From Classical Education to Platform-Based Learning: Artificial Intelligence, Access Inequality, and Poverty Reduction

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Abstract

This theoretical article examines how artificial intelligence is reshaping the architecture of education by extending learning beyond classical institutional settings towards more flexible, platform-based forms of knowledge acquisition. It analyses the relationship between AI-mediated learning, access inequality, and poverty reduction, with particular attention to the conditions under which artificial intelligence may widen educational opportunities or deepen existing socio-economic disparities. Methodologically, the article is based on a critical conceptual synthesis of interdisciplinary literature on education, digital inequality, artificial intelligence in learning, human capital formation, labor-market adaptation, and poverty reduction. Rather than treating these domains separately, it develops an integrated analytical framework linking digital access conditions, platform differentiation, conversion capacity, skills formation, employability, and poverty-reduction potential. The analysis argues that artificial intelligence creates important opportunities for more personalized, rapid, and scalable learning, but that these opportunities are distributed unevenly. It identifies both an inclusive pathway, in which supported access strengthens skills formation and labor-market adaptability, and an exclusionary pathway, in which unequal access produces differentiated educational returns and reproduces disadvantages. Meaningful participation therefore depends not only on nominal access to devices and connectivity, but also on affordability, digital literacy, language accessibility, platform quality, and the ability to convert access into durable skills. On this basis, the article conceptualizes platform stratification as a distinct layer of educational inequality within digital inclusion itself. It concludes that the poverty-reduction capacity of AI-enabled learning is conditional rather than automatic and depends on public policy in infrastructure, capability-building, equitable access, and the public-interest governance of AI-supported educational environments.

Keywords: Artificial intelligence; Platform-based learning; Platform stratification; Access inequality; Poverty reduction; Human capital; Digital divide; Public policy

1. Introduction

Education has long been regarded as a major mechanism of human capital formation, social mobility, and poverty reduction. Yet the literature consistently shows that this relationship is neither automatic nor linear. Education contributes to poverty reduction only under broader social, economic, and institutional conditions that shape who can access learning, what type of learning is available, and whether acquired knowledge can be translated into meaningful economic opportunity (Cremin & Nakabugo, 2012).

The rapid expansion of artificial intelligence is transforming this traditional educational architecture. Learning increasingly extends beyond classrooms, campuses, and formal institutional boundaries into more flexible, interactive, and platform-based environments. AI-enabled systems can provide explanations, summaries, examples, feedback, and adaptive support in real time, making learning more immediate and more responsive to individual demand. Recent OECD work stresses that generative AI can support learning when guided by sound pedagogical principles, while UNESCO emphasises both its educational potential and the need to protect equity, rights, and safety in the process (OECD, 2026; UNESCO, 2025).

This shift from classical education to platform-based learning should not, however, be understood in purely techno-optimistic terms. The apparent openness of AI-mediated learning conceals substantial differences in the material and social conditions of access. Effective participation in digital learning depends on reliable connectivity, appropriate devices, affordability, infrastructure, and digital skills. OECD's work on digital equity and inclusion in education shows that unequal access to digital tools is not only a question of hardware, but also of capability, support, and meaningful participation in learning processes. Recent Elsevier evidence examining generative AI through an equity lens reaches a similar conclusion: the educational effects of generative AI are shaped by the interaction of personalisation, fairness, and access, and equity does not emerge automatically from adoption alone (Gottschalk & Weise, 2023; Mimoudi, 2025).

The issue becomes even more salient once platform differentiation is taken into account. In practice, AI-based learning environments are not experienced equally by all users. Differences in service quality, feature availability, usage limits, and platform capability can affect the depth, continuity, and quality of interaction, thereby shaping learning opportunities in socially stratified ways. In educational terms, formal access does not necessarily imply substantive equality of learning opportunity. The central problem, therefore, is not only whether AI can support learning,

but also who is able to benefit from it effectively and under what conditions (Miao et al., 2021; UNESCO, 2025).

These inequalities matter because AI-mediated learning increasingly affects the accumulation of economically relevant knowledge and skills. Labour-market evidence shows rising demand for AI-related skills and a measurable wage premium attached to them, suggesting that access to AI-compatible learning is becoming part of broader economic competitiveness rather than merely an optional digital advantage (Alekseeva et al., 2021). Recent cross-country evidence also points to a positive relationship between artificial intelligence and human-capital-based educational development, although the magnitude of this effect varies across contexts (Tian & Zhang, 2025).

This problem is particularly consequential in low- and middle-income contexts, where educational inequality often overlaps with poverty, regional disparity, and uneven digital infrastructure. Research on digital technologies and poverty reduction in low-income and lower-middle-income countries shows that digital deployment can contribute to poverty reduction through channels such as education, labour markets, income generation, and broader economic participation. At the same time, these benefits are conditional rather than automatic (Lechman & Popowska, 2022).

