The AI Innovation Divide in Education: Responsible Adoption, Capability, and Inequality

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Article History
Received: 2026-01-04
Revised: 2026-04-09
Accepted: 2026-04-12
Published: 2026-05-02

Keywords
Artificial intelligence
Equity
Governance
Literacy

How to cite:
Madikizela-Madiya, N. Nyangaresi, J. K. (2026). The AI Innovation Divide in Education: Responsible Adoption, Capability, and Inequality. *Journal Science, Innovation and Creativity, 5*(1), 71-84.

Abstract
Artificial intelligence (AI), and generative AI in particular, is accelerating innovation in education by expanding access to tutoring, content creation, learning analytics, and teacher support. At the same time, policy syntheses and recent scholarship suggest that AI adoption can reproduce—and in some cases intensify—existing disparities when systems, data, skills, governance, and infrastructure are unevenly distributed. This conceptual analysis develops and refines the concept of an "AI innovation divide" in education: a multidimensional inequality in the capability to access, govern, and creatively use AI to generate educational value. Using a transparent desktop research strategy, the study analyses contemporary peer-reviewed studies and authoritative policy documents and derives defining attributes, antecedents, consequences, and empirical referents of the AI innovation divide across sources published between 2021 and 2026. Results yield a refined definition and a two-layer model that distinguishes foundational conditions (connectivity, data and compute access, and procurement ecosystems) from conversion conditions (AI literacy, institutional governance, and pedagogical/creative agency) that translate availability into learning and innovation outcomes. The discussion aligns this model with research on equity-conscious AI adoption, responsible AI governance, and AI competency frameworks, and highlights institutional and policy design implications, including capability-oriented investment, governance-by-design, and teacher-centred paths to innovation. The study concludes with limitations and an empirical research agenda to operationalise and quantify the AI innovation divide across educational systems.

Introduction

Artificial intelligence (AI) is increasingly treated as a general-purpose technology shaping scientific output, innovation regimes, and creative economies. In education, the public availability of generative AI, machine learning, and learning analytics has accelerated experimentation in tutoring, content generation, assessment support, and teacher workflow automation (Miao et al., 2021; Miao & Holmes, 2023; Wang et al., 2024). Policy analyses often present AI adoption as a strategy to address learning gaps and adapt to changing skill demands, while also cautioning that many systems are ill-prepared for large-scale implementation (Borgonovi et al., 2025; Varsik & Vosberg, 2024).

From an innovation perspective, AI-enabled educational tools promise three pathways of value creation: (i) personalisation of learning pathways and feedback loops, (ii) augmentation of educators' instructional design and assessment practices, and (iii) expansion of access to learning resources and language support through conversational interfaces and multimodal generation (Miao & Holmes, 2023; Mimoudi, 2025; Varsik & Vosberg, 2024). AI-in-education studies are developing fast, and focus on the problem of distribution and governance is becoming a central theme in the discipline (Mac Fadden et al., 2024; Wang et al., 2024).

Scholars in systematic and bibliometric reviews sustain this innovation framing and emphasise the rate and the extent of diffusion. Large-scale syntheses map AI applications across intelligent tutoring, adaptive learning, assessment automation, learning analytics, and emerging generative AI uses, and document a sharp rise in publications and pilots since 2017, with an additional surge after 2022 as generative AI tools expanded public access (Bahroun et al., 2023; Garzón et al., 2025; Wang et al., 2024). In the meantime, based on these reviews, current barriers to implementation, data quality, pedagogical integration, and ethical risk management mediate the shift between AI becoming a transformative or a fragile add-on innovation (Bahroun et al., 2023; Wang et al., 2024).

Teacher-facing evidence is relevant, as teachers are the mediators who determine whether AI will be an effective classroom innovation. Celik et al. (2022) identify opportunities in planning, implementation, and assessment, as well as ongoing challenges, including conceptual obscurity, workload restructuring, and the risk of losing professional autonomy. AI tools lead to the displacement of agency by the educator and increase disparities in the quality of instructional deliveries without organised professional learning and human-centred design (Laupichler et al., 2022; Miao & Cukurova, 2024).

Nevertheless, the use of AI does not necessarily decrease inequality. Innovation can widen existing disparities when access to and benefits from AI are distributed through stratified architecture, disparate institutional capacity, and socioeconomic privilege. There are many examples of equity risks, a list of which is long and really endless: connectivity; maturity of algorithms; information exclusion based on data and language coverage; uneven teacher training; and educational technology market dynamics (AlâZahrani, 2024; Baker & Hawn, 2022; Varsik & Vosberg, 2024). In most Global Souths, these risks may be further intensified due to the existence of weak procurement ecosystems, access to computing resources, and limitations in regulatory capacity, which influence who is able to adopt, adapt, and gain from AI-enabled education (Madaio et al., 2021; Matjie et al., 2026).

