AI in Education: A Critical Review of Applications, Bias, and Equity Challenges

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Abstract. Artificial intelligence is rapidly transforming higher education, moving from peripheral support to everyday practice in teaching, learning, and assessment. Applications such as learning analytics, intelligent tutoring systems, automated scoring, and generative AI are widely promoted for personalization, scalability, and efficiency. However, evidence shows that these same tools can reproduce bias, compromise fairness, and destabilize pedagogical and ethical norms. Predictive models often privilege students with stronger linguistic or digital resources, tutoring systems struggle with cultural adaptation, automated scoring raises transparency concerns, and generative AI complicates authorship and academic integrity. This paper presents a critical review of 50 peer-reviewed studies published between 2020 and 2025. Rather than providing a systematic mapping, the review synthesizes debates on applications of AI in education and highlights how bias emerges across data, algorithms, social structures, and human–AI interaction. The analysis underscores the tension between opportunity and risk, arguing that AI's educational legitimacy depends less on efficiency gains than on fairness, accountability, and contextual sensitivity. The review concludes with future directions across technical, pedagogical, policy, and interdisciplinary dimensions, calling for equity-centered and human-centered approaches to AI in education.

Keywords: Artificial Intelligence in Education, Fairness, Bias, Equity, Critical Review.

1. Introduction

In recent years, higher education has been confronted with an unprecedented wave of technological change. Tools such as ChatGPT and GPT-4 have moved rapidly from experimental novelties to everyday resources, with students using them for drafting essays, summarizing readings, and even preparing for examinations (Von Garrel & Mayer, 2023; Ibrahim et al., 2023). Surveys across universities show that generative AI is no longer peripheral; it is actively reshaping study habits, assessment practices, and conceptions of academic integrity (Black & Tomlinson, 2025; Bin-Nashwan, Sadallah, & Bouteraa, 2023). These shifts illustrate that AI is not a distant prospect but a present force already influencing classrooms and curricula.

The enthusiasm surrounding AI is grounded in its potential to personalize learning, scale feedback, and facilitate new modes of collaboration. Studies of learning analytics highlight how predictive models can identify at-risk students and inform targeted interventions (Wang et al., 2024). Intelligent tutoring systems and automated assessment tools offer ways to individualize instruction and reduce the workload of grading, while generative AI introduces flexible support for writing and research (Zhang & Aslan, 2021; Deng, Jiang, Yu, Lu, & Liu, 2024b). For many, these applications signify a new stage in digital education, one in which efficiency and adaptivity can be achieved at scale.

Yet alongside these promises lie critical challenges. Evidence shows that algorithmic outputs frequently reproduce data biases, disadvantaging students from underrepresented linguistic or cultural backgrounds (Kim et al., 2025; Kwak & Pardos, 2024). Over-reliance on generative tools can undermine critical thinking and blur ethical boundaries around authorship and integrity (Cotton, Cotton, & Shipway, 2023). Policy analyses further warn that governance frameworks often lag behind technological adoption, leaving equity concerns inadequately addressed (OECD, 2024; Fu & Weng, 2024). In short, the rapid adoption of AI in education risks reinforcing structural inequalities even as it seeks to expand access and innovation.

Against this backdrop, a critical review is needed to interrogate not only what AI can do in education, but also what it should do. This paper synthesizes 50 peer-reviewed studies published between 2020 and 2025, with two aims: first, to map key applications of AI in education and their limitations; and second, to examine how bias and equity concerns intersect with these applications. Rather than celebrating innovation uncritically, the review emphasizes the tension between opportunity and risk, asking how AI might be integrated in ways that support fairness, accountability, and human-centered learning.

2. Applications of AI in Education: Potentials and Limitations

2.1 Learning Analytics (LA)

Learning analytics is often promoted as a way to predict student performance and guide timely interventions. Evidence shows that predictive models can identify at-risk learners and tailor feedback in real time (Zhang & Aslan, 2021; Wang et al., 2024). However, the promise of personalization is undermined by limited empirical validation across contexts. Most models are trained on narrow datasets, raising questions about transferability, and teachers are frequently excluded from decision-making loops, reducing pedagogical legitimacy (Alfredo et al., 2024). Efficiency gains therefore mask a more fundamental concern: analytics risk narrowing education to what can be quantified while neglecting broader learning goals.