Despite the growing literature on artificial intelligence in education, digital inequality, and poverty reduction, these domains are still too often analysed in isolation. What remains underdeveloped is an integrated framework explaining how the shift from classical education to platform-based learning restructures access, produces new forms of inequality, and alters the poverty-reduction capacity of education. This article addresses that gap by linking platform-based learning, access inequality, human capital formation, and poverty reduction within a single analytical model.

This article makes three contributions. First, it conceptualises AI-mediated learning as a structural transition from institutionally bounded education to platform-based knowledge acquisition. Second, it introduces platform stratification as a distinct distributive layer within AI-mediated educational access. Third, it explains how unequal access to AI-supported learning reshapes the relationship between education, skills formation, labour-market opportunity, and poverty reduction. Its central theoretical contribution is to conceptualise educational inequality in the AI era as unequal positioning within access itself, rather than exclusion from access alone.

Against this background, the article examines the transition from classical education to platform-based learning through the lens of artificial intelligence, access inequality, and poverty

reduction. It asks how AI-mediated learning reshapes educational access, generates new inequalities, and affects the poverty-reduction potential of education.

The central argument is that artificial intelligence increases the speed, flexibility, and personalisation of knowledge acquisition, but its developmental effects are unequally distributed. AI-mediated learning may support poverty reduction only where learners can convert digital access into durable skills and labour-market opportunities. Where access to devices, connectivity, digital literacy, language resources, and higher-quality platforms is uneven, platform-based learning is more likely to produce unequal returns and reinforce socio-economic stratification. Artificial intelligence should therefore be understood not as an automatic equaliser, but as a technology that reconfigures the conditions under which education can function as a mechanism of inclusion.

2. Materials and Methods

This article adopts a theoretical and conceptual research design. Its purpose is not to test a single causal hypothesis through original field data, but to develop an analytical interpretation of how artificial intelligence is reshaping educational access and how this transformation relates to inequality and poverty reduction. Such a design is appropriate because the problem examined here lies at the intersection of education, digital technology, social inequality, labour-market change, and public policy. The study therefore focuses on structural relationships among these domains rather than on one isolated institutional case (Cremin & Nakabugo, 2012; Gottschalk & Weise, 2023).

The article is based on a critical interdisciplinary review and conceptual synthesis of literature from education and development, digital inequality, artificial intelligence in education, human capital formation, labour-market change, and public policy. Source selection followed a problem-oriented rather than exhaustive bibliometric logic. Priority was given to studies and policy publications that illuminate the article's core dimensions: changing learning environments, inequalities of digital access, differentiated skills formation, and the relationship between education and poverty reduction. In practical terms, selection prioritised thematic centrality to the research question, recency where rapid technological change was relevant, policy significance, and interdisciplinary complementarity across education, inequality, labour-market, and public-policy debates.

The analytical approach is critical rather than techno-deterministic. The article does not assume that artificial intelligence is inherently emancipatory, nor that digital innovation automatically generates inclusive educational outcomes. Instead, it examines the contradictory character of AI-based learning. Artificial intelligence may support personalisation, rapid feedback, scalability, and self-directed learning, yet these advantages remain conditioned by unequal access to

infrastructure, affordability, digital capability, language accessibility, and institutional support. The purpose of the analysis is therefore not to celebrate or reject AI in education, but to explain the conditions under which its educational and socio-economic effects may diverge (Miao et al., 2021; OECD, 2026; UNESCO, 2025).

To maintain analytical clarity, the study is organised around five thematic domains: educational transformation, artificial intelligence as a learning interface, access inequality, human capital formation, and poverty reduction. The first domain concerns the movement from institutionally bounded learning towards more flexible and on-demand platform-based knowledge acquisition. The second examines AI as a mediating layer between learners and knowledge resources. The third addresses inequalities in connectivity, devices, affordability, digital literacy, language accessibility, and institutional support. The fourth explores how differentiated access to AI-mediated learning may shape the acquisition of economically relevant competencies. The fifth investigates whether AI-mediated learning can function as a mechanism of social mobility and poverty reduction or whether it risks reproducing existing disadvantage.

The conceptual framework treats access inequality as the key mediating variable between AI-enabled learning and poverty reduction. Rather than assuming a direct causal relationship, the article models artificial intelligence as a conditional learning infrastructure whose implications depend on conversion capacity: the ability to transform formal access into meaningful participation, durable skills, and labour-market adaptability. Under favourable conditions, AI-supported learning may strengthen skills formation and expand poverty-reduction potential; under unequal conditions, the same shift is more likely to generate differentiated educational returns and reproduce disadvantage. The framework therefore explains not whether AI matters in education, but how its effects are shaped by the distributive conditions under which learning takes place.

