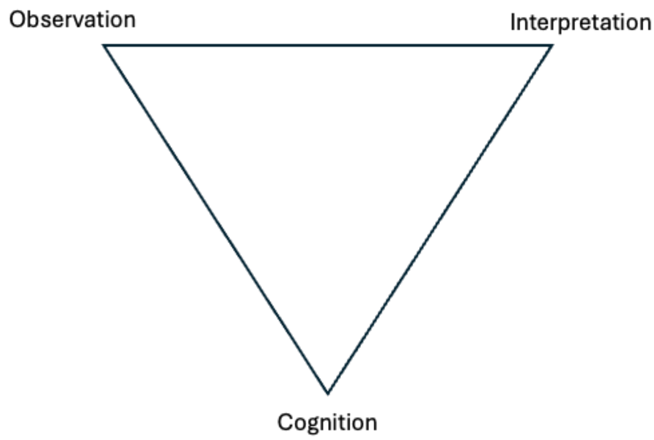

Figure 1. The Assessment Triangle (Pellegrino et al., 2001, p. 44)

With this heuristic in mind, the following discussion focuses on the Cognition vertex and learner models. Given the diverse population of learners in U.S. schools, understanding and implementing effective learner models are imperative for ensuring that all students are assessed accurately and fairly.

The development of learner models integrates theory and research from multiple disciplines including educational psychology and cognitive science, and pedagogy. This process involves extensive data collection and analysis, using both qualitative and quantitative methods, to identify learning patterns and individual variations (McDonald & West, 2021). Theoretical frameworks help interpret data, showing how students engage with content, process information, transfer knowledge, and represent understanding. Leveraging these models, educators can design responsive instruction that enhances access, engagement, understanding, and achievement (Darling-Hammond et al., 2019).

Similar to their role in instructional design, learner models can inform assessment design by providing a detailed map of expected learning progressions, and they can highlight critical considerations about the nature and conditions for students' learning and demonstrations of learning (Sato, 2024). By aligning assessment tasks (Observation vertex) with the learner model, assessment developers can ensure that tasks are appropriately challenging and supportive and accurately measure intended knowledge and skills in a manner appropriate for diverse students, without introducing bias or irrelevant difficulties. Learner models also support the interpretation of assessment outcomes (Interpretation vertex) by providing a framework for understanding student performance in terms of their cognitive and linguistic processes, learning experiences, and individual needs.

The Importance of Accounting for Diversity in Learner Models

Learner models are important because students learn and represent knowledge in various ways. There is a body of research showing that students' experiences and backgrounds affect their meaning making, learning, and representations of knowledge (e.g., de Klerk, 2008; Hall, 1983; Hofstede & Hofstede, 2005; Kulich, 2009; Levine, 1997; Lewis, 2006; Michel & Shyyan, 2024; Nisbett, 2003; Parrish & Linder-VanBerschot, 2010; Pearson & Garavaglia, 2003; Sato, 2017, 2024). Such research explains how students with different backgrounds, when presented with the same information, can have different interpretations of and responses to the information (Hammond, 2015; Ji et al., 2004; Masuda & Nisbett, 2001; Michel & Shyyan, 2024; Sato, 2024; Solano-Flores & Nelson-Barber, 2001; Wang & Leichtman, 2000). Evidence from such research suggests that there are background and experiential factors that are construct relevant and ought to be considered when designing and developing valid and fair assessments (Sato, 2017, 2024).

A mismatch between the expectations of an assessment (task design, administration conditions, evaluation criteria, and interpretations of performance outcomes) and the ways students learn (as shaped by their backgrounds and experiences) undermine assessment validity and can result in misrepresentations or underestimations of student knowledge (Montenegro & Jankowski, 2017). In the U.S. K-12 accountability context, assessments tend to privilege a Western orientation and values which generally reflect analytical and linear or sequential reasoning and typically place value on objectivity and individualism (Preston & Claypool, 2021). To the degree that subgroups of our diverse student population are either unfamiliar with the Western cultural orientation and values or have norms and values that differ, those students potentially may be unable to perform to the best of their abilities on the assessment (eCampusOntario, n.d.; Molle et al., 2015; Sato, 2024; Wexler, 2019, 2021). With more than 10 percent of students identified as English learners and roughly 15 percent of public school students receiving special education or related services under the Individuals with Disabilities Act (IDEA), commonly used assessments in our U.S. K-12 schools may not be accessible to the full range of these more than 12 million students (NCES, 2020, 2023, 2024; Montenegro & Jankowski, 2017). Learners from marginalized backgrounds or with diverse learning styles may be disproportionately affected when assessments do not align with students' ways of learning and understanding, perpetuating inequalities in educational outcomes and opportunities. Moreover, with such lack of alignment, students may feel disengaged, and their motivation and efficacy may be negatively impacted (Ryan & Weinstein, 2009; Usher, 2012). This can have long-term consequences for students' academic trajectories and overall well-being. It is, therefore, critical to develop learner models that reflect the diversity of our K-12 student population -- meticulous consideration of the range of ways students learn and demonstrate their learning is needed to develop sufficiently robust learner models that can support the design, development, and implementation of inclusive, equitable, and valid assessments.