2.2 Intelligent Tutoring Systems (ITS)

ITS have long been cited as exemplars of adaptive teaching, capable of adjusting to individual learners' needs. Reviews confirm that such systems can enhance mastery in structured domains (Zhang & Aslan, 2021). Yet evidence from liberal arts contexts shows difficulties in adapting to diverse epistemologies and cultural expectations (Miao, Zhang, Guo, Luo, & Zhang, 2024). Without accounting for local curricula and pedagogical norms, ITS risks reproducing standardized knowledge at the expense of contextual learning. In practice, cultural adaptation is less a technical afterthought than a condition of educational validity.

2.3 Automated Assessment

Automated scoring tools are increasingly applied to essays, short answers, and scientific explanations. Research demonstrates gains in efficiency and consistency, especially in large-scale testing (Ibrahim et al., 2023). Advances in NLP offer opportunities to reduce discrimination when models are explicitly calibrated for linguistic diversity (Kim et al., 2025). Yet transparency remains limited: when educators and students cannot interrogate why a score was assigned, trust is undermined. Reliability is similarly uncertain, as automated metrics often fail to capture creativity or divergent thinking (Wang et al., 2024). Assessment thus illustrates the trade-off between scalability and validity—a tension unlikely to be resolved by technical optimization alone.

2.4 Generative AI and Large Language Models (LLMs)

Generative AI has quickly moved from novelty to ubiquity in classrooms and research contexts. Large-scale surveys show that students already integrate tools such as ChatGPT into writing, problem solving, and research workflows (Ibrahim et al., 2023; Black & Tomlinson, 2025). Meta-analyses report overall positive effects on learning, though outcomes are highly variable depending on task design (Deng, Jiang, Yu, Lu, & Liu, 2024b). The risks, however, are equally visible. Generative AI blurs boundaries of authorship, complicates academic integrity, and can weaken critical reasoning when over-relied upon (Bin-Nashwan, Sadallah, & Bouteraa, 2023). The challenge is not whether these tools will be used, but under what conditions they contribute to deeper learning rather than shortcut it.

2.5 Synthesis and Interim Conclusion

Across domains, AI applications extend rapidly yet leave unresolved questions of validity, fairness, and ethics. Learning analytics struggle with contextual transfer, ITS with cultural adaptability, automated assessment with transparency and reliability, and generative AI with integrity and epistemic depth. Table 1 summarizes these applications, associated methods, potentials, and critiques. The pattern is clear: while AI expands the toolkit of educators, its educational legitimacy depends on embedding critical oversight and contextual sensitivity rather than celebrating efficiency in isolation.

Table 1: Applications of AI in Education: Potentials and Critiques.

Application	Technical Approach	Potential	Limitations / Critiques
Learning Analytics	Predictive modeling, dashboards	Early intervention, personalized feedback	Limited validation, exclusion of teachers, reductionism (Alfredo et al., 2024; Wang et al., 2024)
Intelligent Tutoring Systems	Adaptive pathways, mastery learning	Individualized instruction, self-paced learning	Weak cultural adaptation, over-standardization (Miao et al., 2024)
Automated Assessment	NLP-based scoring, automated feedback	Efficiency, scalability, reduced grading load	Transparency concerns, weak reliability for creativity/divergence (Kim et al., 2025; Wang et al., 2024)
Generative AI / LLMs	ChatGPT, GPT-4, text generation	Writing support, flexible problem-solving, research aid	Integrity challenges, over-reliance, epistemic shallowness (Black & Tomlinson, 2025; Bin-Nashwan et al., 2023)

3. Fairness and Bias in AI for Education

3.1 Data Bias

Bias often originates at the level of training data, shaping who benefits and who is disadvantaged. Automated scoring in multilingual contexts highlights how systems inherit the limitations of translation, creating distortions in assessment outcomes (Jung, Tyack, & Von Davier, 2024). Even advanced NLP tools reproduce discrimination when minority linguistic practices are underrepresented (Kim et al., 2025b). Evidence from multilingual tagging confirms that large models consistently privilege high-resource languages, reinforcing structural hierarchies in global education (Kwak & Pardos, 2024).

These examples show that equity is not only a matter of how tools are used but of what data they are built upon. Unless datasets are diversified and calibrated for linguistic and cultural variation, AI risks legitimizing exclusion under the guise of objectivity.