This methodological design is appropriate because the article seeks to clarify an analytical mechanism rather than estimate its causal magnitude. It is therefore a theory-building, framework-building study rather than a model-testing one, and it does not assume that a single uniform empirical effect applies across contexts.

This methodological choice also defines the limits of the study. The article does not estimate causal effects empirically, compare a fixed set of countries, or test platform outcomes through original quantitative data. Its contribution is analytical rather than statistical. The purpose is to develop a theoretically coherent framework that clarifies the mechanisms through which AI-mediated learning may influence educational inequality and poverty-reduction capacity under different access

conditions. Future empirical research is needed to assess the extent to which these pathways operate across specific institutional, socio-economic, and national contexts.

The conceptual framework of the article is presented in Figure 1.

3. Results

The following section presents the analytical findings of this conceptual study. Rather than statistical results, it identifies the main structural patterns and interpretive relationships emerging from the literature reviewed in this article.

3.1. From Classical Education to Platform-Based Learning

The expansion of artificial intelligence is accelerating a broader transformation in the organisation of learning: the movement from classical education towards more flexible, platform-based forms of knowledge acquisition. Classical education has historically been structured around institutionally bounded, credential-based, and curriculum-governed settings such as schools, universities, and formal training centres. By contrast, platform-based learning operates through digital environments that reduce the temporal and spatial constraints of face-to-face education and enable learners to access information, training, and guidance on demand. In this sense, the significance of AI is not limited to adding a new tool to existing educational systems; rather, it contributes to a reconfiguration of where learning takes place, how quickly it occurs, and through which intermediaries knowledge is delivered (OECD, 2026; López et al., 2023).

This transition does not imply the disappearance of classical education. Schools, universities, and formal qualification systems remain central to certification, institutional legitimacy, disciplinary depth, and structured curriculum design. However, their exclusive role in knowledge delivery is weakening. OECD notes that generative AI differs from earlier waves of educational technology because much of it is freely accessible, intuitive to use, and often employed beyond institutional control because of its versatility. Learning is therefore increasingly mediated not only by formal institutions but also by open digital platforms that users can access independently, often without teacher supervision, formal enrolment, or traditional entry barriers. As a result, the educational landscape is becoming more decentralised, learner-driven, and technologically mediated (OECD, 2026).

Platform-based learning also changes the logic of educational participation. In the classical model, access to advanced knowledge often depends on admission procedures, tuition, physical attendance, and the pace of institutional teaching. In platform-based settings, by contrast, learners can search, ask, refine, repeat, and personalise interactions on demand. This makes learning more flexible and often more immediate. Evidence from online learning adoption in Spain suggests that

digital learning expands access partly because it relaxes the temporal and spatial constraints of conventional delivery, but the same evidence shows that participation continues to vary by income, educational level, digital skills, age, and place of residence. Flexibility, therefore, broadens access in form without eliminating inequality in effect (López et al., 2023).

A further implication of this shift is the changing political economy of knowledge. Under classical educational arrangements, institutions perform strong gatekeeping functions: they organise curricula, validate expertise, and regulate the distribution of recognised knowledge. Under platform-based conditions, these functions become more dispersed. Knowledge becomes more searchable, more fragmented, more rapidly updated, and more directly accessible through interfaces that are not themselves educational institutions in the classical sense. UNESCO's rights-based approach is especially relevant here because it recognises both the opportunity to broaden learning access and the risk of new inequities if such systems are not governed with inclusion in mind (UNESCO, 2025).

This transformation is especially important from the perspective of poverty reduction. If access to useful knowledge is becoming less dependent on formal institutional enrolment and more dependent on digital interfaces, then educational inclusion is increasingly tied to technological inclusion. The pathway from learning to human capital formation may become faster and more flexible, but it also becomes more contingent on infrastructure, devices, and platform access. Cross-country evidence suggests a positive relationship between AI and human-capital-based educational development, but also shows that the magnitude of this relationship varies across contexts (Tian & Zhang, 2025). The movement from classical education to platform-based learning should therefore not be understood as uniformly democratizing; rather, it should be interpreted as a structural shift that redistributes educational opportunity in new ways.

3.2. Artificial Intelligence as a Mechanism of Flexible and Personalised Knowledge Delivery

Artificial intelligence is central to platform-based learning because it changes how knowledge is delivered. Unlike static repositories of information or conventional one-way online materials, AI systems can respond interactively, generate explanations in real time, rephrase difficult concepts, provide examples, summarise information, and adapt the form of their output to a learner's request. In this sense, AI acts not only as a delivery tool, but also as a learning interface between the user and a wide body of knowledge. OECD's 2026 outlook emphasises that generative AI is reshaping the educational landscape beyond teaching and learning alone, while UNESCO underscores that such systems may create new possibilities for learning support if their use remains anchored in educational rights and equity (OECD, 2026; UNESCO, 2025).

