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Digital divide 2.0: AI literacy and the widening stratification in marginalized communities

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ABSTRACT

The paper presents digital divides as a cycle rather than as separate problems. The previous research documented first digital divide that is concerned on unequal access to devices, electricity, broadband, software, and technical support. The second layer focuses on the skills required to use AI productively, including prompt guidelines, source verification, data interpretation, privacy protection, and the ability to understand a system's limits. Artificial intelligence is transforming how knowledge is produced, assessed, and distributed in education, but access to AI benefits is uneven. This paper examines Digital Divide 2.0, the widening inequality that emerges when communities differ not only in connectivity and hardware but also in AI literacy, data sovereignty, language representation, critical evaluation, and institutional power. Using qualitative content analysis of the academic, policy, and institutional sources assembled in the working paper, the study organizes evidence across seven themes: infrastructural access; digital colonialism and data sovereignty; second-level skills and competency; critical and epistemic inequality; linguistic and cultural exclusion; policy and governance gaps; and intersectional marginalization. The synthesis shows that AI can reproduce educational stratification through several linked mechanisms. Under-resourced schools may lack reliable connectivity, devices, technical support, and trained teachers. Even when access exists, learners may remain excluded from higher-value uses of AI because they lack prompt design, verification, data literacy, or opportunities to participate in system design. This study also argues that AI literacy should be treated as a public educational capability rather than an individualistic skill. Equitable policy therefore requires infrastructure, localized and critical curricula, teacher development, community participation, indigenous data governance, and enforceable accountability mechanisms. Without these measures, AI literacy and education is likely to intensify existing inequalities rather than function as an educational equalizer.

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INTRODUCTION

Artificial intelligence (AI) has become an increasingly significant component of education, influencing not only how learners access and produce information but also how educational institutions organize, evaluate, and mediate learning experiences. AI technologies can generate text, images, mathematical symbols, and equations, recommend and predict answers and solutions, automate administrative decisions, and mediate access to information (Dieterle et al., 2024). The expanding scope of AI has consequently created substantial opportunities for personalized learning and educational innovation. However, the implications of AI in education extend beyond whether students and institutions simply have access to these technologies. More fundamental questions concern who possesses the resources, language support, critical knowledge, institutional authority, and political power necessary to use AI on equitable terms (Dieterle et al., 2024). Thus, the educational significance of AI must be understood not only in terms of technological availability but also through the social structures that determine who can use, understand, influence, and benefit from these systems.

This concern reflects the continuing problem of the digital divide, which involves inequalities associated with geographical location, social status, infrastructure, and access to digital resources. Such inequalities require both institutional policy and government action because unequal access can lead directly to unequal participation in digital learning (Dieterle et al., 2024). Unequal participation can subsequently produce unequal representation in the data generated through digital systems, creating a continuing cycle in which already disadvantaged populations become less visible or inaccurately represented within technology mediated environments. When users are also expected to interpret increasingly complex AI generated information without adequate preparation, existing inequalities may be further intensified through the uncritical acceptance of inaccurate, incomplete, or biased algorithmic outputs. Consequently, access alone does not ensure meaningful digital inclusion.

The concept of Digital Divide 2.0 provides a broader framework for understanding this changing form of inequality. Earlier approaches to the digital divide primarily emphasized physical access to computers, connectivity, and information and communication technologies. These concerns remain fundamental because infrastructure constitutes the foundational layer of digital inclusion. Unequal access to physical hardware, electricity, broadband connectivity, software licenses, appropriate devices, and technical support continues to shape who can participate effectively in technology mediated education (van Dijk, 2020; Warschauer, 2003). A school without reliable internet connectivity cannot consistently utilize AI services, while learners without appropriate devices cannot fully benefit from computational applications that require substantial processing capacity or high bandwidth connectivity (van Dijk, 2020). The first digital divide therefore remains relevant even as educational technologies become increasingly sophisticated.