3.2 Algorithmic Bias

Even when data are improved, algorithms can still perpetuate bias. The push for explainability reflects recognition that opaque “black-box” systems undermine trust and fairness. XAI frameworks demonstrate potential to increase accountability but remain limited if they only provide surface-level interpretability (Khosravi et al., 2022; Farrow, 2023). Empirical work on progress monitoring shows that algorithms can systematically misclassify students along demographic lines, embedding inequality directly into predictions (Idowu, Koshiyama, & Treleaven, 2024).

The critical point is that algorithmic design decisions—such as how categories are constructed or features weighted—are never neutral. Without institutional oversight, AI outputs risk being treated as authoritative while masking embedded assumptions.

3.3 Social Bias

AI systems also interact with broader social inequalities. Studies document how generative AI adoption yields greater productivity benefits for men than women in academic contexts, reflecting pre-existing structural gaps (Tang et al., 2025). Large-scale surveys similarly reveal a "gen-AI gender gap" that mirrors inequities in access and recognition (Aldasoro, Armantier, Doerr, Gambacorta, & Oliviero, 2024). Disparities extend beyond gender: when systems trained in dominant linguistic and cultural contexts are deployed globally, learners in under-resourced settings are further marginalized (Kwak & Pardos, 2024).

The message is clear: technology does not erase social inequality but often amplifies it. Unless equity measures are embedded, AI risks consolidating privilege under the language of innovation.

3.4 Human–AI Interaction Bias

Bias also emerges in how humans interact with AI. Heavy reliance on chatbots and automated responses narrows opportunities for critical thinking and independent problem-solving (Zhai, Wibowo, & Li, 2024). Integrity concerns deepen this problem: evidence shows that ChatGPT blurs boundaries between legitimate assistance and misconduct, destabilizing norms of academic honesty (Cotton, Cotton, & Shipway, 2023). Qualitative accounts from students and faculty further indicate uncertainty about where ethical lines should be drawn, with shifting attitudes toward plagiarism and acceptable use (Karkoulian, Sayegh, & Sayegh, 2024).

This dimension underscores that bias is not only technical but cultural. Human choices about how AI is used—whether as supplement or crutch—affect both learning outcomes and institutional trust.

3.5 Summary

Bias in educational AI is multifaceted: data, algorithms, social structures, and human interactions each contribute to inequity. Together, these forces create what can be called an "equity trap," where AI promises inclusivity yet risks entrenching exclusion. Table 2 summarizes these categories of bias, typical cases, and affected groups. Recognizing these dynamics is essential if AI is to be adopted critically rather than naively celebrated.

Table 2: Types of Bias in Educational AI.

Type of Bias	Typical Examples	Representative Studies	Affected Groups
Data Bias	Multilingual disadvantages; unbalanced datasets	Jung et al. (2024); Kim et al. (2025b); Kwak & Pardos (2024)	Low-resource language learners; English language learners
Algorithmic Bias	Opaque models; limited explainability; biased monitoring	Khosravi et al. (2022); Farrow (2023); Idowu et al. (2024)	Students differentiated by gender, age, disability
Social Bias	Gender and regional disparities	Tang et al. (2025); Aldasoro et al. (2024); Kwak & Pardos (2024)	Female students; learners in under-resourced regions
Human–AI Interaction Bias	Over-reliance; blurred academic integrity	Zhai et al. (2024); Cotton et al. (2023); Karkoulian et al. (2024)	Students relying on ChatGPT; educators redefining norms

4. Discussion: The Tension Between Opportunities and Risks

4.1 The Contradiction Between AI Applications and Educational Equity

The evidence suggests that AI is simultaneously celebrated as a tool for personalization and efficiency while also reproducing inequities. Meta-analyses highlight gains in learning outcomes, but the benefits remain heterogeneous and often privilege students already advantaged in terms of language and digital access (Deng et al., 2024b). International reports emphasize that equity must be designed into AI adoption rather than treated as a secondary concern (OECD, 2024). Without sustained attention to contextual and linguistic diversity, AI risks amplifying rather than reducing disparities (Fu & Weng, 2024). This tension reveals that efficiency narratives often obscure who benefits and who is excluded.