The educational appeal of AI lies largely in its flexibility. OECD notes that general-purpose generative AI is widely accessible to anyone with an internet connection, intuitive to use, and capable of supporting a wide range of tasks within seconds. From the standpoint of educational access, this matters because it lowers some of the practical barriers that previously limited individualised support. Learners no longer need to wait for office hours, scheduled class time, or formal institutional mediation in order to receive explanations, guided practice, or structured assistance. In principle, this immediacy can strengthen self-directed learning and make knowledge acquisition more responsive to learners' needs (OECD, 2026).

Personalisation is another major feature of AI-mediated learning. UNESCO argues that AI can create opportunities for more personalised learning and improved educational management, while OECD emphasises that positive learning effects are most plausible when AI is embedded in clear pedagogical frameworks. In practice, personalisation means that learners can ask follow-up questions, request simplification, adjust the level of difficulty, and explore topics from multiple angles in ways that are difficult to reproduce in standardised mass instruction. For students with uneven preparation, interrupted educational trajectories, or specific learning needs, such responsiveness may improve the usability of educational resources and increase the likelihood of sustained engagement. Recent review evidence further suggests that the distributive consequences of generative AI depend on how personalisation is balanced with fairness and access across educational settings (Miao et al., 2021; OECD, 2026; Mimoudi, 2025).

At the same time, flexibility and personalisation do not automatically produce deep learning. OECD cautions that generative AI can improve immediate task performance without necessarily generating genuine learning gains when it is used without pedagogical guidance. Fast access to information is not equivalent to robust knowledge formation. AI can assist learning, but it can also simulate competence if learners rely on it merely to complete tasks more quickly rather than to build durable understanding. The educational value of AI therefore depends not only on access, but also on the quality, purpose, and pedagogical framing of its use (OECD, 2026).

This is why the distinction between AI as a convenience tool and AI as a learning partner matters. Used superficially, it may accelerate task completion without building durable competence. Used critically and pedagogically, it may support iterative learning and strengthen knowledge acquisition. For that reason, artificial intelligence should be understood as a mechanism of flexible and personalised knowledge delivery with conditional educational effects.

3.3. Access Inequality in AI-Mediated Learning

The expansion of AI-mediated learning does not eliminate inequality; rather, it reorganises it around new conditions of access and use. In classical education, inequality was often expressed through differences in school quality, tuition affordability, geographic location, and institutional prestige. In platform-based learning, these classical forms do not disappear, but they are increasingly supplemented by digital inequalities related to connectivity, devices, affordability, infrastructure, and user capability.

The crucial distinction is not simply between access and exclusion, but between formal access and effective access: between being technically connected to AI-enabled learning environments and being able to participate in them in sustained, meaningful, and educationally productive ways. Effective participation depends on connection quality, device reliability, digital literacy, language accessibility, and the ability to formulate, interpret, verify, and refine interactions with AI systems. The key issue is therefore not access per se, but unequal conversion capacity: the ability to transform formal access into meaningful participation, durable skills, and educational returns (Miao et al., 2021; UNESCO, 2025).

The empirical literature on digital learning supports this interpretation. Evidence from Nigeria's pandemic-era remote learning experience, Australia's move to online testing, and cross-national research on students' digital skills all indicate that formally available digital learning systems remain socio-economically stratified (Azubuike et al., 2021; Posso & Miranti, 2026; van de Werfhorst et al., 2022).

Access inequality in AI-mediated learning is cumulative rather than static. Learners with reliable devices, stable broadband, stronger digital literacy, and better prior preparation are more likely to use AI systems critically and repeatedly, whereas those with weaker conditions are more likely to engage sporadically and with lower confidence. AI-mediated learning may therefore amplify pre-existing inequality by creating unequal returns to the same formal technological shift (Gottschalk & Weise, 2023).

From the perspective of poverty reduction, the decisive inequality is not technological access alone, but unequal capacity to convert access into sustained learning returns, transferable skills, and adaptive economic capability.

3.4. Paid and Free Platforms and the New Educational Divide

A particularly important dimension of inequality in AI-mediated learning concerns stratification within access itself. Tiered AI environments differentiate learners not only by entry, but also by the depth, continuity, and sophistication of cognitive support available within connected

learning systems. In practice, this often appears through free and paid tiers, unequal feature access, usage limits, and differences in model capability.

This layered structure of access can be described as platform stratification. Two learners may both appear digitally included, yet their educational experience may differ substantially depending on affordability, platform tier, language compatibility, digital confidence, and institutional support. Platform-based learning therefore introduces a new educational divide within inclusion itself.