The Promise of AI-Driven Learner Models in Assessment

While effective accessibility and inclusion solutions continue to emerge to support the learning and achievement of K-12 students (Cawthon & Shyyan, 2022; Michel & Shyyan, 2024), the integration of AI technology in education has the potential to significantly advance and transform how we understand and assess learner capabilities. Especially for students who are currently and have historically been systemically marginalized and underserved, AI-driven learner models offer the promise of more personalized, equitable, and inclusive educational experiences.

AI-driven learner models can help to address challenges faced by current K-12 assessments (Holmes et al., 2019; USED, 2023). For example, AI-driven learner models have the potential to support more student-centered assessment for diverse test takers through the analysis of student data, identification of learning patterns, and the leveraging of algorithms to adapt assessment content and format and match them to the capabilities and needs of individual test takers (Li et al., 2018). Accessibility can be enhanced by matching assessment content and formats (e.g., audio or tactile versions, translations, language adaptations to the student grade and age levels) to test taker needs so that each test taker is provided optimal conditions to demonstrate what they know and can do (Holmes et al., 2019; Li et al., 2022). Improving accessibility affects the accuracy of the measures of student knowledge and, subsequently, the validity of the interpretations of what students know and can do. Additionally, AI-driven learner models can help to ensure that assessments are as free from bias as possible and provide fair and equitable opportunities for all students (Grover, 2024). Bias can be mitigated through data analyses and the identification of patterns that indicate bias in assessment items and scoring algorithms, thereby supporting more inclusive and equitable assessment (Deshpande et al., 2023; Holmes et al., 2019).

Designing and implementing assessments at scale also poses a challenge in K-12 education, particularly given the number and diversity of students in our educational system (Holmes et al., 2019; Li et al., 2022). AI-driven learner models offer the potential for scalability by automating aspects of assessment design, development, and administration (Attali, 2018). Such models have the potential to generate more personalized assessment tasks, analyze large datasets efficiently, and provide timely feedback to students and educators, thereby streamlining the assessment process and reducing logistical and administrative burdens (Grover, 2024; Holmes et al., 2019).

By purposefully gathering information to understand the characteristics and preferences of learners (e.g., cultural backgrounds, language proficiency, learning styles, accessibility needs and preferences) and developing robust learner models that have the potential to be AI-driven and responsive to these characteristics and preferences, assessment designers can determine upfront the features necessary for accessible and engaging assessment tasks that place students in optimal conditions to demonstrate what they know and can do (Hansen & Mislevy, 2008; Mislevy, 2004; Sato, 2024). Developing such learner models, however, requires careful consideration of ethical, practical, and theoretical factors to ensure they meet the diverse needs of all students (Holstein et al., 2019; He & von Davier, 2016). The following section presents a review of literature with particular focus on the degree to which diverse learner characteristics currently are considered and incorporated into AI applications in U.S. K-12 education. More specifically the literature was evaluated with the intention of addressing the following questions:

Regarding the development of an AI-driven learner model:

1. In what ways can AI technology responsibly be leveraged to support a more robust understanding of K-12 learner capabilities and needs for assessment of students, especially those with disabilities, from culturally and linguistically diverse backgrounds, and who are currently and historically systemically marginalized and underserved?

2. What factors are needed to develop an AI-driven learner model that can accommodate a range of learning styles and minimize assessment bias to ensure inclusivity and equity?

Regarding the implementation of an AI-driven learner model:

3. How can AI-driven learner models be employed to improve decision-making processes in the areas of accessibility and inclusion in assessment (e.g., a priori matching of supports vis-a-vis student capabilities and needs)?

4. What are the potential successes and challenges of implementing AI-driven learner models in K-12 assessments? Given recent paradigm shifts in accessibility and inclusion, what intersectional opportunities with AI ought to be prioritized?

5. What are the ethical considerations associated with the use of AI in developing learner models for K-12 assessments, particularly with respect to fairness and validity?

Examining Learner Characteristics in AI Applications: A Review of Recent Literature on U.S. K-12 Education

This section describes a systematic literature review that examines how learner characteristics, particularly those relevant to students who are currently and have been historically systemically marginalized and underserved, are considered and incorporated into AI applications in U.S. K-12 education. Information from this review is used to address the questions listed above as well as informs the validity framework presented in a subsequent section of this paper.

Method

There were multiple steps involved in the systematic review of literature. First, a literature search of several electronic databases and online search engines, including ERIC, Google Scholar, Semantic Scholar, and PsychINFO was conducted. The list of search engines considered for this review is presented in Table 1. Keyword searches included but were not limited to terms such as “artificial intelligence,” “accessibility,” “equity,” and “inclusion.” Key topical areas such as empirical research, ethics, policy, and theory also were incorporated into the search. Table 1 provides the complete list of keywords used, both individually and in combination, for the literature review search. Inclusion and exclusion criteria were meticulously considered. Documents were required to be publicly available, published in English language journals or documents, and have publication dates ranging from 2014 to 2024. Documents needed to focus on one of the key topic areas—theoretical, empirical, policy, or ethical—and be framed within the context of the U.S. K-12 school setting. Additionally, journal articles had to be peer-reviewed. Any search findings that did not meet these criteria were excluded from the review. This literature search yielded an initial pool of documents that researchers considered for inclusion in their review of literature.