These issues are usually presented as a so-called digital divide, but AI can contribute to a new level of inequality. Compared to many previous educational technologies, AI systems rely more on high-quality data, robust cloud- or platform-based services, and ongoing maintenance. This also involves institutional knowledge about how to design, manage, and assess systems in practice (Laupichler et al., 2022; Matjie et al., 2026; Varsik and Vosberg, 2024). Moreover, generative AI transforms authorship, creativity, and epistemic power in ways that could reform what defines legitimate knowledge work in teaching (Kooli, 2023; Miao & Holmes, 2023).

An emerging body of literature on governance states that institutional decision-making influences the process of achieving equity in AI diffusion. The major ones are the distribution of responsibilities, the presence of transparency and accountability tools, and the negotiation of trade-offs among stakeholders regarding innovation, safety, and integrity (Papagiannidis et al., 2025; Wu et al., 2024). Governance forms in education affect the degree to which AI reinforces or weakens academic integrity, the right to privacy, and non-discriminatory assessment in non-codisciplinary fields (Baker and Hawn, 2022; Oncioiu and Bularca, 2025; Wu et al., 2024). The question of equity, however, is not whether AI will be adopted, but who may and can creatively utilise it to generate educational value and social good.

This study develops a theoretical and conceptual response to that question by refining the concept of an "AI innovation divide" in education. The AI innovation divide posits the potential to translate AI accessibility into educational and innovation outputs through literacy, governance, and creative pedagogical agency, whereas the digital divide conventionally focuses on access to devices and connectivity (Matjie et al., 2026; Miao & Cukurova, 2024; Papagiannidis et al., 2025). The framework draws on three complementary lenses: capability-oriented equity in technology use (Madaio et al., 2021; Varsik & Vosberg, 2024), responsible AI governance as a socio-technical practice (Papagiannidis et al., 2025; Wu et al., 2024), and competency-based approaches that distinguish "acquire–deepen–create" levels of AI literacy for educators (Laupichler et al., 2022; Miao & Cukurova, 2024).

Beyond the rapid growth in the development of AI-in-education applications, however, there is a lack of conceptual clarity in explaining how AI innovation yields disproportionate educational outcomes. The prevailing definitions are inclined to unify three notions, namely infrastructure access, AI literacy, and governance, and lead to the loss of a chance to design interventions, measure progress, and compare environments. Based on this, the following research questions are the focus of this study:

i. What are the defining characteristics, antecedents, consequences, and empirical referents of the AI innovation divide in education?

ii. How does the concept of the AI innovation divide extend traditional digital-divide frameworks by foregrounding governance and creative capacity as central determinants of educational equity?

Conceptual analysis of the answers to these questions provides the study with a theory-based model and practical propositions aligned with the interests of the Journal of Science, Innovation and Creativity in understanding the mechanisms underlying uneven social outcomes in innovation systems.

Materials and Methods

This study used a conceptual analysis design to clarify and refine the concept of an "AI innovation divide" in education and to derive a theoretically grounded model with practical and research implications. The conceptual analysis is suitable where the innovation area is rapidly changing, and the operationalisations are inconsistent, the terminologies used in identification of the concepts are contested, and the empirical evidence is fragmented; it facilitates the systematic questioning of how the concept is applied, what its attributes are, and what processes it elucidates in socio-technical settings (Laupichler et al., 2022; Matjie et al., 2026). Since the current aim consisted of theory building, not determining effect sizes, the study adopted a transparent desktop research strategy aimed at analytical depth, conceptual coherence, and traceability of claims to sources.

PRISMA flow and study selection transparency

Table 1: Compact PRISMA flow (2021–2026)

Stage	Count
Records identified	536
Duplicates removed	86
Records screened (title/abstract)	450
Records excluded (title/abstract)	382
Full texts assessed	68
Full texts excluded	47
Final studies included	21