Digital Divide 2.0 extends this analysis by recognizing that technological inequality persists even after physical access has been established. The second layer concerns the procedural and cognitive competencies required to use digital and AI technologies effectively (van Deursen & Helsper, 2015; van Dijk, 2020). In AI mediated educational environments, meaningful participation requires more than knowing how to operate a device or access an application. Learners must be able to construct appropriate prompts, verify sources, interpret data, protect privacy, evaluate generated information critically, and understand the capabilities and limitations of AI systems. They must also recognize errors and bias and communicate with systems that may not adequately support their languages or cultural contexts. From this perspective, AI literacy is not simply a technical skill. It represents an educational, cultural, and political responsibility because it influences learners' capacity to participate critically and safely in increasingly automated educational environments.

These inequalities become particularly important when differences in institutional resources shape how students encounter AI. Learners in well-funded and well-equipped educational institutions may receive systematic instruction and assistance in generative AI use, prompt design, data ethics, source evaluation, and critical assessment of algorithmic outputs. In contrast, students in under resourced settings may encounter AI primarily as an obscure technological system used to monitor, classify, or evaluate them rather than as a resource they are empowered to understand and control. This distinction reflects the difference between becoming a capable and informed AI user and becoming an object of AI influenced decision making. Because educational institutions distribute credentials, competencies, opportunities, and pathways to social and economic advancement, unequal AI literacy can reproduce broader patterns of educational stratification. Aoun (2017) argues that education in the age of artificial intelligence must develop human judgment alongside technical competence. The equity concern, however, is that access to education capable of developing these forms of judgment and competence is itself socially stratified.

Digital Divide 2.0 therefore encompasses a third layer concerned with tangible outcomes, agency, and the distribution of power. This dimension examines whether AI integration produces meaningful educational, economic, and civic benefits for learners or merely exposes marginalized populations to automated decision making and algorithmic governance designed elsewhere (van Deursen & Helsper, 2015; Sharma, 2026). From this perspective, meaningful digital inclusion concerns not only access and skills but also whether individuals and communities possess the agency to influence the systems that affect them. This includes questions of epistemic authority, cultural representation, data sovereignty, and the right to question or contest algorithmic decisions (Kukutai & Walter, 2021; Sharma, 2026). Consequently, the educational effects of AI cannot be assessed solely by counting devices, internet connections, or application users. They must also be evaluated according to who gains meaningful benefits, who bears technological risks, and who possesses authority over data and automated decisions.

The global structure of AI development intensifies these concerns. AI systems are predominantly developed by firms and institutions concentrated in wealthier regions and are frequently trained using datasets that overrepresent dominant languages and social groups. These systems may subsequently be introduced into communities characterized by substantially different cultural, legal, linguistic, and educational circumstances (United Nations Development Programme [UNDP], 2025). Such inequalities cannot be explained exclusively through individual differences in technological competence because they emerge from broader systems of infrastructure, markets, governance arrangements, curricula, and historical relations of power (Couldry & Mejias, 2019; Capraro et al., 2024). The unequal distribution of technological resources and decision-making authority therefore transforms AI inequality from an individual educational concern into an institutional and global issue requiring coordinated educational reforms and political priorities.

The concept of digital colonialism provides an additional perspective for examining these relationships. Data intensive platforms can collect behavioral, cultural, educational, and linguistic information from communities while concentrating ownership, technological control, and economic value within external companies. Couldry and Mejias (2019) conceptualize this process of data extraction as a form of appropriation capable of reproducing colonial relationships within digital environments. When applied to education, this perspective raises important questions regarding who owns student data, who determines how these data are collected and interpreted, who benefits from their use, and whether schools and local communities possess meaningful authority to refuse, modify, or shape the AI systems deployed within their educational environments. Digital inequality therefore concerns not only access to technology but also control over the resources, knowledge, and data generated through technological participation.