4.2 Teachers' Roles: Enhancement or Substitution?

AI's integration unsettles the question of whether teachers are to be empowered or displaced. Surveys of higher education consistently show skepticism that AI could fully substitute for educators, yet there is broad recognition that teaching practices will change (Chan & Tsi, 2024). Evidence from professional development reviews indicates that AI functions most productively as a complement, enriching teachers' ability to diagnose needs and tailor instruction (Tan, Cheng, & Ling, 2024). At the same time, gaps in AI literacy among pre-service educators point to risks of superficial adoption (Kohnke et al., 2025). Collaborative studies further demonstrate that pairing human judgment with AI tools can increase engagement and sustain relational aspects of teaching (Ding, Li, & Hui, 2025). These findings converge on the view that teacher agency must be strengthened rather than diminished if AI is to play a legitimate role in classrooms.

4.3 Policy and Ethics: Regulatory Gaps and Social Responsibility

The regulatory environment has not kept pace with the rapid proliferation of educational AI. Reviews underline the fragmented nature of current oversight, leaving institutions with uneven standards and unclear accountability (Matos et al., 2025). Governmental guidance frames equity and transparency as central principles, yet gaps between aspirational statements and implementation remain evident (U.S. Department of Education, 2023). European policy discussions similarly call for enforceable safeguards such as auditability and human oversight (DAAD Brussels, 2025). Moreover, evidence of differential impacts, including gender disparities in academic outcomes, illustrates that neutrality in governance simply entrenches existing inequalities unless addressed explicitly (Tang et al., 2025). Effective regulation therefore requires moving beyond generic ethical codes toward targeted mechanisms that confront inequities directly.

4.4 Critical Reflection: Blind Spots in Current Research

Despite rapid growth in publications, the research base shows recurring blind spots. Systematic reviews indicate that many studies marginalize vulnerable populations, limiting the generalizability of claims about AI's fairness (Mouta, Pinto-Llorente, & Torrecilla-Sánchez, 2023). The literature is also saturated with optimism, often foregrounding efficiency while downplaying negative or inconclusive findings (Al-Zahrani, 2024). Ethical discussions, moreover, are frequently abstract, neglecting how specific cultural and institutional contexts shape the consequences of AI adoption (Fu & Weng, 2024). This narrowness risks reinforcing an innovation-driven narrative that overlooks structural inequities and silences critical perspectives.

4.5 Conclusion of the Discussion

Taken together, these strands form a paradoxical picture: AI promises transformative gains but simultaneously generates new forms of exclusion. Equity tensions, contested teacher roles, regulatory deficits, and research blind spots are not peripheral but central to the debate. Figure 1 illustrates this dynamic as an "opportunity–risk double helix," showing how potential benefits and risks are intertwined rather than opposed. The implication is that responsible AI in education cannot be achieved by pursuing innovation alone. What is required is a shift in orientation—from faster adoption to critical scrutiny, from efficiency metrics to equity benchmarks, and from abstract enthusiasm to context-sensitive practice.

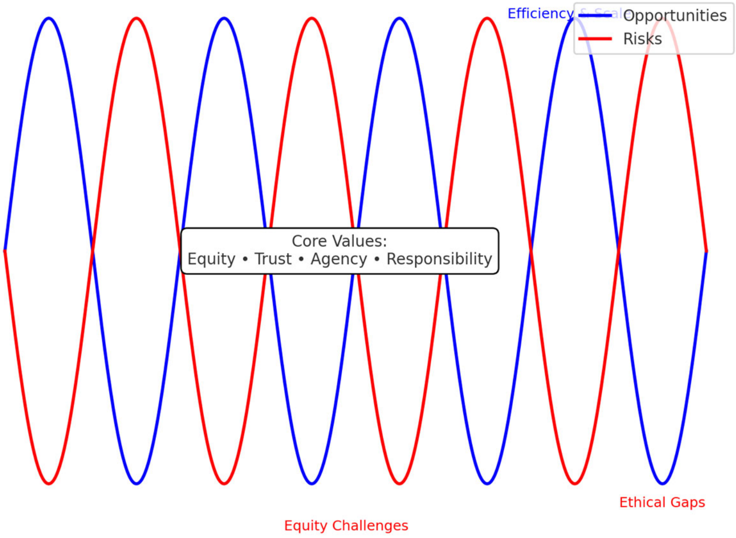

Figure 1: The Opportunity–Risk Double Helix of AI in Education.