Research Design and Rationale

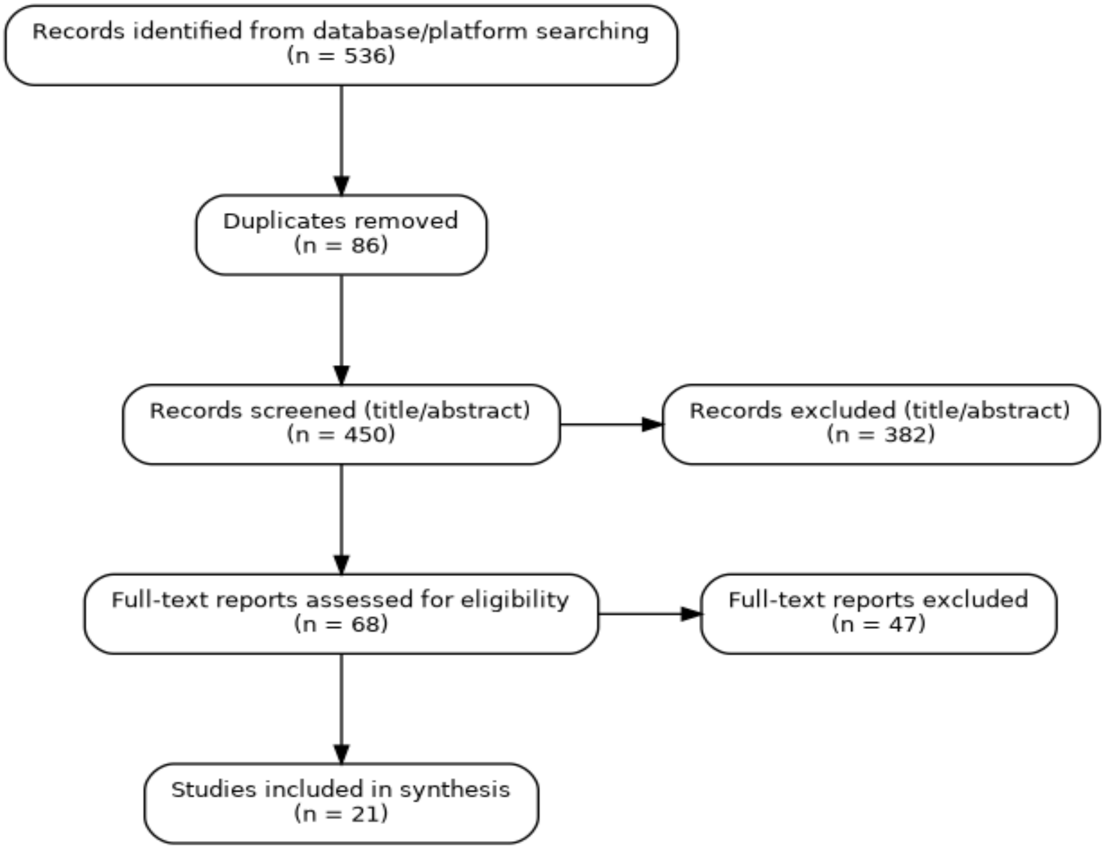

Figure 1: PRISMA 2020 flow diagram for study identification, screening, and inclusion

The analysis was conducted in four successive stages: (i) concept delimitation and initial definition built upon the extant literature on the policy and review regarding AI adoption and equity; (ii) identification and extraction of conceptual and empirical statements of the presence of AI-related educational inequality; (iii) synthesis to draw defining attributes, antecedents, consequences, and empirical referents; and (iv) integration with governance and competency frameworks to develop testable propositions. The strategy is consistent with recent equity-oriented arguments for shifting beyond access-only accounts toward models that reflect capabilities, governance, and meaningful use (Papagiannidis et al., 2025; Varsik & Vosberg, 2024).

Identifying and Ensuring the Eligibility of the Source

A systematic desktop search was used to identify relevant sources. We searched multidisciplinary databases, including Google Scholar and Scopus/Web of Science (via indexed results and publisher hubs), as well as reputable policy libraries from the OECD and UNESCO. The search terms were a combination of AI-related terms, including artificial intelligence, generative AI, ChatGPT, digital divide, inequality, inclusion, algorithmic bias, AI literacy, and governance, and equity-related terms. The search query was narrowed to January 2021 to January 2026 to capture post-pandemic acceleration in digital technologies and the proliferation of generative AI in education (Borgonovi et al., 2025; Miao & Holmes, 2023).

The inclusion criteria were: (a) peer-reviewed journal articles or research syntheses or authoritative policy papers discussing AI in educational institutions and its effects on equity, access, inclusion, or governance; (b) inclusion of an explicit conceptualisation or operationalisation of AI related inequality, including AI divides, algorithmic bias, techno abilityism, or language barriers; and (c) availability in a publisher, institutional repository, or open library. The exclusion criteria included: (a) technical modelâdevelopment articles without an educational or equity connotation; (b) opinion articles without substantiation; and (c) retracted articles or those having severe integrity issues. Retraction status was verified through publisher notices and bibliographic flags where possible. Table 1 summarises the protocol. The study selection process is summarised in Figure 1, which presents the identification, screening, eligibility, and inclusion stages of the source-selection procedure used in this conceptual analysis.

