Jurnal Penalaran dan Riset Matematika
Vol. 5, No. 2, 2026, pp: 59-68
p-ISSN 2961-8134, e-ISSN 2962-4150

ALGORITHMIC BIAS AND ETHNOMATHEMATICS IN AI-BASED MATHEMATICS EDUCATION: A CRITICAL REVIEW AND INCLUSIVE PEDAGOGY

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ARTICLE HISTORY:
Received: Sept 20, 2026
Revised: Sept 30, 2026
Accepted: Oct 20, 2026
Published: Oct 30, 2026

KEYWORDS:
Artificial Intelligence; Algorithmic Bias; Ethnomathematics; Critical Mathematics Education; Numeracy Equity; Digital Agency.

ABSTRACT
The use of artificial intelligence (AI) in mathematics education expands opportunities for adaptive feedback and learning support but also raises concerns regarding algorithmic fairness, access, cultural representation, and student agency. This article aims to explain how these opportunities and risks are interconnected and to develop a pedagogical framework integrating ethnomathematics, critical mathematics education, and equitable AI governance. The study employs a critical integrative review of methodological, theoretical, empirical, and policy literature whose publication details can be verified. The literature is interpreted through four analytical dimensions: the learning benefits of AI, sources of inequity, recognition of culturally grounded mathematical knowledge, and conditions for implementation and governance. The synthesis indicates that the effects of AI cannot be generalized as invariably harmful or invariably beneficial. Inequities may arise when data, assessment design, device access, and pedagogical decisions disregard learners' contexts. Conversely, technology can support conceptual exploration when teachers retain instructional control and provide meaningful tasks. The article develops the Critical Techno-Ethnomathematics Pedagogical Framework (KPT-EK), comprising four pillars: algorithmic fairness auditing, dialogic cultural modeling, critical socioeconomic numeracy, and digital agency. The framework is operationalized through five instructional phases, multilevel evaluation indicators, and propositions for empirical testing. The article contributes a more balanced argument about AI and a testable pedagogical design. Its findings do not yet constitute evidence of the framework's effectiveness or a completed scoping review with an audited corpus of studies.

Introduction

Artificial intelligence has entered mathematics education through intelligent tutoring systems, adaptive platforms, learning analytics, automated assessment, and generative models. These technologies can provide rapid feedback, adjust task sequences, and help teachers identify students' difficulties. However, the speed and accuracy of predictions are not the only measures of pedagogical quality. Mathematics learning also requires reasoning, communication, justification, recognition of identity, and equitable opportunities for development (Bakker et al., 2021; Schindler et al., 2026).

Debates about AI are often framed in binary terms: technology is expected to eliminate disparities through personalization, or it is viewed as inevitably perpetuating economic domination. Neither position is adequate. A meta-analysis by Yi et al. (2025), covering 21 studies and 40 samples, reported a relatively small positive overall effect on K–12 students' mathematics achievement (0.343). This finding indicates potential benefits but does not establish that those benefits are distributed equally across social groups. Conversely, Baker

and Hawn (2022) describe evidence and mechanisms of algorithmic bias in education, including differences in risk across groups and stages of system development.

Equity in mathematics education must be distinguished from uniform treatment. Providing identical access to devices does not ensure that students have equivalent internet connectivity, language support, digital experience, or opportunities to explain their reasoning. Recommendation systems may produce inequities when prior performance is treated as fixed ability or when success is measured solely by answer accuracy and speed. Conversely, personalization that allows revision, dialogue, and teacher assistance may create opportunities for previously underserved students (Idowu, 2024; UNESCO, 2023a).

An ethnomathematical perspective extends the question of equity from who can access technology to whose mathematical knowledge is recognized in the classroom. D'Ambrosio (1985) demonstrates that mathematical activities cannot be separated from social practices and cultural histories. Rosa and Orey (2013) distinguish emic, etic, and dialogic perspectives in ethnomathematical modeling. Accordingly, local cultural practices should not merely serve as decorative illustrations; they should be understood according to community logics and then carefully negotiated with representations used in school mathematics.

Critical mathematics education adds questions about power relations, resource distribution, and the use of numeracy to interpret social realities. Gutiérrez (2013) emphasizes the need for a sociopolitical orientation in mathematics education research, while Gutstein (2003) demonstrates how mathematical activities can be used to examine social justice issues in classrooms. Both traditions are relevant when algorithmic recommendations and digital learning materials may determine which problems are considered valuable and which students are considered capable.