The framework depicts two entwined strands: opportunities (personalization, efficiency, collaboration) and risks (bias, substitution anxiety, regulatory gaps, blind spots). Their interdependence illustrates that risks cannot be disentangled from opportunities; both must be addressed in tandem to guide AI toward equitable and responsible futures.

5. Future Directions

5.1 Technical Dimensions: Explainable AI, Bias Detection, Multilingual Models

Technical innovation in education must move beyond accuracy claims. Explainable AI (XAI) has shown value in making algorithmic reasoning accessible to teachers and learners, yet practical adoption still lags (Prentzas & Binopoulou, 2025). Oversight cannot be retrofitted; accountability needs to be designed into AI systems from the start (DAAD Brussels, 2025).

Bias detection is equally urgent. Evidence from NLP-enabled assessment shows that linguistic discrimination persists unless explicitly addressed through design choices (Kim et al., 2025). Without systematic bias monitoring, low-resource languages and marginalized learners will remain disadvantaged. Technical progress will therefore be judged less by speed or accuracy than by whether systems are explainable, fair, and inclusive.

5.2 Educational Dimensions: Constructivist and Humanistic Applications

Pedagogical integration must align with constructivist and humanistic principles. Research on AI-supported collaboration suggests that generative systems can deepen problem-solving when embedded in well-structured tasks, but they risk shallow engagement when treated as answer machines (Feng, 2025). Evidence from higher education shows positive effects on learning outcomes, yet gains are uneven and depend on whether activities require active reasoning (Pallant, Blijlevens, Campbell, & Jopp, 2025).

Students also adapt AI tools in varied ways, often blending instrumental and exploratory uses. Pedagogy must therefore focus on reflective practice rather than blanket adoption (Black & Tomlinson, 2025). Preparing teachers is critical; without AI literacy, integration risks privileging efficiency over deeper learning (Kohnke, Zou, Ou, & Gu, 2025). The principle is clear: AI should scaffold inquiry and self-reflection, not collapse them.

5.3 Policy and Ethics: Equity-Oriented Governance

The proliferation of AI applications expands the governance challenge. Reviews of emerging trends highlight the absence of clear accountability structures, with risks of fragmented or inconsistent oversight (Matos et al., 2025). Federal guidance has begun to frame equity as a design condition for AI in teaching and assessment, but policy-to-practice gaps remain (U.S. Department of Education, 2023).

Ethical governance must also address unequal impacts. Reports from Europe stress embedding transparency and human oversight into regulatory frameworks (DAAD Brussels, 2025). Evidence of gendered differences in AI's benefits further demonstrates that neutrality reproduces inequality unless corrective measures are enforced (Tang, Li, Hu, Zeng, & Du, 2025). Policies that fail to anticipate disparities risk endorsing efficiency while externalizing inequity.

5.4 Interdisciplinary Collaboration: Education, Data Science, and Sociology

The future of AI in education will depend on whether interdisciplinary teams can align methods with values. Studies of teacher–AI collaboration illustrate how engagement metrics and interface design intersect, requiring behavioral science, pedagogy, and computing to be co-developed (Ding, Li, & Hui, 2025). Broader reviews also call for research pipelines that connect theoretical framing from education with empirical validation from data science (Matos et al., 2025).

Adoption is equally shaped by cultural and institutional contexts; students' uses of AI reflect norms as much as technology (Black & Tomlinson, 2025). This suggests a model where educators, data scientists, and sociologists co-design systems, ensuring both technical feasibility and social legitimacy. Figure 2 summarizes these pathways, emphasizing their interdependence rather than isolation.