Second, each researcher selected one of the four topical areas of focus (i.e., theoretical, empirical, policy, ethical) and reviewed relevant documents in the initial pool. The researcher verified that a document met the inclusion criteria and should be included in the final analysis, and if it did, reviewed the document, extracting the following information:

- Theoretical documents: purpose; intended audience; underlying theory/theories; conceptual framework, models, and/or theory of action;
- Empirical documents: type of study; data source(s); subjects; n-size; research question(s)/purpose; factors/variables; analyses; key findings; key implications;
- Ethical documents: key considerations;
- Policy documents: by whom the policy was created; for whom the policy is intended; focus (e.g., principles, standards, guidelines); whether it is elective or required; and
- Additionally, for all documents, information related to fairness, equity, inclusion, and accessibility.

Each document was reviewed by a second researcher to verify inclusion in the final analysis as well as the information extracted from each document. If there was disagreement between the two reviews, a third researcher reviewed the document in question and made a consensus-based decision regarding the document's inclusion in the final analysis and the information extracted from the document.

Finally, data from each topic area were synthesized to surface and articulate general themes vis-a-vis fairness and accessibility in AI, as well as gaps and needs. Researchers conferred with each other throughout the process to ensure the accuracy and consistency of the interpretations. The syntheses for each topic area follow.

Table 1
Review of Literature: Summary of Sources, Key Words Searched, and Criteria

Sources	• ArXiv (post-print articles used only; confirmed with second academic search engine) • Elicit • ERIC • Google Scholar • Google search • Research Gate • Science Direct • Semantic Scholar • PubMed • PsychINFO • Digital Commons
Key words used (and combinations)	• Accessibility • Artificial Intelligence (AI) • Assessment • Equity • Empirical • Ethics • Fairness • Inclusion • K-12 education • Policy • Student learning • Theory • U.S. (schools, context) • Validity
Inclusion criteria	• Publicly available • English language journals/documents • Publication date range: 2014-2024, seminal work excepted • Theoretical, empirical, policy, ethical • K-12 • U.S. context • Peer reviewed (applies to articles/papers)
Exclusion criteria	• Not publicly available, fee/purchase required • Not an English publication • Publication date range before 2014 • Not peer reviewed (for articles/papers)

Findings

The initial search yielded 59 documents, all of which were recorded for tracking purposes. Of these, 23 documents met the criteria for inclusion in the final analysis (see Appendix A). In total, 5 empirical studies, 4 ethical texts, 10 policy-related documents, and 4 theoretical documents were analyzed for this literature review. Outcomes of the qualitative analysis of the documents and syntheses of information are summarized below.

Theoretical Documents

Four documents that address theoretical perspectives met the required inclusion criteria and were reviewed. Three of the documents address general K-12 educational contexts; one document focuses more specifically on language education. All four documents specifically address diverse learners, learning styles and preferences, and culturally and linguistically responsive approaches.

Song et al. (2024) present a framework based on Universal Design for Learning (UDL) to create inclusive AI education for K-12 students. This framework integrates AI learning design principles with UDL's multiple means of engagement, representation, and action and expression. It provides practical pedagogical examples and emphasizes project-based learning, collaborative learning, and interactive demonstrations. The framework aims to guide educators in designing AI curricula that cater to diverse learners' needs and promote fairness and accessibility.

Similarly, Mizumoto (2023) explores the integration of data-driven learning (DDL) and generative AI (GenAI), such as ChatGPT, in language learning. Mizumoto introduces the Metacognitive Resource Use (MRU) framework, which positions DDL within a broader ecosystem of language resources, including GenAI tools. The MRU framework emphasizes metacognitive knowledge and regulation, guiding learners to strategically use diverse language resources. The article suggests pedagogical strategies for enhancing learners' self-awareness and resource use and calls for future research to empirically assess the integrated DDL-GenAI approach and the MRU framework.

In considering how AI technologies can be utilized to enhance English language teaching for diverse learners, Anis (2023) outlines strategies for integrating AI tools such as language models and adaptive learning systems into educational practices. It emphasizes the potential of AI to address individual learning needs, offer personalized feedback, and support diverse learning styles. The article also discusses the implications of AI adoption in education, highlighting the importance of teacher training, ethical considerations, and the need for inclusive pedagogical frameworks to ensure equitable access to learning opportunities for all students.