These concerns become especially significant when AI systems interact with linguistic and cultural diversity. Systems developed primarily from dominant language datasets may provide different levels of accuracy, representation, and functionality for users from less represented linguistic and cultural communities (UNDP, 2025). Learners who communicate through languages that receive limited technological support may consequently experience AI differently from students whose languages and cultural contexts are extensively represented within training data. Such differences can influence access to information, the accuracy and relevance of generated content, and learners' ability to participate fully in AI mediated education. Questions of AI equity must therefore include cultural representation and epistemic authority alongside infrastructure and technological skills, particularly when educational technologies developed in one social context are deployed in communities with different knowledge systems and cultural conditions.

A sociological perspective further clarifies why these inequalities cannot be treated as purely technological problems. Technology operates within institutions rather than independently of them, and schools translate social resources into educational outcomes through curricula, teaching practices, assessment systems, organizational routines, and access to opportunities. When AI becomes embedded within these processes, it introduces assumptions concerning language, intelligence, achievement, normal behavior, and risk. If such assumptions remain invisible or cannot be questioned by the individuals affected by them, automated systems may reproduce existing inequalities while presenting their decisions as technically objective. The apparent neutrality of AI can therefore obscure the social values, institutional priorities, and power relations embedded within its development and application.

Technological stratification is also intersectional because social class, race, gender, disability, geography, indigeneity, and language do not operate independently. Rather, these dimensions may interact to create different experiences of digital inclusion and exclusion. A rural indigenous learner, for example, may simultaneously experience unreliable connectivity, limited support for a local language, under resourced educational institutions, and data practices that do not recognize community governance. An urban low-income learner may possess a smartphone and therefore appear to have technological access while lacking a suitable study environment, institutional support, advanced AI instruction, or other resources necessary for meaningful participation. These examples demonstrate why physical access cannot serve as the sole indicator of digital inclusion. Individuals with access to the same technology may experience substantially different educational outcomes because the social and institutional conditions surrounding their use are unequal.

The convergence of these perspectives establishes Digital Divide 2.0 as a multidimensional framework consisting of interconnected inequalities in infrastructure, competence, outcomes, representation, and power. The first layer concerns whether learners and institutions possess the material resources required to access AI, including devices, electricity, connectivity, software, and technical support (van Dijk, 2020; Warschauer, 2003). The second concerns whether users possess the procedural, cognitive, and critical competencies required to engage with AI effectively and responsibly, including prompt construction, source verification, data interpretation, privacy protection, bias recognition, and understanding technological limitations (van Deursen & Helsper, 2015; van Dijk, 2020). The third concerns whether technological participation produces meaningful benefits and genuine agency or instead reinforces dependence on externally designed systems and automated forms of governance (van Deursen & Helsper, 2015; Sharma, 2026). Questions of cultural representation, epistemic authority, data sovereignty, and the ability to contest algorithmic outcomes further demonstrate that digital inclusion ultimately involves the distribution of power as much as the distribution of technology (Kukutai & Walter, 2021; Sharma, 2026).

Within education, these dimensions are mutually reinforcing. Inadequate infrastructure can restrict participation in AI mediated learning, which can limit opportunities to develop advanced AI competencies. Limited competence can then weaken learners' capacity to recognize misinformation, algorithmic bias, privacy risks, or inappropriate automated decisions. At the same time, unequal participation can contribute to unequal data representation, potentially reinforcing systems that inadequately reflect marginalized populations. When technological ownership, data control, and decision-making authority remain concentrated outside the communities affected by AI, inequalities in access and competence can consequently develop into inequalities in agency and educational outcomes. Digital Divide 2.0 therefore describes not a single technological gap but a continuing cycle through which social inequality can shape technological participation and technological systems can, in turn, reproduce existing social inequalities.

The literature consequently indicates that equitable AI integration in education requires a broader response than simply providing schools and students with access to digital tools. Infrastructure remains essential, but meaningful inclusion also requires AI literacy, critical judgment, privacy awareness, cultural and linguistic representation, institutional support, data governance, and opportunities for learners and communities to participate in decisions regarding the technologies that affect them. As Aoun (2017) emphasizes, education in the age of artificial intelligence must develop human judgment alongside technical competence. When such educational opportunities are distributed unequally, however, AI may deepen rather than reduce existing inequalities. Addressing Digital Divide 2.0 therefore requires synergy among educational reforms, institutional policies, technological governance, and broader political priorities.