The research gap addressed here concerns conceptual integration: how to connect AI fairness audits with the development of culturally grounded reasoning and the use of numeracy to critique inequality. Research on AI in mathematics education has advanced rapidly (Schindler et al., 2026), while proposals to integrate AI and ethnomathematics have also begun to emerge (Age & Machaba, 2026). Novelty therefore cannot rest merely on combining the terms "AI" and "ethnomathematics." A more defensible contribution must lie in pedagogical mechanisms, operational indicators, and a design for testing.

This article addresses three questions: (1) through what mechanisms can AI design and use increase or reduce inequity in mathematics learning? (2) How can culturally grounded mathematical knowledge and critical mathematics education strengthen students' reasoning activities in digital environments? and (3) How can a pedagogical framework integrating these perspectives be formulated, implemented, and empirically evaluated?

assuming that each category invariably experiences the same effects. Fairness metrics must be selected according to the decisions made by AI and examined alongside qualitative evidence of students' experiences.

Ethnomathematics and Dialogic Modeling

Ethnomathematics recognizes that activities such as measuring, estimating, classifying, dividing, bargaining, constructing patterns, or designing artifacts can embody mathematical knowledge developed through cultural practices. Its classroom use requires care so that community knowledge is not reduced to a collection of motifs, geometric shapes, or numbers stripped of their social contexts (D'Ambrosio, 1985; Rosa & Orey, 2013).

An emic approach seeks to understand meanings, rules, and terms from the perspectives of cultural practitioners. An etic approach uses the language and concepts of academic mathematics for modeling. A dialogic approach brings these perspectives together through questioning, verification with knowledgeable community members, and student reflection. In AI environments, these three steps help teachers assess whether digital interpretations of cultural practices are accurate, accepted by the community, and mathematically meaningful.

Critical Numeracy and Mathematical Agency

Critical numeracy entails using quantitative representations to analyze, question, and communicate issues affecting collective life. Data on income distribution, transportation costs, price disparities, or school availability can support the learning of proportions, statistics,

functions, and optimization. To remain mathematically rigorous, discussions of social justice must rest on accurate data, models, assumptions, and testable arguments (Gutstein, 2003; Gutiérrez, 2013).

Mathematical agency is understood as students' opportunities and capacity to choose strategies, critique representations, request evidence, correct errors, and reject unreasonable system recommendations. Digital agency extends this capacity to selecting technologies, testing AI outputs, understanding data traces, and claiming the right to explanations of decisions. Teachers remain responsible for ensuring that every student receives the necessary support.

Methods

Review Type and Evidentiary Position

This article employs a critical integrative review to develop explanations across research traditions and formulate a pedagogical framework. This approach was selected because the available material includes primary research, systematic reviews, theoretical articles, and policy guidelines with differing purposes and levels of inference. The manuscript does not claim to be a completed critical scoping review because records of search results, deduplication, dual screening, and extraction matrices supporting figures in an earlier draft are not available for audit. The designation of the design and the conclusions are deliberately aligned with the strength of verifiable evidence.

Identification and Selection of Sources

Literature was purposively selected for its direct relevance to four domains: (i) AI and mathematics education, (ii) algorithmic fairness in education, (iii) ethnomathematics and critical numeracy, and (iv) AI governance and synthesis methodology. Publication details of selected foundational works were checked against publishers' websites, bibliographic indexes, scholarly repositories, or official issuing organizations. Articles reporting effectiveness evidence, bias analyses, and contrasting arguments were prioritized to avoid predetermining the synthesis. The literature covers foundational theory and developments published through October 2026. This purposive selection does not yield estimates of the frequency or prevalence of findings across the entire literature.

Analytical Procedure

The analysis proceeded in four steps: distinguishing empirical statements from theoretical arguments and normative recommendations; identifying mechanisms of AI benefits and risks; connecting those mechanisms to culturally grounded learning practices and critical numeracy; and translating the conceptual relationships into activities, indicators, and testable propositions. Each conclusion was interpreted in relation to the type of evidence, context, and limitations of its source.

To avoid overstating claims, "indicates," "proposes," and "may" are distinguished from "proves." Work on AI in education generally is used to explain mechanisms across contexts, not as direct evidence that identical patterns have occurred in all mathematics classrooms. Similarly, ethnomathematics and critical pedagogy literature provides a foundation for design but does not automatically demonstrate the effectiveness of the integrated model developed here.