Search Yield and Selection Transparency

To make the evidence base traceable, the manuscript should report the number of records identified, screened, excluded, and included. Since the current study is not a systematic review but a conceptual analysis, we employed those counts only to document the search process, not to estimate the effects. The search also yielded 536 records (n = 536), of which 86 duplicates were discarded (n = 86); thus, 450 titles and abstracts were sifted (n = 450). These were reduced to 382 records removed during the title and abstract phase (n = 382). Sixty-eight full texts were evaluated (n = 68), and 47 full texts were filtered out (n=47). The analysis group gave 21 sources (n = 21).

Table 2: Protocol of source identification and synthesis followed in this conceptual analysis

Stage	Decision rule	How applied in this study	Output for analysis
Scoping	Prioritise recent (2021–2026) sources and authoritative policy syntheses	Seed set assembled from OECD/UNESCO guidance and recent systematic/narrative reviews on AI in education and equity	Initial working definition; preliminary attributes and debates
Search	Use multi-database desktop search with combined AI + equity terms	Keyword combinations used in Google Scholar and indexed platforms; OECD/UNESCO repositories searched by title and tags	Corpus of potentially relevant records
Screening	Retain sources linking AI in education to equity, inclusion, governance, or literacy	Title/abstract screening followed by full-text eligibility check; technical-only papers excluded	Final analytic set for extraction
Quality/integrity check	Exclude retracted or integrity-flagged publications	Publisher notices and bibliographic flags checked when available; ambiguous cases excluded or treated as contested evidence	Credible evidence base
Extraction	Extract conceptual statements and empirical claims relevant to inequality mechanisms	Key claims coded (access, bias, governance, capability conversion factors) with source attribution	Evidence-to-construct mapping
Synthesis	Iteratively refine definition and model; resolve contradictions via triangulation	Constant comparison across sources; alignment with governance and competency frameworks	Final concept definition, attributes, antecedents, consequences, propositions

Data Analysis
Thematic and relational coding were used to extract the structure of the AI innovation divide. We first extracted statements into initial coding categories: infrastructure access; data/compute dependence; AI literacy; institutional governance; pedagogical and creative agency; and educational outcomes. We then examined co-occurrence patterns and the causal pathways proposed in the sources, linking infrastructure, capability conversion conditions, and outcomes. Finally, overlapping categories were consolidated into defining attributes when they consistently differentiated AI-linked inequity from general digital inequity. To strengthen discriminant validity, we refined the concept by comparing it against an illustrative model and contrary cases described in the literature (Matjie et al., 2026; Varsik & Vosberg, 2024).

Ethics and Transparency
This research consisted of reviewing publicly available sources and did not involve taking human subjects. Support of transparency was provided by a clear description of source identification, inclusion/exclusion criteria, and the rationale of the synthesis. Because conceptual analysis involves interpretive judgment, the article strengthened credibility by triangulating across peer-reviewed scholarship and authoritative policy sources, and by prioritising convergent findings where multiple independent sources supported the exact mechanism (Miao et al., 2021; Papagiannidis et al., 2025; Varsik & Vosberg, 2024).

Results

Constructed Meaning of the AI Innovation Gap in Education
Across the reviewed literature, disparities in AI adoption boiled down to one recurring finding: the spread of AI tools does not align with the spread of the ability to create educational value with those tools. Although the access and infrastructure are often the foregrounds of policy papers (Borgonovi et al., 2025; Varsik & Vosberg, 2024), scholars in contemporary research noted that the outcomes are determined by literacy, institutional governance, and the capacity to customise tools based on linguistic, cultural, and curricular contexts (Laupichler et al., 2022; Mac Fadden et al., 2024; Matjie et al., 2026). By combining these strands, the AI innovation gap in education can be defined as follows:

the AI innovation gap in education is a multidimensional inequity in the ability of learners, educators, and institutions to (a) access AI-enabled educational resources and infrastructure, (b) establish and assess AI systems responsibly, and (c) imaginatively use AI to the pedagogical and knowledge production ends, which leads to unequal learning opportunity, innovation potential, and educational achievement.