Taken together, the reviewed perspectives demonstrate that the contemporary digital divide must be understood as a complex sociological and educational issue shaped by access, skills, outcomes, institutional structures, cultural representation, data relationships, and power. The transition from the traditional digital divide to Digital Divide 2.0 reflects the changing nature of technological inequality in an era when AI increasingly mediates learning, information, assessment, and educational decision making. While AI offers significant possibilities for personalized learning and expanded access to knowledge, these possibilities are not distributed equally. Learners differ not only in whether they can access AI but also in whether they possess the knowledge to evaluate it, the linguistic and cultural representation necessary to benefit from it, the institutional resources required to use it productively, and the authority to question how it influences their educational opportunities. Examining these interconnected dimensions is therefore essential to understanding whether AI integration contributes to educational inclusion or reinforces existing patterns of social and technological stratification. This framework provides a basis for examining Digital Divide 2.0 as an issue of educational equity and for identifying the conditions necessary to ensure that the benefits, opportunities, and decision-making power associated with artificial intelligence are distributed more fairly across learners and educational communities.

METHODOLOGY

This study employed a qualitative research design using content analysis. It analyzed the academic, policy, institutional, and conceptual sources assembled in the working paper rather than collecting new survey, interview, or experimental data. The unit of analysis was the documented text describing how AI literacy, infrastructure, governance, language, or algorithmic systems affect educational opportunity in particular social and geographic contexts. The purpose of the method was to identify recurring meanings, concepts, mechanisms, and patterns across the selected documents.

The content analysis followed three stages. First, the documents were read closely and organized by region: Africa, Asia, Europe, North America, South America, and Oceania. Second, meaningful statements and recurring concepts were highlighted, compared, and assigned provisional codes. Third, related codes were grouped into seven themes: infrastructural access; digital colonialism and data sovereignty; skills and competency; critical and epistemic inequality; linguistic and cultural exclusion; policy and governance gaps; and intersectional marginalization. The coded themes were then interpreted comparatively to identify common mechanisms and context-specific expressions of educational stratification.

The study is a qualitative content analysis and not a systematic review or a primary empirical study. The sources were assembled for the working paper and were not selected through a fully reproducible database search, formal quality appraisal, or meta-analysis. Some materials are peer-reviewed research, while others are books, reports, policy documents, or institutional frameworks. To strengthen trustworthiness, the analysis used repeated reading, explicit thematic coding, comparison across regions, and attention to convergence and difference among sources. The findings should therefore be read as an interpretive account of documented patterns, not as prevalence estimates or causal effect sizes. Future research should use a transparent search protocol, an auditable coding matrix, and additional primary data from schools and communities that are often absent from technology research.

This research paper asks to seek answers from these three questions: (1) How do different forms of the AI divide shape educational opportunities in marginalized communities? (2) Through what mechanisms do AI literacy gaps reproduce socioeconomic, cultural, and epistemic stratification? and (3) What educational and governance responses could make AI development more equitable? The paper argues that AI literacy should be treated as a public good and a collective capability. Expanding access to devices without expanding critical agency, local representation, and institutional accountability will leave the deepest layers of the divide intact.

Research design

This study employed a qualitative research design using content analysis. Qualitative content analysis is a systematic research method used to analyze text data and interpret its contextual meaning through the identification of themes, patterns, and categories (Elo & Kyngäs, 2008; Hsieh & Shannon, 2005). Rather than merely quantifying word frequencies, qualitative content analysis focuses on subjective interpretations of text data by systematically classifying content into explicit coding schemes (Krippendorff, 2019).