Results of the Critical Synthesis

Source Map and Status of Contributions

Table 1 presents traceable key sources and their analytical contributions. It is a map of selected sources for an integrative synthesis, not a final PRISMA-ScR selection list or a claim that all studies meet a single set of scoping-review criteria.

Table 1. Core literature map and limits of inference

Source	Type of evidence	Contribution to synthesis	Limit of inference
Baker & Hawn (2022)	Review of educational AI research	Stages at which bias arises and between-group differences	Not specific to mathematics classrooms
Idowu (2024)	Systematic review	Debiasing strategies and fairness indicators	Varies by educational application
Yi et al. (2025)	K–12 meta-analysis	Positive average effect of AI on mathematics achievement	Does not test distribution of benefits
Schindler et al. (2026)	Meta-review	Taxonomy of AI technologies and functions in mathematics	Integrates review-level research
Mavrikis et al. (2022)	Educational technology design research	Combining exploration and structured practice for fractions	Specific intervention design and context
Gutiérrez (2013)	Theoretical review	Identity, power, and sociopolitical approach	Does not evaluate AI
Gutstein (2003)	Qualitative practitioner research	Mathematics as a means of examining social issues	One school context
D'Ambrosio (1985)	Conceptual work	Basis for recognizing culturally grounded mathematics	Not an AI evaluation
Rosa & Orey (2013)	Theoretical framework	Emic, etic, and dialogic approaches	Not a platform evaluation
Age & Machaba (2026)	Conceptual synthesis	AI, ethnomathematics, and cultural data sovereignty	Framework requiring testing
UNESCO (2023a, 2023b)	Policy guidance and reports	Inclusion, privacy, teacher role, and digital costs	Does not measure effects of this model

AI Can Support Learning, but Its Benefits Are Conditional

The claim that AI inherently undermines mathematical reasoning is inconsistent with the full body of evidence. Yi et al. (2025) found a mean effect of 0.343 favoring AI over comparison instruction in the studies they synthesized; AI type was a prominent moderator. Mavrikis et al. (2022) likewise demonstrate the relevance of designs combining exploration and structured practice for fraction knowledge. These sources support the possibility of designs richer than drill-based practice alone, but do not establish the superiority of every AI product.

Consequently, critiques of AI should focus on testable mechanisms, such as the dominance of closed-ended questions, restrictions on exploration, feedback quality, and the transfer of decision-making to systems. Outcome indicators should include mathematical justification, conceptual transfer, and willingness to question digital answers, rather than only increases in correct-answer scores.

Bias Can Arise Before, During, and After Prediction

The algorithmic fairness literature identifies at least five risk points: data that underrepresent certain groups; proxies such as devices, location, and connectivity patterns correlated with social circumstances; narrow success labels; unequal model errors across subgroups; and teacher or institutional decisions that accept recommendations without examining context (Baker & Hawn, 2022; Idowu, 2024). These risks do not establish that all female students or low-income students are invariably disadvantaged. The magnitude and direction of inequity must be examined in relation to specific data and decisions. One mechanism requiring investigation involves students with limited internet access generating fewer digital traces, which a system may then interpret as lower engagement or ability. If subsequent recommendations contain only basic tasks, disparities in opportunities to reason may widen. This sequence is a hypothesized mechanism, not an empirical finding from a sample in this article. Removing gender or economic attributes from data does not necessarily eliminate bias because other attributes may act as proxies. A more meaningful audit examines the purpose of decisions, error distributions, user experiences, appeal procedures, and whether teachers can override inappropriate recommendations.

Cultural Recognition Is Not the Same as Cultural Romanticization

Students can discuss local measurement, trade, architecture, and production patterns as sources of mathematical questions. However, task validity does not follow automatically from invoking a particular culture. Researchers and teachers need to examine representational authenticity, community permission and consent, accessibility to students from diverse backgrounds, and the quality of the mathematical concepts developed (D'Ambrosio, 1985; Rosa & Orey, 2013).

AI may support the documentation of community mathematical practices, the generation of alternative representations, and the translation of terminology, as conceptually discussed by Age and Machaba (2026). However, systems may also misinterpret terms, reduce living practices to fixed patterns, or use cultural data without appropriate governance. Cultural communities must therefore remain sources of authority, while teachers verify the accuracy of AI outputs.

Numeracy Equity Requires Changes in Design and Governance

Equity cannot be achieved through algorithms alone. Curriculum, assessment, language of instruction, device distribution, teacher capacity, accessibility, and funding all shape the benefits of technology. UNESCO (2023a) cautions that evidence of the added value of educational technology remains uneven and that implementation should consider feasibility, equity, and sustainability. UNESCO (2023b) emphasizes a human-centered approach to generative AI, including privacy protection, cultural diversity, and learner agency.