Madaio et al. (2022) also critique the typical emphasis on performance gaps in AI fairness evaluations, pointing out that they overlook deeper systemic inequalities inherent in the development of the system itself. Drawing on critical theory and Black feminist scholarship, they show how educational AI technologies continue to reinforce historical injustices, even when the technologies seem to perform equally well. For example, the authors note that fairness approaches often focus on treating all groups the same, thereby reinforcing inequities because the algorithms fail to account for the societal complexities present within categories such as race and gender. The authors call for justice-oriented approaches and a complete redesign of educational AI to foster equity, stressing the importance of addressing and changing the structural inequalities that are built into these technologies. The authors argue that it is not enough to focus on identity and inclusion, but instead to address structural inequalities through participatory design.

All four documents emphasize the importance of creating inclusive and accessible learning environments using AI technologies. They highlight the potential of AI to provide personalized learning experiences, noting that AI can tailor educational content to meet the unique needs and preferences of individual students, enhancing engagement and learning outcomes. Each document introduces a framework or set of strategies for integrating AI in education. The documents address the need for responsible use of AI, ensuring data privacy, avoiding algorithmic bias, and promoting fairness and equity in educational practices. All documents call for ongoing research to evaluate the effectiveness of AI in education. They emphasize the importance of collaboration among educators, researchers, and policymakers to develop and implement effective AI-driven educational practices.

Policy-Related Documents

The search for policy and related documents yielded 10 documents that met the inclusion criteria. All of these documents included elective (rather than mandatory) guidance on AI considerations, with each framing these considerations as guidelines, and some also delineating principles (Burstein, 2023; TeachAI, 2023; UNESCO, 2021; UNICEF, 2020), standards (Burstein, 2023), and strategies (Roshanaei, 2023). The overarching intended audiences described in these publications included educators, policymakers, and researchers. Educational institutions were also specifically named as an intended audience in several documents (Burstein, 2023; TeachAI, 2023; UNESCO, 2021), while Cardona and Rodriguez (2024) defined their intended audience as developers of AI-enabled products and services in the educational sector, including product leads, innovators, designers, developers, customer-facing staff, and legal teams across research, nonprofit, and for-profit organizations.

Generally, these documents point out that the integration of AI in U.S. K-12 education presents both opportunities and challenges, particularly regarding the inclusion of diverse learners. Despite the potential benefits of personalized learning and enhanced assessment accuracy, current AI applications often lack comprehensive consideration of the diverse spectrum of learners, and this oversight can inadvertently reinforce existing biases, disproportionately affecting currently and historically systemically marginalized and underserved student groups. Several policy documents emphasize the importance of considering diverse learner characteristics in AI applications (e.g., Burstein, 2024; Cardona & Rodriguez, 2024).

The literature reviewed also highlights the challenges and potential biases in AI applications. White et al. (2024) advocates for "the adoption of new K-12 educational policies to ensure equitable access to AI education” (p. 1). Marino et al. (2023) note that while AI has the potential to revolutionize how students with disabilities learn, it also risks perpetuating existing biases if not carefully implemented. UNESCO (2021) and UNICEF (2020) underscore that it is essential that AI’s ethical deployment in education includes transparent and bias-minimizing practices to avoid exacerbating inequalities.

As AI tools continue to influence educational landscapes, their integration requires careful ethical and educational policy frameworks. Research suggests that machine learning may offer a more transparent alternative to certain AI applications, especially when considering the algorithmic oversight needed to maintain fairness and minimize bias (TeachAI, 2023). Roshanaei et al. (2023) note that AI has improved accessibility for students with disabilities by providing assistive technology solutions for them, such as screen readers and braille translators. They also state that “AI systems must be grounded in datasets reflecting diverse experiences and viewpoints to avoid biases and ensure fairness” (p. 138). Salas-Pilko et al. (2024) point out that AI technologies can enhance accessibility in education by providing personalized learning experiences that cater to individual student needs, including those with disabilities and multilingual learners. This personalized approach can help bridge the gap in educational outcomes for currently and historically systemically marginalized and underserved students.

The need for robust policy and ethical considerations is a recurring theme in the reviewed literature. UNESCO (2021) and UNICEF (2020) both emphasize the importance of developing policies that ensure the ethical use of AI in education, particularly regarding data privacy and the protection of children’s rights. To align with a broader goal of transformative justice in educational AI applications, policies must be designed to safeguard against the misuse of AI and ensure that all students benefit equitably from technological advancements, and they must include transparency and accountability to ensure that AI-driven decisions are fair and just.

Empirical Studies

Five relevant empirical studies met the required inclusion criteria and were reviewed. Park et al. (2022) investigated a visual interface designed to teach AI planning concepts to upper elementary students (grades 3-5), finding that while the interface showed promise in making AI concepts accessible to students, it also revealed usability challenges, particularly for students using different input devices. This study underscores the importance of designing AI-enhanced educational tools with accessibility in mind (e.g., resizable text and customizable color schemes). Similarly, Ali et al. (2021) focused on educating middle school students about deepfakes and misinformation, emphasizing the critical need for developing AI literacy in young students to navigate an increasingly AI-influenced information landscape.

In the realm of assessment and feedback, Li et al. (2018) and Hastings et al. (2018) explored the use of machine learning models to evaluate students’ writing. They developed models that demonstrate the potential for AI to provide automated feedback on complex writing tasks. Li et al. (2018) suggest that automated assessments of students’ language use could inform the development of personalized scaffolding to support learners with varying levels of academic language proficiency. Hastings et al.