When applied to document analysis, this method systematically evaluates print or electronic materials—such as policy reports, academic literature, and institutional briefs—to elicit meaning, gain understanding, and develop empirical knowledge (Bowen, 2009). The process involves Document Selection and Verification ((Bowen, 2009); Textual Immersion and Coding (Elo & Kyngäs, 2008; Hsieh & Shannon, 2005); and Pattern Identification and Synthesis (Bowen, 2009; Krippendorff, 2019).

Data analyses procedure

The unit of analysis was the documented text describing how AI literacy, infrastructure, governance, language, or algorithmic systems affect educational opportunity in particular social and geographic contexts. The purpose of the method was to identify recurring meanings, concepts, mechanisms, and patterns across the selected documents.

RESULTS AND DISCUSSION

This analysis draws upon a synthesis of source material examining the AI-related digital divide within educational contexts, structured around seven interconnected dimensions: infrastructural access, data sovereignty, skills and competency, epistemic equity, language and culture, governance, and intersectionality. The discussion that follows is grounded in the comparative synthesis of these dimensions and is interpreted in relation to the broader objective of understanding how artificial intelligence adoption in education reproduces and compounds existing inequities. Across the source material, the seven themes operate as a connected system in which limited infrastructure restricts access, limited access reduces opportunities to develop advanced skills, limited skills make it harder to challenge biased outputs, linguistic exclusion reduces the usefulness of systems, weak governance limits accountability, and intersectional disadvantage concentrates these burdens in particular communities. The result is not a single digital divide but a layered structure of educational stratification, in which each dimension interacts with an identifiable educational mechanism, produces a corresponding equity consequence, and points toward a priority response, ranging from public investment in connectivity, devices, maintenance, and open access for infrastructure, to local governance, consent, data protection, and community ownership for data sovereignty, to critical AI curricula and sustained teacher professional development for skills, to participatory design, local datasets, and mechanisms to contest outputs for epistemic equity, to multilingual development, localization, and culturally responsive pedagogy for language and culture, to audits, transparency, human review, and enforceable remedies for governance, and to equity impact assessments and targeted, community led support for intersectionality.

Infrastructure represents the most visible layer of the AI divide, yet it remains foundational to all subsequent dimensions of exclusion. AI enabled education depends on reliable electricity, affordable broadband, suitable devices, data storage, software access, and technical support, resources that are distributed unevenly both between and within countries. Under-resourced regional and rural schools often face the combined problem of weak connectivity, limited maintenance, and insufficient funding, and this access divide may manifest less as total exclusion and more as differences in device quality, home access, privacy, and the ability to use advanced services in well-resourced settings. The educational mechanism underlying this disparity is cumulative in nature, as students who cannot regularly access AI tools have fewer opportunities to learn how to question, adapt, and create with them, and they may therefore enter higher education or the labor market with less confidence and fewer opportunities to develop advanced digital practices. This problem becomes especially serious when institutions assume that all students can complete AI-mediated assignments outside school. Wang (2024) emphasizes that technology can reduce inequality only when the educational conditions for meaningful use are present, and consequently, infrastructure policy should move beyond one time device distribution to include maintenance, teacher support, accessible software, safe spaces for learning, and affordable connectivity, since without these elements, the formal availability of an AI platform may conceal continued exclusion.

Closely related to infrastructural access is the issue of digital colonialism and data sovereignty. AI systems depend on data, and platforms collect information about students, teachers, language use, behavior, and learning performance; when these data are stored, processed, and monetized by external companies, communities may lose control over how educational identities are represented. Couldry and Mejias (2019) argue that data colonialism transforms everyday life into a source of extraction, and in education, this process can turn learners into data subjects without giving them meaningful influence over the systems that classify them. The issue carries economic dimensions as well, since technology companies can capture value from data generated in marginalized regions while selling services back to schools and governments, and imported systems may encode assumptions about curriculum, intelligence, acceptable behavior, or risk that do not fit local contexts. De Freitas (2025) frames digital sovereignty as the capacity of societies to govern their data and technological infrastructure rather than relying entirely on external providers, and educational equity within this dimension requires data governance that includes consent, transparency, security, and community participation. For indigenous communities in particular, governance should recognize collective rights over cultural knowledge and language data rather than addressing only individual privacy, and students should learn not only how to use AI but also how data are collected, who benefits, and how communities can contest harmful uses.