The importance of platform stratification extends beyond subscription status alone. Tiered access interacts with broader socio-economic inequalities in income, prior education, device quality, and learning support environments, producing unequal educational returns not only through disconnection, but also through differentiated positioning within connected learning environments.

These divides may be further reinforced by language asymmetries and differences in user competence. Recent research on the 'GenAI divide' among university students links more productive use of generative AI to stronger AI literacy and more confident engagement, suggesting that user capability is itself stratified (Beckman et al., 2025). Comparative evidence from Kenya, Nigeria, and South Africa likewise reports significant variation by country and level of study in students' perceptions of AI-supported learning, underscoring the need for tailored rather than uniform strategies of educational inclusion (Oyelere & Aruleba, 2025). Institutional policy evidence reinforces this view: universities are developing guidelines, training, and academic-integrity measures, yet important gaps remain around privacy and equitable access, indicating that governance conditions are part of the learning environment itself (Jin et al., 2025).

3.5. AI, Skills Formation, and Human Capital

The expansion of AI-mediated learning is economically significant because it increasingly affects how individuals build market-relevant skills and, therefore, how human capital is formed. Recent labour-market evidence shows that demand for AI-related skills has grown rapidly across industries and occupations rather than remaining confined to narrow technical sectors. Research published in Labour Economics documents a dramatic increase in demand for AI skills in the United States between 2010 and 2019 and identifies a wage premium associated with such skills. This AI-related skill premium suggests that access to AI-compatible learning is becoming more than an educational convenience; it is gradually turning into a channel through which economically valuable capabilities are acquired and differentiated (Alekseeva et al., 2021).

Platform-based learning changes both the speed and the modality through which such skills can be accumulated. AI systems can support iterative practice, personalised explanation, task decomposition, and immediate feedback, all of which may strengthen self-directed learning and

reduce some of the frictions associated with conventional upskilling. Cross-country evidence published in Technology in Society likewise suggests a positive relationship between artificial intelligence and human-capital-based educational development across 29 countries, although the strength of that relationship differs between developed and developing contexts (Tian & Zhang, 2025).

A further implication is that AI-mediated learning may alter the distribution of adaptive capacity in the labour market. If some learners can use AI to acquire new skills more quickly, navigate knowledge more efficiently, and respond faster to changing occupational requirements, then the gap between technologically advantaged and disadvantaged groups may widen over time. Under such conditions, the capacity to engage productively with AI becomes embedded in wider educational and socio-economic inequalities rather than standing apart from them. AI-mediated learning therefore contributes not only to new patterns of knowledge delivery, but also to new forms of differentiation in who can accumulate the skill sets most valued in digital and AI-intensive economies (Alekseeva et al., 2021; Tian & Zhang, 2025).

For the purposes of this article, the key analytical point is that AI-mediated learning affects human capital through a distributive mechanism. Where access is broad, sustained, and supported, AI can reinforce learning flexibility, competence-building, and labour-market preparedness. Where access is uneven, however, the same technology may concentrate skill accumulation among already advantaged groups. Thus, the human-capital implications of artificial intelligence are inseparable from the question of educational access.

3.6. AI-Mediated Learning and Poverty Reduction

The relationship between AI-mediated learning and poverty reduction is mediated through the effects of education on employability, income opportunity, and social mobility. Education has long been linked to poverty reduction, but the literature also makes clear that this relationship depends on wider economic and institutional conditions rather than unfolding automatically. In the context of AI-mediated learning, this means that digital access to knowledge may support poverty reduction only when it strengthens meaningful skills formation and improves the capacity of individuals to participate in labour markets and broader economic life. Research published in Telecommunications Policy on low-income and lower-middle-income countries finds that growing digital deployment can contribute to poverty reduction, but also shows that these effects depend on enabling conditions rather than emerging as an independent technological cure (Lechman & Popowska, 2022).

This mediated logic becomes even clearer when digital literacy is considered. Recent evidence from China suggests that digital literacy can reduce the risk of returning to poverty by promoting

employment pathways and strengthening economic resilience, especially for disadvantaged groups. Although digital literacy is not identical to AI literacy, the implication is directly relevant: the ability to use digital tools productively can affect long-term economic opportunity. When AI-mediated learning becomes part of how individuals acquire such capabilities, unequal access to AI systems may begin to shape not only educational outcomes, but also poverty trajectories (Zhou et al., 2024).

The article's central poverty-reduction pathway can therefore be summarised as follows: AI-enabled access expands learning opportunity; learning opportunity supports skills accumulation; skills accumulation improves employability and income potential; and these changes, in turn, shape poverty-reduction capacity.