Defining Attributes
Five defining attributes consistently distinguished the AI innovation divide from narrower "digital access" divides. Across the literature, AI-enabled education depends on unevenly distributed compute, data, and platform requirements (Borgonovi et al., 2025; Matjie et al., 2026). Meaningful use also depends on AI literacy and the long-term professional development of educators and leaders (Laupichler et al., 2022; Miao & Cukurova, 2024). Furthermore, policies and oversight procedures, along with accountability systems, influence the exposure to risk and the formation of benefits (Oncioiu & Bularca, 2025; Papagiannidis et al., 2025; Wu et al., 2024). Linguistic and cultural responsiveness is important because models do not necessarily reflect local languages, curricula, and cultural knowledge, which limits the individuals whom AI-mediated learning can help (Matjie et al., 2026; Miao et al., 2021). Moreover, the agency of pedagogy and creativity determines whether AI is deployed to support deeper learning or surface-level performance, and this involves consequences for

integrity and innovation (Kooli, 2023; Miao and Holmes, 2023). These attributes and indicative empirical referents are summarised in Table 2.

Table 3: Characterising traits of the AI innovation divide in education and representative empirical referents

Attribute	How it manifests in education	Indicative empirical referents	Innovation-equity implication
Compute/data/platform dependence	AI tools require reliable connectivity, cloud services, and data governance; costs and procurement favor well-resourced institutions	Access to devices/connectivity; availability of cloud/computer; procurement and licensing capacity	Creates 'innovation enclaves' where only some institutions can experiment and scale
AI literacy and professional capability	Educators need foundational AI understanding, prompt/interaction skills, and critical evaluation of outputs	Teacher AI competency frameworks adoption; training coverage; assessment of AI literacy	Determines whether AI augments learning design or produces superficial automation
Responsible governance capacity	Policies for privacy, integrity, bias, vendor accountability, and human oversight; monitoring and incident response	Presence of AI governance policy; audit practices; data protection compliance; integrity guidelines	Controls harm distribution and enables trustworthy innovation pathways
Linguistic and cultural responsiveness	AI models may under-serve local languages/curricula; cultural bias and exclusion in datasets and outputs	Support for local languages; documented bias incidents; localisation of content and curricula	Affects whose knowledge is amplified and whose is marginalised in AI-mediated learning
Pedagogical and creative agency	Human-centred design enables co-creation, inquiry, and higher-order thinking; misuse enables plagiarism or deskilling	Pedagogical integration strategies; assessment redesign; evidence of creative learning tasks using AI	Shapes whether AI expands capabilities (create) or narrows them to compliance and copying

Enabling Conditions and Antecedents

In the literature, there are three sets of antecedent factors that lead to the creation or deterrence of the AI innovation divide. Prerequisites for AI-powered learning include infrastructure conditions, such as connectivity, devices, and digital preparedness at the school level (Miao et al., 2021; Varsik & Vosberg, 2024). Procurement capacity, the vendor ecosystem, and access to information and computing resources are also essential components of an innovation system that determines whether institutions can pilot and maintain AI tools (Borgonovi et al., 2025; Papagiannidis et al., 2025). Some of the capability conditions include professional learning systems, some form of curriculum flexibility, and leaders' willingness to incorporate AI in an ethical and pedagogical way (Laupichler et al., 2022; Wu et al., 2024).

Some sources claim that the post-pandemic fast-tracking of online learning generated expectations for digital delivery without implementing the institutional routines required to deploy AI responsibly (Miao et al., 2021; Varsik & Vosberg, 2024). As AI becomes widespread, a shadow adoption issue is likely to arise: students and employees will adopt new tools without education, supervision, or explicit rules and policies, and the consequences will fall on less-protected populations (Miao & Holmes, 2023; Oncioiu & Bularca, 2025).

Learning, Innovation, and Inequality Consequences

The effects identified in evidence-based studies include learning outcomes, institutional legitimacy, and innovation capacity. The AI innovation divide at the learner level can cause unequal access to tutoring, feedback, and language assistance, benefiting some and leaving others further behind (Mimoudi, 2025; Varsik & Vosberg, 2024). At the educator level, differences in access to training and conducive governance may also widen disparities in professional capability, which are concentrated in advantaged schools and universities (Laupichler et al., 2022; Miao & Cukurova, 2024). At the system level, inequitable adoption can reinforce stratification between 'AI-ready' institutions and those constrained by infrastructure and governance deficits, shaping long-run disparities in human capital formation and scientific/creative participation (Borgonovi et al., 2025; Mac Fadden et al., 2024; Matjie et al., 2026).

Negative externalities are also evident when governance capacity is low: harm to privacy, integrity crises, biased evaluation, and erosion of trust in credentialing systems (Baker & Hawn, 2022; Kooli, 2023; Varsik & Vosberg, 2024). Notably, such harms are not concentrated at the extremes, with learners in low-resource environments and marginalised language and disability populations being the most vulnerable to AI technologies when they are not localised, accessible, or ethically regulated (Matjie et al., 2026; Varsik & Vosberg, 2024).