The skills and competency divide constitutes a second-level disparity that emerges even where nominal access exists. Advanced users can formulate comprehensive prompts, compare outputs, verify sources, automate tasks, and integrate AI into research and creative work, while other users may rely on default outputs without recognizing hallucinations, hidden assumptions, or privacy risks. Sarkar and Nouskit (2026) describe this as an educational equity problem because institutions with more resources can provide sustained instruction while under-resourced schools may offer only basic exposure. This divide extends to teachers as well, who require time, professional development, curriculum resources, and institutional guidance, and without these supports, they may be asked to implement AI systems without understanding how they work or how to evaluate them. Dodick (2025) argues for contextualized AI in education rather than simply transferring models designed in one region into another, emphasizing that local teacher expertise is essential for judging whether an AI tool supports or undermines learning. Accordingly, AI literacy should include operational, critical, ethical, and civic competencies, with operational competence concerning the use of tools, critical competence concerning the evaluation of accuracy and bias, ethical competence concerning privacy, consent, and harm, and civic competence concerning participation in decisions about automated systems; limiting AI literacy to prompt engineering alone would leave the power structure of the technology unexamined.

A fourth dimension concerns the critical and epistemic divide, wherein AI systems influence what counts as relevant information, credible language, and acceptable knowledge. When training data and evaluation standards privilege dominant groups, marginalized learners may encounter systems that misrepresent their histories or fail to recognize their ways of knowing, constituting an epistemic problem concerning whose knowledge is made visible and authoritative. Students who do not see their communities, histories, or languages represented may experience school knowledge as externally imposed, whereas students with strong critical AI literacy can use the same tools to question sources, compare perspectives, and produce counter-narratives, indicating that the difference lies not in the technology alone but in the educational capacity to interrogate it. Capraro et al. (2024) caution that generative AI can widen socioeconomic inequalities when benefits accrue disproportionately to groups with greater resources and expertise, and an equity-oriented approach must therefore treat AI outputs as contestable claims rather than authoritative answers, with schools teaching students to ask what data a system uses, what assumptions it makes, whose interests it serves, and who is absent from its representation.

Language operates as a central mechanism of AI inclusion and exclusion. Widely spoken languages such as English, Mandarin, and Spanish are processed well by artificial intelligence models due to the vast availability of web-scraped corpora (Bender et al., 2021), whereas low-resource, regional, or indigenous languages remain poorly understood and severely underserved by current state-of-the-art models (Bender et al., 2021; Moshagen et al., 2024). Systems generally perform more reliably in languages with large digital datasets, standardized spelling, and commercial demand, while minority, indigenous, regional, and non-standard varieties may receive weaker translation, transcription, search, and generative performance, creating a linguistic hierarchy in which access to high-quality AI assistance depends on proximity to dominant languages. The consequences of this hierarchy extend beyond mere convenience, since when learners must translate their experiences into a dominant language to obtain useful assistance, cultural meaning can be lost, and teachers may also receive inaccurate outputs about local history, community practices, or indigenous concepts, resulting in a form of cultural exclusion in which technology appears universal while reproducing a narrow knowledge base. Linguistic equity therefore requires investment in local-language datasets, community review, multilingual teacher resources, and models that are evaluated for cultural as well as technical accuracy, along with recognition that communities should have authority over whether their linguistic and cultural materials are used for training, positioning language support as both a pedagogical issue and a data sovereignty issue.