(2018) investigated techniques to reduce the amount of human-annotated training data needed for such models, suggesting that AI could make sophisticated writing assessment and feedback more feasible across diverse educational contexts. In complement to these studies, Attali (2018) examined the large-scale deployment of automatic item generation for math assessment, finding that automatically generated items performed similarly to manually created ones. This approach has significant potential for providing more adaptive and personalized math assessments for learners with diverse abilities and backgrounds, which can be expanded to other content areas.

Ethical Texts

The search for articles with a focus on ethics yielded four relevant texts. Adams et al. (2023) identified several core ethical principles adapted for K-12 education, including justice and fairness, beneficence, and freedom and autonomy. They also uncovered principles unique to this context (e.g., pedagogical appropriateness and children’s rights) that underscore the need for AI systems in education to be designed with the specific needs and rights of all students in mind. Bulathwela et al. (2024) further emphasize this point, arguing that while AI in education (AIEd) shows promise for personalized learning and improved access, it risks exacerbating existing inequalities if not implemented thoughtfully. They caution against “techno-solutionism” and stress the importance of addressing underlying political and social issues while developing AIEd solutions.

Dieterle et al. (2022) provide a framework for understanding these challenges by identifying five interrelated divides in AI education: access, representation, algorithms, interpretations, and citizenship. These divides can create either virtuous or vicious cycles in educational outcomes. Dieterle et al. (2022) propose strategies such as empowering diverse interest holder communities, infusing evidence-based decision making with cultural responsiveness, and building human capacity through professional development. These approaches align with Porayska-Pomsta and Holmes’s (2023) emphasis on transparency, explicability, and human autonomy in AI educational systems. They argue that AIEd must critically examine its assumptions, involve diverse interest holders, and consider its broader societal impact to ensure ethical implementation.

Discussion

AI-driven learner models in U.S. K-12 education show promise for personalized learning and improved outcomes, particularly when integrated with UDL, offering real-time adjustments and individualized feedback (Mizumoto, 2024; Song et. al, 2023). When AI addresses student diversity, it supports inclusivity and equity, helping all students succeed.

Limitations

Despite a systematic and rigorous approach, this literature review has several limitations. Relying on English-language documents excludes insights from non-English publications, potentially limiting comprehensiveness. Focusing on peer-reviewed documents from 2014 to 2024 may exclude critical works outside this timeframe. The specific focus on U.S. K-12 education, while relevant, may exclude important international and post-secondary information. Additionally, excluding non-peer-reviewed documents, aimed at ensuring methodological rigor, might overlook innovative or emerging work. These limitations highlight the need for ongoing examination to understand AI applications in U.S. K-12 education promoting accessibility, inclusion, equity, and validity. Nonetheless, the reviewed literature underscores critical implications and gaps, particularly for currently and historically systemically marginalized and underserved groups.

Implications

AI has the potential to tailor educational experiences to individual students' needs, preferences, and learning styles. Frameworks such as UDL and MRU emphasize creating inclusive and accessible learning environments. These frameworks can guide educators in designing AI curricula that engage diverse learners through multiple means of engagement, representation, and action and expression, promoting fairness and accessibility (Mizumoto, 2023; Song et al., 2024).

The ethical integration of AI in education is paramount. Ensuring data privacy, avoiding algorithmic bias, and promoting fairness and equity in AI-driven educational practices are crucial. Theoretical perspectives advocate for justice-oriented approaches and the need to confront systemic inequities embedded in educational technologies (Madaio et al., 2022). Furthermore, policy documents emphasize the necessity of robust ethical guidelines and multi-interest-holder collaboration to ensure AI applications do not exacerbate existing biases and inequities (Burstein, 2023; UNESCO, 2021).

Effective implementation of AI in education requires significant investment in teacher training. Educators must be equipped with the knowledge and skills to leverage AI tools effectively while understanding their ethical implications and potential biases (e.g., Anis, 2023). The reviewed policy documents provide guidelines and principles for integrating AI in education, focusing on accessibility and inclusion of diverse learners. These documents underscore the importance of developing policies that ensure the ethical use of AI, safeguard data privacy, and protect children's rights. They advocate for AI systems that are tested and validated with diverse populations to ensure broad applicability and fairness (Cardona & Rodriguez, 2024; Roshanaei, 2023).

Gaps and Challenges

Despite the potential benefits of AI, there is a risk of perpetuating existing biases if AI systems are not carefully designed and implemented. Studies highlight the disproportionate impact of AI biases on marginalized communities and the exclusion of these groups from AI development processes (Marino et al., 2023; White et al., 2024). Ensuring that AI systems are developed using diverse datasets and are inclusive of all student groups is crucial to mitigating these risks. While theoretical and policy documents provide valuable guidelines, empirical studies are necessary to validate these approaches and understand their impact on diverse learners.