Implications of Empirical Fits and Measurements

The concept also suggests measurable dimensions that go beyond conventional digital divide indicators. Access measures such as devices and connectivity remain necessary, but measurement should also capture AI literacy and professional-learning coverage, institutional governance maturity, localisation and cultural-linguistic responsiveness, and equity in innovation participation. In practical terms, participation can be assessed by who pilots and evaluates AI tools, whose data are processed, and whose learning needs drive design priorities (Miao & Cukurova, 2024; Papagiannidis et al., 2025).

In this regard, assessment frameworks should monitor both adoption and conversion: whether AI availability is translating into meaningful learning benefits and expanded creative potential under secure and responsible conditions. Competency frameworks that differentiate progression levels, such as "acquire–deepen–create", offer a practical scaffold for operationalising capability expansion and for avoiding purely compliance-oriented training (Miao & Cukurova, 2024).

Suggestions and Examples

In mapping the conceptual model into claims to be clustered into testable claims, the study formulated four propositions that synthesise convergent mechanisms in the evidence base.

i. Proposition 1. Equity threats (privacy harms, biased assessment, integrity crises) will also be concentrated in resource-poor institutions and disadvantaged groups of learners where the spread of AI tools is high, and the capacity to regulate it is low (Baker & Hawn, 2022; Varsik & Vosberg, 2024; Wu et al., 2024).

ii. Proposition 2. The relationship between AI access and learning outcomes will be moderated by AI literacy and teacher professional learning: the systems in which the competency development is prioritised will generate more meaningful and creative learning benefits than the ones in which focus is placed more on tool acquisition (Celik et al., 2022; Laupichler et al., 2022; Miao & Cukurova, 2024).

iii. Proposition 3. AI adoption may reproduce inequality even where connectivity is adequate if local languages and curricula are poorly supported; under such conditions, AI use can increase exclusion rather than inclusion (Matjie et al., 2026; Miao et al., 2021).

iv. Proposition 4. Equal participation in innovation (who drives, who judges, and who customises AI tools) will be positively correlated with equal innovation outcomes; investing in experiments at high-end institutions will increase the AI innovation gap in the long term (Borgonovi et al., 2025; Mac Fadden et al., 2024).

Model case (illustrative). An example is a ministry, district, or university where AI-assisted tutoring and evaluation are piloted, and equity is designed in. In addition to access to devices, the programme invests in connectivity that is robust to low bandwidth and intermittent power, including offline-first resources, local caching, and shared community access points. The progression of teacher professional learning operates on an acquire-deepen-create model, and the routines of governance are internalized to procurement and deployment, such as language coverage visibility, data security measures, and prejudice-testing fact. Independent evaluation monitors learning gains and distributional effects, and incident reporting provides feedback for system redesign. In this model, AI is employed as a component of an innovation infrastructure that broadens capacity without replicating stratification (Miao & Cukurova, 2024; Papagiannidis et al., 2025; Varsik & Vosberg, 2024).

Contrary case (illustrative). Without institutional directives, learners and staff would use generative AI informally. Procurement decisions are made to prioritise cost or convenience over equity protection, and AI outputs are estimated or graded without bias testing, disclosure, or accountability. Little attention is given to language competence and disability access, and the enforcement of integrity itself is not punitive. In this case, AI is a stratifying technology: favoured groups receive better performance optimisation, and disadvantaged groups are directly observed and misclassified, denied access to educational opportunities (Baker & Hawn, 2022; Kooli, 2023; Matjie et al., 2026).

Discussion

Framing the Digital Divide to Innovation Capability

The refined concept clarifies why ‘AI in education’ debates can talk past one another: some treat inequity as primarily infrastructural, while others foreground algorithmic bias, commercialisation, or literacy. OECD studies specifically claim that the implementation of equity-sensitive AI should be accompanied by consideration of access, in addition to teacher training, ethical considerations, and institutional integrity (Borgonovi et al., 2025; Varsik & Vosberg, 2024). The findings are an aggregation of these strands, in which the foundational conditions (infrastructure and access to platforms/computing) are contrasted with conversion conditions (literacy, governance, and pedagogical agency) that shape availability into outcomes. This difference aligns with recent reviews highlighting that the second- and third-level divides, skills, meaningful use, and outcomes are under-theorised in AI-in-education studies (Mac Fadden et al., 2024; Matjie et al., 2026).