At the same time, the poverty-reduction potential of AI-mediated learning is constrained by the same inequalities that structure access. If low-income learners rely on weak connectivity, low-quality devices, limited digital skills, or restricted service tiers, their participation in platform-based learning may remain shallow and intermittent. Evidence from Costa Rica similarly shows low completion rates in free online training programmes, higher completion among wealthier participants, and no significant labour-market effects after two years (Novella et al., 2024). Related evidence from MOOCs also suggests that participation can improve employment retention without necessarily increasing wages, reinforcing the point that digital learning may support labour-market attachment without automatically generating broad income gains (Castaño-Muñoz & Rodrigues, 2021). Under those conditions, AI does not operate as a broad equaliser; it risks reproducing existing educational and labour-market hierarchies in digital form.

AI-mediated learning should therefore be understood as a conditional mechanism of poverty reduction rather than as a universal equaliser. It can widen opportunity by lowering barriers to knowledge acquisition. Yet it can also deepen socio-economic polarization when high-quality AI-supported learning environments are concentrated among already advantaged groups. Platform-based learning expands the poverty-reduction potential of education only under conditions of equitable access and meaningful capability-building; without those conditions, it may reorganise poverty rather than reduce it.

4. Discussion

4.1. Why Artificial Intelligence Does Not Automatically Reduce Poverty

The preceding analysis suggests that artificial intelligence should not be understood as an automatic mechanism of poverty reduction. Although AI-mediated learning can widen access to explanations, training materials, and adaptive support, its socio-economic effects depend on the

distributive conditions under which that access is organised. OECD's work on digital education and equity shows that participation in digital learning environments is shaped not only by connectivity and devices, but also by affordability, institutional support, and the capacity to use digital tools meaningfully. UNESCO adopts a parallel position, insisting on a human-centred, rights-based approach to AI in education and warning that technological change must strengthen, rather than undermine, the right to education for all learners (Gottschalk & Weise, 2023; OECD, 2026; UNESCO, 2025).

For this reason, the relationship between AI and poverty reduction is mediated rather than direct. AI can support inclusion only when learners are able to convert access into competence and competence into improved labour-market opportunity. If that chain is interrupted by weak connectivity, inadequate devices, limited digital literacy, or insufficient pedagogical support, the poverty-reduction potential of AI remains constrained even where technical access exists. Technology availability is therefore not equivalent to developmental effectiveness.

A further reason why AI does not automatically reduce poverty lies in the distinction between informational access and substantive learning. AI systems can provide fast answers, summaries, and task support, but rapid access to information is not equivalent to durable capability formation. Long-term socio-economic advancement depends less on episodic exposure to information than on the sustained acquisition of transferable, market-relevant competencies. Even where AI is accessible, therefore, its contribution to poverty reduction remains uncertain unless learners have the support structures needed to turn platform interaction into long-term human capital development.

This caution is reinforced by broader economic research. Emerging studies suggest that advanced AI may have substantial implications for the distribution of income and opportunity. Vesely and Amaris (2025), for example, treat AI-driven inequality as a serious economic issue rather than a speculative possibility. Such findings do not imply that AI necessarily increases inequality in every context, but they do underscore that technological change does not unfold in a socially neutral environment. AI enters systems already marked by unequal education, infrastructure, income, and institutional capacity; under those conditions, a technology that lowers barriers for some may still intensify relative disadvantage for others.

The most defensible theoretical conclusion, then, is that AI expands the poverty-reduction potential of education without guaranteeing inclusive outcomes. It creates a new opportunity structure, but whether that structure becomes socially inclusive depends on access conditions, conversion capacity, and the quality of governance.

4.2. The Reproduction of Inequality in the Platform-Based Knowledge Economy

The movement from classical education to platform-based learning does not dissolve inequality; instead, it relocates and reorganises it within a new platform-based knowledge economy. In classical systems, educational inequality was structured through school quality, tuition, institutional prestige, geographic location, and admission barriers. In platform-based systems, these older forms persist, but they are joined by new stratifying mechanisms: the quality of connectivity, the reliability of devices, the affordability of access, digital capability, language compatibility, and the tiered architecture of AI platforms themselves.

This new structure of inequality can be understood as layered inclusion. Many learners may be technically connected to AI systems, yet their educational opportunities still differ according to the depth and quality of that connection. The platform-based knowledge economy does not erase inequality; it digitises and re-stratifies it by producing unequal returns within inclusion itself.

Because AI-mediated learning increasingly affects the speed and quality of skills acquisition, differences in platform access can accumulate into broader differences in employability, adaptability, and income opportunity. Once AI-related competence becomes economically valuable, uneven access to AI-supported learning environments can reproduce and intensify socio-economic disparities (Vesely & Amaris, 2025).