The sixth dimension addresses policy and governance gaps, reflecting the observation that AI adoption is moving faster than the capacity of many educational institutions to govern it. Policies may encourage innovation without specifying how student data are protected, how automated decisions are audited, or how families can challenge errors. The European Commission (2022) emphasizes trustworthy AI principles such as human oversight, transparency, technical robustness, and accountability, though the challenge remains translating these principles into everyday school procedures. Governance gaps become especially dangerous in high-stakes settings where automated tools may be used for admissions, student monitoring, risk prediction, assessment, or resource allocation, since if an error cannot be explained or appealed, the affected learner may have no effective remedy. Voluntary guidelines are insufficient when schools lack technical expertise and procurement power, and the United Nations Development Programme (2025) similarly warns that rapid AI adoption can widen divergence when social protections and institutional capacity do not develop alongside technology. Educational governance should therefore require impact assessments before deployment, clear limits on sensitive data collection, independent or publicly accountable audits, human review of consequential decisions, and accessible complaint mechanisms, with students and communities included in these processes rather than treated only as end users.

The seventh and final dimension, intersectional marginalization, captures how the benefits and risks of AI are distributed through existing social structures. A learner's experience is shaped by the interaction of class, race, gender, disability, geography, language, age, and indigenous identity, and these factors can combine to create conditions in which the same AI system is convenient for one group and exclusionary for another. For example, a low-income rural student may face limited broadband, an older device, a school without AI-trained teachers, and a home environment that makes online study difficult; a multilingual student may have access to a platform but receive weaker language support; and an indigenous community may face both infrastructural disadvantage and the extraction of cultural data without collective consent. These are not separate problems but reinforcing ones. Intersectional analysis changes the policy question from whether an average user can access AI to which groups are systematically disadvantaged by a particular deployment, and equity assessments should therefore disaggregate outcomes and include the testimony of affected communities. Loble and Stephens (2024) argue that digital equity requires attention to structural conditions rather than assuming that access alone will produce fair outcomes.

Taken together, the seven dimensions examined in this synthesis, namely infrastructural access, data sovereignty, skills and competency, epistemic equity, language and culture, governance, and intersectionality, demonstrate that the AI-related digital divide in education is not a singular or static phenomenon but a layered and cumulative structure of educational stratification. Each dimension produces distinct educational mechanisms and equity consequences, yet they consistently interact to concentrate disadvantage among already marginalized communities, whether through unequal infrastructure, external control over data, unequal skill development, epistemic exclusion, linguistic hierarchy, weak institutional accountability, or the compounding effects of intersecting social identities. These findings underscore that meaningful educational equity in the age of artificial intelligence requires coordinated responses across all seven dimensions rather than isolated interventions, spanning public investment, community governance, critical literacy development, participatory design, multilingual and culturally responsive practice, enforceable regulatory oversight, and targeted, intersectionally informed support. This layered understanding of the digital divide provides the conceptual foundation for the recommendations and policy considerations to be addressed in the subsequent section.

CONCLUSION

Digital Divide 2.0 is a layered structure of inequality in which unequal infrastructure, skills, data control, language representation, epistemic authority, and governance interact. The educational significance of AI cannot be reduced to the question of whether a student has internet access or can open a chatbot. The more important questions rely on whether the student can use AI critically, whether the system represents the student's language and community, whether data are governed fairly, whether their data are being protected from risks, and whether harmful decisions can be challenged.

The comparative synthesis shows that AI can widen stratification when it is introduced into unequal educational systems without redistribution of resources and power. Affluent institutions are more able to provide advanced instruction, technical support, and protective governance. Marginalized communities are more likely to experience AI as an external system that evaluates, extracts, or excludes. This pattern is not inevitable, but changing it requires policy that treats AI literacy as a collective educational right.

Sociology of education contributes by making visible the institutional mechanisms through which technologies distribute opportunity. The goal should not be to make every learner adapt to AI on unequal terms. It should be to build educational systems in which communities have the resources and authority to shape what AI becomes. An equitable future therefore depends on more than innovation. It requires public investment in infrastructure, critical and localized curricula, teacher professionalism, multilingual design, community data sovereignty, and enforceable accountability.

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