Theoretically, the AI innovation divide makes equity a matter of innovation capacity: who can be included in the design, experimentation, and testing of AI-enabled pedagogy, and who becomes a passive consumer of opaque systems. This matters because AI is increasingly embedded in educational ‘infrastructures of decision’, adaptive learning pathways, assessment models, and risk flags that shape learner trajectories (Baker & Hawn, 2022; Wu et al., 2024). Educational innovation as a stratifying force but no longer a public good occurs when only a fraction of institutions are capable of constructing the socio-technical routines to oversee such systems.

Equity Mechanism of Responsible AI

One of the model's fundamental contributions is to present governance capacity as a characteristic feature rather than an adjunctive issue. The broader information systems literature contextualises responsible AI governance as a range of structural, relational, and procedural practices that define how organisations balance innovation and accountability (Papagiannidis et al., 2025). In the context of education, it means that equity cannot be attained by distributing tools only, but it also hinges on the ability of schools and universities to introduce procurement safeguards, data protection routines, audit and monitoring procedures, and their ability to establish human oversight clearly (Oncioiu & Bularca, 2025; Wu et al., 2024).

AI ethics in organisational studies has focused on translating principles into practice; thus, it is necessary to have routinised governance based on clear roles, processes, and escalation pathways, rather than a one-off statement. The evidence on organisational reactions to AI ethics indicates a combination of avoidance, compliance, and active redesign, and the outcomes for equity will be determined by the level of integration of ethics into organisational operations (Papagiannidis et al., 2025; Stahl et al., 2022). This underlines the model's assertion that governance is a condition of conversion: it determines how benefits are distributed and how risks are shared within AI-powered educational systems.

The UNESCO recommendations on AI and education state that policy and regulation tend to lag behind the diffusion of technology, and learner data and learning environments may be left underprotected when governance capacity is limited (Miao et al., 2021; Miao & Holmes, 2023). This delay has been the centrepiece of the AI innovation divide: poor governance is a conversion barrier to the equitable creation of value and the concentration of harm. In practice, governance by design entails introducing equity checks into adoption decisions and day-to-day business. Such testing comprises bias and accessibility testing, privacy impact assessment, integrity protection, and stakeholder participation, rather than treating ethics as a compliance task at the end of the process (Baker & Hawn, 2022; Varsik & Vosberg, 2024).

Creativity, Agency, and the 'Create' Level of AI Capability

Since the journal focuses on innovation in how it incorporates creativity, pedagogical and creative agency emerge as equity factors in the model. The UNESCO AI competency framework for teachers specifically distinguishes between acquiring minimal knowledge, followed by increased pedagogical integration, and the development of new practices and AI-based learning designs (Miao & Cukurova, 2024). This resonates with the capability-oriented interpretation of equity: inclusion requires not only access to AI, but also the freedom and skill to use AI to expand one's educational and creative opportunities, rather than narrowing them to template-based production or surveillance-driven personalisation (Madaio et al., 2021; Miao & Holmes, 2023).

From this perspective, generative AI can either democratise creativity by scaffolding writing, translation, and ideation, or commodify it by homogenising outputs and rewarding those who can optimise performance artefacts (Kooli, 2023; Miao & Holmes, 2023). The AI innovation divide is therefore not only distributive (who receives tools) but also epistemic: it shapes whose ways of knowing and expressing are recognised and supported in AI-mediated learning systems. Linguistic and cultural responsiveness is critical to avoiding further hierarchies of knowledge and language (Matjie et al., 2026; Miao et al., 2021).

Policy, Institution, and Innovation Ecosystems Implications

Reviews of generative AI in education also provide implementation advice that can support an innovation-ecosystem approach. Bibliometric and content analyses underline that such transformative impact requires interdisciplinary collaboration, model behaviour transparency, and clear plans to reduce bias and misuse, which are consistent with invested capabilities and governance-by-design but not the utilisation of tools of opportunity (Bahroun et al., 2023; Wang et al., 2024). In the case of innovation systems, this equitable scaling would presuppose mutual assessment infrastructures and open pedagogical facilities, rather than market diffusion.

Implications

Artificial intelligence policies that yield equity should feature a capability-investment rationale: the modernisation of infrastructure should be accompanied by continuous professional education and the preparation of leaders so that the institution can go beyond the race to the surface (Miao & Cukurova, 2024; Varsik & Vosberg, 2024). AI governance should be considered an extension of the innovation infrastructure, and vendor subcontracting, data custodianship, data quality, reporting (incidents), and data security must be held accountable (Papagiannidis et al., 2025; Wu et al., 2024). Equity should also be localised and inclusive: not only are the tools to be evaluated regarding language coverage, cultural bias, accessibility to people with disabilities, and whether they match the curriculum, but procurement should be based on evidence that it is responsive and not on marketing statements (Kooli, 2023; Matjie et al., 2026). Finally, piloting and evaluation should not be concentrated in elite institutions; under-resourced schools and universities should be supported to participate in experimentation so that innovation capacity is shared rather than enclosed (Borgonovi et al., 2025; Mac Fadden et al., 2024).