Thus, debiasing policies should not be limited to a single measure of model accuracy. Schools need complaint mechanisms, regular audits, human oversight, and non-AI learning options of equivalent educational value. Ethnomathematics programs must also be connected to conceptual learning outcomes and reasoning skills rather than ending with cultural appreciation activities.

Development of the Critical Techno-Ethnomathematics Pedagogical Framework

Premises and Limits of Claims

The Critical Techno-Ethnomathematics Pedagogical Framework (KPT-EK) is positioned as a proposed model for instructional design and evaluation. It rests on the premise that the quality of reasoning, recognition of cultural knowledge, and equitable distribution of learning opportunities should be pursued as joint goals. AI is treated as a resource open to critique, not the sole determinant of learning. The following four pillars retain the core of the original manuscript and elaborate it into researchable activities, responsibilities, and indicators.

Table 2. Four KPT-EK pillars, core actions, and observable indicators

Pillar	Core actions	Examples of observable indicators
P1. Algorithmic fairness audit	Examine input data, recommendation patterns, between-group errors, and teachers' right to override.	Proportion of recommendations reviewed; between-group differences in false negatives; teacher decision records.
P2. Dialogic cultural modeling	Identify local practices with communities; develop emic–etic–dialogic models.	Contextual authenticity; quality of explanations connecting models and practices; informant consent.
P3. Critical socioeconomic numeracy	Analyze real data, evaluate assumptions, compare distributions and alternative decisions.	Analytical accuracy; interpretation of data limitations; quality of evidence-based arguments.
P4. Emancipatory digital agency	Students choose strategies, examine AI, revise, and raise reasoned objections.	Frequency of independent justification; identification of AI errors; quality of reflection and revision.

Mechanisms Linking the Pillars

The four pillars influence one another. P2 provides relevant mathematical objects and language; P3 turns them into activities for evaluating information and social consequences; P4 ensures that students remain the principal agents of reasoning; and P1 examines whether digital systems and decisions provide equitable opportunities. Teacher mediation and

community legitimacy are cross-cutting conditions. Expected outcomes include conceptual reasoning, the capacity to critique data, equitable participation, and mathematical agency. These relationships should not be interpreted as established causal laws. For example, cultural contexts may increase engagement for some students but may not be relevant to everyone. Algorithmic audits may reduce disparities in decisions but are insufficient by themselves to improve instructional quality. Evaluation must therefore examine the effects of each pillar, interactions among pillars, and implementation costs.

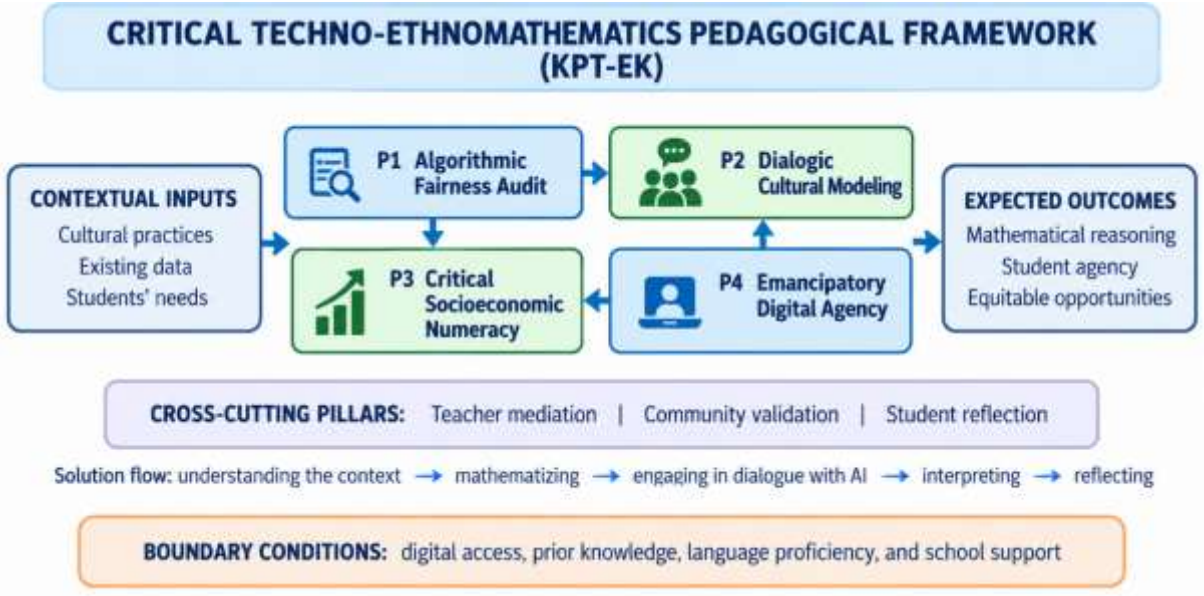


Figure 1. Conceptual flow of KPT-EK (proposed model)