Addressing the structural inequalities that AI technologies may perpetuate is a significant challenge. Research by Madaio et al. (2022) call for a fundamental redesign of educational AI systems to promote equity and justice, emphasizing the need to confront and transform the structural inequalities embedded in these technologies. This requires a comprehensive approach that involves diverse interest holders in the design and implementation of AI-driven educational tools.

AI-driven learner models can enhance personalized learning and promote educational equity, but significant challenges remain. Addressing these requires ethical guidelines, empirical validation, and a commitment to inclusivity. Collaboration among educators, researchers, policymakers, and communities is crucial to harness AI's potential in education equitably. The following section presents a fairness- and transformative justice-based validity framework to ensure AI applications in K-12 assessments are inclusive of students with disabilities, culturally and linguistically diverse students, and other marginalized groups.

Validity Framework for Equitable AI Applications in K-12 Educational Assessment

To ensure the equitable application of AI in K-12 educational assessment, the authors propose the following validity framework, the Fair AI Framework. Centered on fairness and transformative justice, this framework is intended to prioritize equitable access to AI tools and ensure these tools do not perpetuate existing biases or inequalities. Generally, fairness refers to designing AI systems that treat all students justly, providing equal opportunities for success. Transformative justice goes further by actively aiming to address and dismantle systemic barriers and inequities within educational environments. This approach aims to prevent harm and create positive, inclusive changes that benefit currently and historically systemically marginalized and underserved student groups so that they can thrive. The framework includes five key components: Accessible and Inclusive Design, Ethical Implementation, Continuous Monitoring, Evaluation, and Improvement, Interest Holder Engagement, and Policy and Advocacy. Each component is grounded in theory and research and linked through a coherent theory of action.

Framework Components

Accessible and Inclusive Design: Involves designing AI tools that are responsive to the diverse visual, auditory, cognitive, and physical accessibility needs and preferences of students, as well as sensitive to their cultural and linguistic backgrounds. Creates an AI-driven accessible and inclusive learning environment that moves away from a deficit-based model that focuses on what students may be "missing" to an asset-based model leveraging the richness of student diversity and allows for diverse frames of reference, ways of knowing, and means of communication. Additionally, integrates assistive technologies to support students, including features like screen readers, voice recognition, and customizable interfaces. Relevant resources include: UDL principles to ensure AI tools provide multiple means of engagement, representation, and action and expression (CAST, 2018; Christensen et al., 2014; Christensen et al, 2023; Sato, 2023); the Sociocultural Dimensions Matrix (Sato, 2023, 2024) to systematically consider sociocultural factors that affect learners' understanding of information and their demonstration of knowledge; the Leading for Equity Framework (National Equity Project, 2024) that emphasizes inclusive design that considers equity, complexity, and user-centered approaches to address systemic oppression; and guidelines for reviewing demographic data for use in measuring "fairness and bias" in AI systems (Bogen, 2024).

Ethical Implementation: Involves ensuring AI algorithms are trained on diverse datasets and regularly audited for biases to maintain algorithmic fairness. Uses fairness-aware algorithms that minimize disparate impacts on different student groups (e.g., Ferrara et al., 2023). Establishes robust data governance policies to protect student data privacy and ensure that data collection, storage, and usage comply with ethical standards and legal regulations. Promotes transparency in AI decision-making processes by providing clear explanations of how AI tools make decisions and establishing accountability mechanisms for addressing any adverse impacts. Relevant resources include: guidance emphasizing fairness-aware AI algorithms, data governance policies protecting student privacy, regular auditing for biases, transparency in AI decision-making processes, and engagement with diverse interest holders to ensure ethical and equitable use of AI in educational settings (Council of the Great City Schools & Consortium for School Networking, 2023; Miao & Holmes, 2021; National Institute of Standards and Technology, 2023).

Continuous Monitoring, Evaluation, and Improvement: Involves conducting regular impact assessments to evaluate the effectiveness and fairness of AI applications, using both quantitative and qualitative data to measure educational outcomes and identify disparities. Establishes mechanisms for improvement that include (1) continuous feedback from students, educators, and other interest holders and (2) consideration of the emerging body of knowledge on diversity and innovations to iteratively improve AI tools and ensure they meet the evolving needs of diverse learners. Implements longitudinal studies to understand the effects of AI applications on student learning and equity, tracking educational outcomes over time to identify trends and areas for improvement. Relevant resources include: guidance and frameworks that focus on continuous monitoring and evaluation of AI applications in education, recommend regular impact assessments, mechanisms for interest holder feedback, longitudinal studies to understand long-term effects on student learning and equity, and engagement with diverse perspectives (Council of the Great City Schools & Consortium for School Networking, 2023; Miao & Holmes, 2021; National Institute of Standards and Technology, 2023).