Third, equity needs to be localised and inclusive: AI tools should be assessed based on their language coverage, cultural bias, accessibility of disabled people, and curriculum validation, and their procurement criteria should emphasise responsiveness demonstration over blanket marketing promises (Kooli, 2023; Matjie et al., 2026). Fourth, the pilot and evaluation of AI tools should be decentralised by including under-resourced schools and universities in innovation ecosystems, supporting their experimentation, thereby reducing the concentration of innovation among a small number of institutions (Borgonovi et al., 2025; Mac Fadden et al., 2024).

Limitations

The analysis of the current literature, as a conceptual investigation, is organised around a review of contemporary peer-reviewed literature and authoritative policy documents rather than an empirical study. In this regard, its value is mainly theoretical; it polishes the idea of the AI innovation divide and offers a two-layer explanatory framework, yet it does not empirically test that framework using primary data from schools, teachers, students, or education systems. This argument should be understood as an interpretive synthesis that organises existing evidence into a consistent analytical framework, rather than as a claim to causal verification.

The second limitation concerns the nature of the evidence base itself. Generative AI in education research and policy undergoes continuous transformation, and, as is the nature of technological change, definitions, risks, practice governance, and reported use may swiftly vary. In instances where the review favoured valid and recent sources, some conclusions may require periodic revision as new empirical studies emerge. In addition, the literature is overrepresented in contexts with more resources, as seen in well-resourced systems, while a relatively limited number of African and other Global South contexts are represented. This is a threat because the proposed model would replicate patterns that might be larger in high-income schools than in under-resourced or language-diverse education systems. Finally, the analysis is a synthesis of the published content; thus, it is unable to fully encapsulate informal institutional practices, local procurement practices, and informed pedagogical modifications that are more likely to determine the degree to which AI becomes an inclusion tool or a stratifying process. These limits indicate that future empirical studies are required to operationalise the AI innovation divide, delineate its dimensions, and investigate its functioning across different academic environments.

Future Research

The future research direction is to transform the AI innovation divide into a measurable construct and to track how it relates to learning outcomes and innovation engagement across diverse contexts. Mixed-method designs can isolate conversion conditions by using different levels of governance maturity or teacher AI competency distributions across institutions with similar connectivity levels, a strategy that is empirically viable. In methodological terms, methodology must incorporate the governance indicators (policy maturity, audit routine, vendor accountability) as well as literacy and infrastructure measures (Oncioiu & Bularca, 2025; Papagiannidis et al., 2025).

Future research also requires context-sensitive analysis in African and other Global South systems, where linguistic diversity, data scarcity, and procurement constraints may produce unique exclusion patterns. Research that analyses the relationships among local language resources, open models, regional governance collaboration, and educational equity would further contribute to current findings, which are largely based in high-income environments (Matjie et al., 2026; Miao et al., 2021).

Conclusion

This theoretical discussion repackaged the issue of equity in AI-enhanced education as a problem of narrow access to a problem of innovation capability. The gap in AI innovation was established as a disparity in the ability to access, manage, and creatively utilise AI to generate educational value, resulting in stratified education, institutional legitimacy risks, and unequal engagement in knowledge-making. Based on a synthesis of current research and authoritative guidelines, the study determined five defining features: compute/data/platform dependence, AI literacy, governance capacity, cultural-linguistic responsiveness, and pedagogical/creative agency, and formulated quantifiable referents of each.

The implications for science, innovation, and creativity are straightforward: only when institutions invest in developing capabilities (not merely in acquiring tools) and incorporate responsible governance as fundamental infrastructure can AI be used to enhance educational creativity and innovation. For policy suppliers and institutional managers, it denotes integrating infrastructure and building teacher competency in tandem, assuming governance-by-design routines and demanding localisation and accessibility as prerequisites for procurement.

Conceptual analysis is interpretive and has limitations given the rapidly changing, evolving evidence base of generative AI. While the synthesis prioritised accessible and credible sources and excluded retracted or integrity-flagged publications, the field’s rapid change implies that definitions and best practices will require periodic updating. Future studies are advised to create validated measures of the AI innovation divide, empirically test the model systematically in educational systems, and develop interventions that focus on eliminating the capability and governance gap and enabling the creative, human-focused applications of AI.

Acknowledgments

The authors acknowledge the scholarly and policy communities whose open-access publications and resources informed this conceptual analysis. This study received no external funding.

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