Five Phases of Instructional Implementation

The KPT-EK cycle comprises five phases that can be used within one topic or across several lessons. The sequence is designed so that AI provides support without replacing independent reasoning and collective discussion.

Table 3. KPT-EK phases and collected process evidence

Phase	Student and teacher activities	Artifacts or evidence
1. Understanding the context	Teachers and communities validate narratives, measurements, or data; students formulate questions.	Records of data provenance; initial questions; consent to use materials.
2. Mathematizing	Students independently formulate variables, diagrams, tables, relationships, or models.	Initial model drafts; explanations of assumptions; alternative strategies.
3. Dialoguing with AI	AI provides alternative models or feedback; students check errors and defend decisions.	Prompt transcripts; identified errors; revision records.
4. Critiquing impacts	Students test sensitivity to assumptions, interpret distributions of impacts, and compare options.	Graphs; justifications; statements of data limitations.
5. Reflecting and assessing fairness	Teachers assess reasoning and opportunities for participation; the class reflects on AI use.	Rubrics; reflection journals; recommendation-review logs.

Illustrative Application in School Mathematics

As a design illustration, teachers could develop a statistics and functions unit using commodity-price data from several local markets in South Sulawesi. Students collect or use open data on unit prices, transportation costs, and weekly price changes. They examine source reliability, construct tables, calculate percentage changes, represent trends, and test whether price comparisons remain fair after differences in units and quality are taken into account.

Teachers may ask AI to suggest three ways to visualize the data. Students then check whether axis scales, extreme values, and selected time periods mislead readers. Groups compare manual calculations with AI outputs and document errors. For the cultural dimension, local trading terminology and practices are verified with business practitioners without assuming that a single homogeneous practice represents every community.

Critical questions might include: “Does the conclusion about the cheapest market remain the same when buyers’ travel costs are considered?” or “Under what conditions is the mean less appropriate than the median?” The final product is a brief mathematical report stating the data, assumptions, model, limitations, and recommendations. This illustration has not been empirically tested and is not a report of an intervention already conducted.

Model Evaluation Rubric

The evaluation rubric is developed at the student, classroom-process, and system levels. A 0–3 scale can be used for each dimension: 0 = not yet evident; 1 = evident with substantial assistance; 2 = consistently evident in the main task; and 3 = demonstrated independently and defensibly in a new context. These criteria constitute an initial design requiring content validation, inter-rater testing, and assessment of measurement invariance when comparisons are made across groups.

Table 4. KPT-EK assessment dimensions

Dimension	Key evidence	Unit of analysis
Mathematical reasoning	Accuracy of models, arguments, and verification	Student responses and interviews
Critical data literacy	Interpretation of graphs, assumptions, and distributional consequences	Data-based tasks
Digital agency	Questions directed at AI, strategy choices, revision records	Interaction logs and observations
Cultural recognition	Contextual validity and emic–etic dialogue	Community and student assessments
Equity of opportunity	Between-group differences in access, participation, and recommendations	Classroom data and platform audits
Implementation sustainability	Teacher readiness, costs, connectivity, data protection	Schools and policy

Testable Theoretical Propositions

Proposition 1. When tasks based on cultural practices are designed dialogically and combined with formal modeling, students are expected to produce richer conceptual explanations than when cultural contexts merely decorate problems.

Proposition 2. When students are required to verify AI outputs using mathematical reasoning before accepting answers, the quality of their justifications and their error-detection ability are expected to improve, provided teachers offer adequate support.

Proposition 3. When fairness audits are conducted on recommendations and learning opportunities, disparities between groups in the allocation of higher-order reasoning tasks are expected to narrow compared with the use of unreviewed automated recommendations.

Proposition 4. The effects of KPT-EK on learning outcomes are hypothesized to be mediated by mathematical agency and the quality of classroom interaction, and moderated by digital access, prior ability, language, and teacher readiness. All propositions require testing; this article does not yet provide causal evidence.