Interest Holder Engagement: Includes involving a diverse group of interest holders in the design and implementation of AI tools, including educators, students, parents, community members, and experts. Ensures that the voices of currently and historically systemically marginalized and underserved groups are heard and valued. Provides ongoing professional development for educators on the ethical use of AI in assessments. Fosters partnerships with community organizations, advocacy groups, and local institutions, as appropriate, to support the inclusive implementation of AI, engaging these partners in co-creating and disseminating AI-driven educational assessment practices. Relevant resources include: The Emerging Technology Adoption Framework which provides a structured approach for engaging diverse interest holders, including educators, students, and families, throughout the process of evaluating, adopting, and implementing AI and emerging technologies in PK-12 education (Ruiz et al., 2022).

Policy and Advocacy: Includes advocating for policies that promote equity in AI applications in educational assessment, including funding for research on equitable AI, support for inclusive design practices, and regulations to prevent discriminatory practices. Develops and disseminates ethical guidelines for AI in educational assessment, informed by principles of fairness, justice, and inclusivity, to be adopted by educational institutions and technology developers. Raises awareness about the importance of ethical AI in educational assessment across interest groups and advocate for responsible and equitable AI adoption. Relevant resources include: The Education Technology Industry's Principles for the Future of AI in Education framework which advocates for implementing AI in education with purpose, transparency, and equity (Software & Information Industry Association, 2023).

The proposed validity framework operates within a theory of action that integrates its components to achieve equitable AI applications in K-12 educational assessment (see Figure 2). The starting point is the accessible and inclusive design of AI tools to meet the diverse needs of all students. Ethical implementation ensures that AI applications are fair, transparent, and secure, with algorithms regularly audited for biases and data privacy rigorously protected. Continuous monitoring, evaluation, and improvement provide critical insights into the impact of AI on student learning and equity, with feedback loops and longitudinal studies informing iterative improvements to AI tools. Active engagement of diverse interest holders ensures that AI tools are relevant and effective, supported by professional development and community partnerships that promote ethical AI use. Finally, equity-focused policies and ethical guidelines create a supportive environment for the fair and inclusive implementation of AI, with public awareness campaigns advocating for responsible AI adoption.

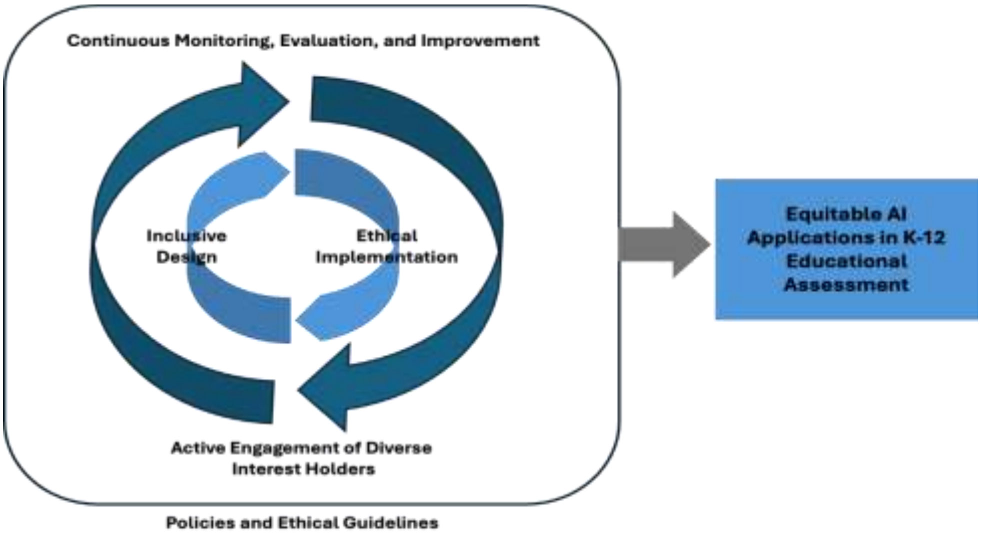

Figure 2. Theory of Action: Fair AI Framework

By integrating these components, the framework aims to create a system where AI-driven tools are used ethically and inclusively, enhancing learning outcomes for all students. This approach aims to promote AI applications in educational assessment that contribute to transformative justice, promoting equity and fairness for diverse learners.

Recommendations for Next Steps

The importance of AI-driven learner models in promoting accessible, inclusive, equitable, and valid assessments for all learners necessitates a strategic and multifaceted approach. The authors recommend a path forward that includes specific considerations across research, policy, practice, and collaboration. The recommended next steps are designed to advance the development and implementation of AI technologies that address the diverse needs of students, particularly those from currently and historically systemically marginalized and underserved groups.

Research should involve a multidisciplinary (e.g., education, computer science, ethics) and holistic approach to consider the effects of socio-economic, cultural, and linguistic factors in educational assessment. It also should include input from various interest holders to ensure AI validity. Empirical studies must evaluate AI's effectiveness and fairness across varied contexts. Regular bias audits are crucial, and methodologies should be developed to detect and mitigate biases. Longitudinal studies are necessary to track the effects of AI-driven assessments on educational outcomes and equity. Scalable AI solutions adaptable to different contexts and accessible to schools with varying resources are essential.