The central distributive question is no longer only who is connected, but who can convert connection into durable competence, employability, and mobility.

These effects are not technologically predetermined, however. The distributive outcomes of AI depend on governance, institutional design, and policy response.

From this perspective, inequality in AI-mediated learning should be understood as a process of social reproduction through differentiated digital capability. Learners who are already advantaged can engage more intensively, critically, and continuously with AI-supported environments, whereas learners with fewer resources may remain only partially connected and therefore accumulate fewer benefits from the same technological shift. The result is a re-stratified knowledge economy in which digitally mediated learning reproduces advantage through unequal capability and unequal returns.

4.3. The Role of the State

The analysis developed in this article implies that the state occupies a central position in the transition from classical education to platform-based learning because it shapes the distributive conditions under which AI-mediated learning becomes either inclusive or exclusionary. If artificial intelligence is reorganising access to knowledge, its consequences cannot be left entirely to market dynamics or private platform providers. The state should therefore be understood not merely as a

regulator, but as a coordinator of the infrastructural, institutional, and distributive conditions through which AI-enabled learning opportunities are structured (Gottschalk & Weise, 2023; UNESCO, 2025).

From this perspective, the role of the state is fourfold. It must reduce infrastructural inequality, strengthen conversion capacity through digital and AI literacy as well as institutional support, provide public-interest governance, and create affordable pathways to higher-quality AI-supported learning environments. Comparative evidence across the United States, Colombia, Germany, and Macau likewise suggests that uneven AI uptake is shaped by differences in training, institutional support, and policy priorities, not merely by the presence of tools (Davin et al., 2026). In this sense, the state acts as a distributive coordinator of educational opportunity in the AI era.

Because AI-mediated learning increasingly shapes how individuals acquire market-relevant skills, the state's role in education also becomes a role in shaping the long-term distribution of human capital and socio-economic mobility. Educational AI should therefore be treated not only as a pedagogical issue, but also as a matter of economic policy and distributive justice (Alekseeva et al., 2021; Tian & Zhang, 2025).

4.4. Economic Policy Implications

If AI-mediated learning is becoming an important mechanism of human capital formation, its implications extend directly into economic policy. Platform-based learning should therefore be understood not only as an educational innovation, but also as part of the policy architecture through which states shape productivity, employability, and long-term development (Alekseeva et al., 2021; OECD, 2026).

From an economic-policy perspective, the key issue is not simply digital access but the distribution of returns to AI-mediated learning. Cross-country evidence from 20,242 students across 58 countries shows that learners in more digitally developed environments are more likely to use ChatGPT chiefly because they possess stronger digital competences and functional access, while institutional and linguistic support shape use more indirectly (Bencsik et al., 2026). Comparative evidence from Kenya, Nigeria, and South Africa likewise reveals significant variation by country and educational level in students' perceptions of generative AI, underscoring the need for context-sensitive rather than one-size-fits-all strategies of adoption and inclusion (Oyelere & Aruleba, 2025). Together, these findings suggest that policy must focus on the conditions that convert availability into effective use, not on availability alone.

A first implication concerns infrastructure and capability. Where reliable connectivity, devices, and digital access are widespread, AI-mediated learning may support broader participation in

knowledge acquisition and skills formation. Where these remain unevenly distributed, educational modernisation without digital equalisation risks reproducing regional and class-based inequalities in new technological forms. Even broad technical access, moreover, will yield uneven gains unless policy also addresses learners' ability to convert access into durable skills and labour-market readiness (Rajasekaran et al., 2024; Gottschalk & Weise, 2023; Tian & Zhang, 2025; OECD, 2026).

A second implication concerns labour-market policy. Traditional schooling alone is unlikely to be sufficient in an environment where AI changes both the pace and the content of skill demand. States will increasingly need lifelong learning systems, short-cycle retraining, AI-literacy pathways in vocational education, regional upskilling programmes, and targeted support for workers and learners at risk of exclusion from AI-intensive labour markets (International Labour Organization, 2025).

A third implication concerns inclusion and redistribution. Because platform-based learning can generate layered inequalities within nominal access, economic policy must address affordability and quality of access as well as basic connectivity. If richer access environments produce stronger learning outcomes, governments may need subsidised connectivity, public procurement of educational AI services, targeted access schemes for low-income learners, and public-interest digital learning infrastructures.

Taken together, these implications suggest that AI-mediated learning should be incorporated into economic policy as part of a wider developmental framework. The central question is no longer simply whether AI exists in education, but whether access to high-quality AI-supported learning is distributed broadly enough to function as a mechanism of social mobility rather than a driver of deeper stratification.