Discussion

Contributions to Research on AI in Mathematics Education

The principal contribution of KPT-EK is not the assertion that all AI is biased, but a shift in the research question from “Does AI improve scores?” to “For whom, through which mechanisms, under what conditions, and at what costs or consequences does AI support mathematical reasoning?” This question complements the evidence of average effectiveness reported by Yi et al. (2025) and the mapping of technological functions by Schindler et al. (2026).

APOS or Realistic Mathematics Education may be considered as additional lenses for specific studies, but relationships among APOS levels, AI features, and task types must be established through data. Without evidence of learning transitions, it would be inappropriate to conclude that adaptive systems invariably confine students to the Action stage. Similarly, recognizing everyday contexts in RME is not automatically equivalent to ethnomathematics or critical pedagogy; these perspectives can complement one another but have different conceptual emphases.

Contributions to Ethnomathematics and Critical Pedagogy

The model operationalizes the emic–etic–dialogic encounter through documentation, modeling, and evaluation of AI outputs. Culture is therefore not used merely to attract interest. Students are expected to construct formal representations while explaining the limitations and consequences of those representations. The sociopolitical perspective also directs learning toward evaluating the quality of evidence and identifying who may gain or lose benefits from the use of numbers.

Community involvement creates ethical implications that require governance. Community stories, photographs, measurements, or economic practices should not automatically be entered into external AI models. Data use must be governed by consent, clearly specified purposes, identity protection, and opportunities for communities to review researchers’ representations.

Implications for Policy and Practice

At the school level, policy priorities include ensuring that teachers understand the limitations of AI systems, providing high-quality nondigital alternatives, and overseeing automated decisions that affect learning opportunities. Audits should be proportionate to risk: a feature recommending practice examples has different consequences from a system determining remedial pathways or graduation decisions. Technology use must also meet data-protection and accessibility standards (UNESCO, 2023a, 2023b).

At the developer level, training data and interface designs should be tested across languages, devices, network conditions, and cultural contexts. Developers should provide teachers with understandable explanations for recommendations, correction options, and reports on testing the distribution of outcomes. At the curriculum level, teachers should be supported in designing tasks that connect numeracy, authentic local contexts, and data-based social analysis without sacrificing mathematical conceptual depth.

In Indonesia, a realistic step would be to begin design-based development in several schools with differing geographical characteristics and connectivity. Research could compare conventional instruction, AI without KPT-EK, and AI with KPT-EK where ethical and design conditions permit. Assessment should combine test results, argument quality, revision traces, interviews, AI logs, and disparities in learning opportunities rather than relying on a single final score.

Limitations and Research Agenda

First, this integrative review does not estimate the prevalence of bias or the number of studies supporting each theme across the entire literature. Selection-process figures from an earlier manuscript are not presented as results because the search and extraction records cannot yet be audited. If the article is to be published explicitly as a critical scoping review, the search must be repeated or verified and reported in accordance with PRISMA-ScR and JBI guidance (Tricco et al., 2018; Peters et al., 2020).

Second, literature on inequities in educational AI generally cannot be fully extrapolated to mathematics classrooms in Indonesia. Third, KPT-EK remains a design proposition; its validity, feasibility, and empirical effectiveness have not been tested. Fourth, cultural contexts are dynamic and cannot be treated as a single representation of students' identities.
The next research agenda includes (i) systematically mapping studies from 2019 to 2026 using an open protocol and documented searches; (ii) participatory design studies with teachers, students, and communities; (iii) validation of indicators and rubrics; (iv) longitudinal research on reasoning, agency, and the distribution of opportunities; and (v) multigroup audits attentive to measurement equivalence and risks of data leakage. Such evidence is needed before recommendations for large-scale implementation can be made.

Conclusion

The use of AI in mathematics education offers genuine opportunities alongside risks of inequity arising from data, algorithmic decisions, task design, and schools' social circumstances. Available evidence does not support claims that AI universally worsens inequality or that automated personalization invariably produces equitable learning. Equity must be evaluated in terms of the distribution of opportunities to reason, cultural representation, interaction quality, and students' capacity to question digital results. This article proposes the Critical Techno-Ethnomathematics Pedagogical Framework, comprising four pillars and five instructional phases that can be operationalized and evaluated. The framework is a conceptual contribution requiring empirical research, not a model whose effectiveness has already been demonstrated.

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