Equity-focused policies at the federal, state/territory, and local levels should require rigorous testing for fairness and inclusivity of AI tools. Establishing and promoting ethical frameworks based on principles of fairness, transparency, accountability, and respect for student privacy and autonomy is essential. Securing funding for the research and development of equitable AI technologies and providing resources for schools and educators to implement and sustain inclusive and fair AI-driven learner models is vital.

Investment in professional development for educators should cover inclusive design principles, ethical considerations, and practical AI applications in the classroom, particularly vis-a-vis assessment. Promoting the adoption of inclusive design practices in developing AI tools is essential, ensuring these applications are co-designed with input from diverse interest holders. Employing AI-based language translation and adaptation applications is essential for supporting culturally and linguistically diverse students. Integrating assistive technologies into AI-driven assessments to support students with disabilities ensures these technologies are adaptable to various needs and are user-friendly.

Interest holder collaboration should focus on co-creating AI tools responsive to diverse learners' needs. Engaging communities, especially those currently and historically systemically marginalized and underserved, in developing and implementing AI-driven learner models ensures their voices are heard and their needs are addressed in design and implementation. Maintaining transparency in developing and using AI in education by clearly communicating the purposes, benefits, and risks of AI tools to all interest holders is essential.

Conclusion

This paper examined advancements in methods and technologies, particularly through the integration of innovative tools that incorporate AI, and the implications of such advancements, focusing on learner models that are AI-driven, and their potential to transform educational assessment practices within the U.S. K-12 assessment context. As a result of the literature review and development of the Fair AI Framework, responses to the five questions articulated at the beginning of this paper are as follows:

First Question: The literature underscores that AI technology can be responsibly used to enhance understanding of diverse learner capabilities by incorporating principles and practices related to UDL and socioculturally responsive pedagogy, for example. By leveraging AI to tailor assessments and support mechanisms based on individual needs, AI tools can provide more nuanced and effective educational support. The proposed validity framework further emphasizes integrating assistive technologies and socioculturally responsive design to ensure AI applications meet the diverse needs of all students.

Second Question: Developing an AI-driven learner model includes: the application of inclusive design principles, which support diverse learning styles and needs; ensuring algorithmic fairness and conducting bias audits to minimize assessment bias; and integrating feedback mechanisms and continuous evaluation processes to refine AI tools to promote inclusivity and equity, as well as address both the potential and limitations of AI technologies.

Third Question: AI-driven learner models can significantly enhance decision making in accessibility and inclusion by using data-driven insights to match educational supports with student needs proactively. The literature suggests that AI tools can help ensure that students receive appropriate accommodations based on their unique capabilities and needs, providing a more responsive and equitable assessment experience for students.

Fourth Question: The implementation of AI-driven learner models can enhance personalization and support for diverse learners; however, challenges include bias and equitable access. Recent paradigm shifts highlight the need for intersectional approaches that consider socio-economic, cultural, and linguistic diversity.

Fifth Question: The literature and framework highlight the value of fairness-aware algorithms, protecting data privacy, and maintaining transparency in AI decision-making processes. Ensuring that AI systems are regularly audited for biases and that ethical guidelines are followed is essential, aligning with the broader goals of transformative justice and equity.

Integrating AI-driven learner models in K-12 education can transform equity but requires addressing ethics, inclusivity, and fairness. The Fair AI Framework offers a comprehensive, research-informed approach, recommending interdisciplinary research, policy advocacy, collaboration, and evaluation for continuous improvement to ensure accessible, inclusive, and equitable educational assessments for all learners.

Declarations

Gen-AI use: The authors of this article declare (Declaration Form #: 2711240909) that ChatGPT, developed by OpenAI, and Claude, developed by Antropic, were used for Data Analysis and interpretation as well as for checking grammar, style, and coherence in up to 10% of this article. They further affirm that all content generated by GenAI has been carefully reviewed, and they assume full responsibility for its inclusion.

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Ethical Approval: We declare that all ethical guidelines for authors have been followed by all authors. Ethical approval is not required as this study uses data shared with the public.

Consent to Participate: All authors have given their consent to participate in submitting this manuscript to this journal.

Consent to Publish: Written consent was sought from each author to publish the manuscript.

Competing Interests: The authors have no relevant financial or non-financial interests to disclose.

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Appendix A

Documents That Met the Full Inclusion Criteria and Were Reviewed

Document name	Theoretical	Empirical	Policy	Ethical
Adams et al., 2023				x
Ali et al., 2021		x		
Anis, 2023	x			
Attali, 2018		x		
Bulathwela et al., 2024				x
Burstein, 2023			x	
Cardona & Rodriguez, 2024			x	
Dieterle et al., 2024				x
Hastings et al., 2018		x		
Li et al., 2018		x		
Madaio, 2024	x			
Marino et al., 2023			x	
Mizumoto, 2023	x			
Park et al., 2022		x		
Porayska-Pomsta & Holmes, 2023				x
Roshanaei et al., 2023			x	
Salas-Pilco et al., 2022			x	
Song et al., 2024	x			
TeachAI, 2023			x	
UNESCO, 2021			x	
UNICEF, 2020			x	
White et al., 2024			x	
Woodruff et al., 2023			x	