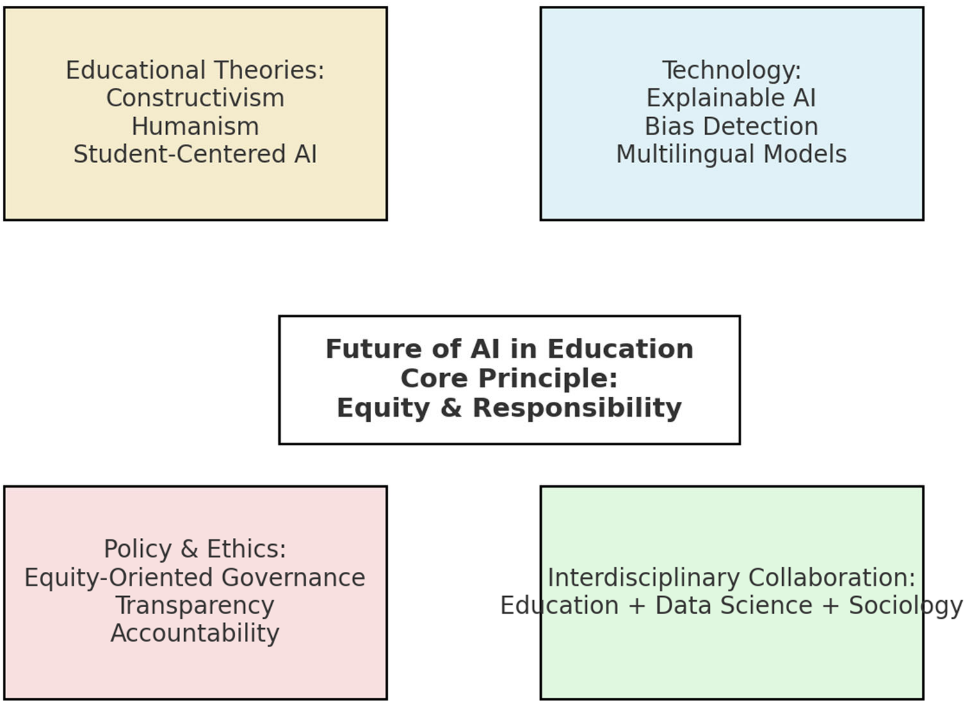

Figure 2: Future Pathways for AI in Education

The framework depicts four interlinked strands: technical (XAI, bias detection, multilingual inclusivity), pedagogical (constructivist and humanistic design), policy (equity-oriented governance), and interdisciplinary collaboration. Future progress depends not on advancing each strand independently but on aligning them in practice.

5.5 Conclusion

The future trajectory of AI in education hinges on balancing innovation with responsibility. Technical advances must prioritize explainability and fairness (Prentzas & Binopoulou, 2025; Kim et al., 2025). Pedagogical integration should preserve learner agency and construct meaning rather than short-circuit it (Feng, 2025; Pallant et al., 2025). Governance must embed equity and transparency into enforceable standards, not aspirational guidelines (U.S. Department of Education, 2023; Tang et al., 2025; DAAD Brussels, 2025). Finally, interdisciplinary collaboration is needed to align design with social realities and educational goals (Ding et al., 2025; Black & Tomlinson, 2025; Matos et al., 2025).

A credible future will be judged not by whether AI makes education faster, but by whether it makes it fairer, more human-centered, and more accountable.

6. Conclusion

This review has traced the expanding role of artificial intelligence in education, highlighting both its promise and its pitfalls. Applications such as learning analytics, intelligent tutoring systems, automated assessment, and generative AI hold clear potential for personalization, efficiency, and new forms of collaboration. Yet the evidence is equally clear that these innovations can entrench bias, compromise fairness, and unsettle established pedagogical roles if they are not carefully governed. The tension between opportunity and risk is therefore not incidental; it defines the trajectory of AI in education.

Three themes emerge. First, technical progress without transparency and bias detection is insufficient. The field must move toward systems that are interpretable and equitable, particularly in multilingual and low-resource contexts. Second, pedagogy cannot be treated as an afterthought. Constructivist and humanistic traditions remind us that the value of AI lies in how it supports learners' agency, not in how quickly it produces answers. Third, governance and research require a stronger ethical anchor. Current policies gesture toward fairness but often fall short in implementation, and research too often privileges efficiency while neglecting marginalized voices.

These insights converge on a critical point: the future of AI in education will be judged less by technical capability than by whether it fosters equity and responsibility. International bodies have already urged that educational AI be framed as a socio-technical system shaped by cultural and institutional contexts, not merely by algorithms (OECD, 2024). Systematic reviews likewise stress that ethical oversight and contextual sensitivity must become central, lest the rhetoric of innovation obscure structural inequities (Fu & Weng, 2024).

What is required, then, is not just more AI in classrooms but a different orientation to its design and governance—one that places fairness, accountability, and human flourishing at the core. Only under such conditions can AI deliver on its transformative promise rather than reproduce familiar exclusions under the guise of progress.

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