4.5. Theoretical Implications

The central theoretical contribution of this article is the concept of platform stratification. Educational inequality in the AI era cannot be captured adequately through a simple binary distinction between access and exclusion because platform-based learning generates hierarchies within inclusion itself. Learners may be formally connected to the same digital ecosystem while remaining unequally positioned within it because of differences in service tier, platform capability, language accessibility, user competence, and institutional support. The concept therefore reframes digital inequality as a problem of differentiated access to cognitive infrastructures, not merely of technical connection.

A second implication is that access inequality must be treated as a mediating variable rather than a peripheral constraint. The social and economic effects of AI depend on whether access is materially

stable, educationally meaningful, and institutionally supported. This is why conversion capacity becomes analytically central: access matters only insofar as learners can transform it into knowledge, durable skills, and labour-market adaptability. The relationship between AI and poverty reduction is therefore conditional, layered, and socially mediated rather than direct or automatic (Gottschalk & Weise, 2023; Rajasekaran et al., 2024; Alekseeva et al., 2021; Tian & Zhang, 2025).

More broadly, artificial intelligence should not be treated merely as an educational technology, but as part of a reorganisation of the political economy of knowledge. The transition from classical education to platform-based learning changes the location of learning, the mechanisms of access, and the distribution of educational advantage. The platform-based knowledge economy does not erase inequality; it redistributes it through unequal access to cognitive support and unequal returns within connected learning environments.

Finally, the article links education, AI, and poverty reduction through a mediated developmental chain: access to learning resources influences skill accumulation; skill accumulation shapes employability and adaptability; and these outcomes affect the poverty-reduction potential of education. The framework is intended not to claim one universal empirical effect, but to specify the mechanism and scope conditions under which AI-supported learning is more likely to widen opportunity or reproduce disadvantage.

5. Conclusion

This article argues that artificial intelligence in education should be understood not simply as a pedagogical innovation, but as a structural shift in how knowledge is accessed and organised. AI-mediated learning expands the scope for flexible, personalised, and scalable education, yet its benefits remain unevenly distributed across infrastructures, devices, digital capabilities, language environments, and platform tiers.

Its central theoretical contribution is to show that educational inequality in the AI era emerges not only through exclusion from access, but also through unequal positioning within access itself. The article conceptualises that condition as platform stratification. The key issue, therefore, is not technological connection alone, but the unequal capacity to convert connection into meaningful participation, durable competence, and labour-market adaptability.

The developmental significance of AI in education therefore depends less on technological novelty than on how learning opportunities are distributed, supported, and governed. Where equitable access, digital capability, and public-interest governance are weak, AI-mediated learning may reproduce existing educational and socio-economic inequalities. Where these conditions are strengthened, however, platform-based learning may widen the poverty-reduction capacity of

education. Equitable access to high-quality AI-mediated learning should thus be treated as a long-term question of human capital formation, distributive justice, and poverty reduction.

This article also has clear limitations. It does not estimate causal effects empirically, compare a fixed sample of countries, or test platform outcomes through original quantitative data. Its purpose is analytical rather than statistical: to clarify the mechanism through which AI-mediated learning may reshape educational inequality and poverty-reduction capacity under different access conditions.

Future research should test these relationships empirically across varied institutional, socio-economic, and national contexts, especially by comparing free and paid AI-learning environments, lower-income and better-resourced learners, and institutionally supported and self-directed learning settings. Testing these contrasts would show more clearly whether AI-mediated learning broadens opportunity or redistributes educational advantage within connected environments. In the AI era, the central question is no longer only who can access learning, but who can convert access into competence, mobility, and socio-economic opportunity.

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Declaration of Interest

The author declares no conflict of interest.

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Tables

Table 1. Layers of Access Inequality in AI-Mediated Learning

Dimension	Minimal Access	Enhanced Access	Likely Educational Consequence
Internet connectivity	Intermittent or low-speed connection	Stable broadband access	Continuity and depth of learning differ significantly
Device quality	Shared phone or weak device	Personal laptop/tablet with stable functionality	Stronger capacity for sustained and complex interaction
Digital literacy	Basic or limited user competence	Advanced search, prompting, and verification skills	Higher-quality knowledge conversion into skills
Language accessibility	Limited language compatibility	Strong compatibility with dominant academic and digital languages	Unequal comprehension and learning efficiency
Platform access	Restricted free tier	Paid or institutionally supported enhanced tier	More consistent, richer, and less constrained learning experience
Institutional support	Little or no guidance	Teacher, peer, or institutional support environment	Greater likelihood of converting access into durable competence

Source: Author's conceptualization based on the reviewed literature.

Figures and Figure Captions

Figure 1. Conceptual Framework of AI-Mediated Learning, Access Inequality, and Poverty Reduction.

Source: Author's conceptualization based on the reviewed literature.

