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Artificial Intelligence and Global Inequality: Algorithmic Power and the Global North–South Divide

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Abstract

Artificial Intelligence (AI) has become a major infrastructure of contemporary economic, political, and social transformation, yet its benefits and governing capacities remain unevenly distributed across the world. This paper examines AI as a source of algorithmic power and investigates how technological capabilities, data ownership, computational infrastructure, research capacity, digital labour, and regulatory authority reinforce the Global North–South divide. Rather than treating algorithmic inequality solely as a problem of technical bias, the paper conceptualizes it as a structural outcome of unequal control over the resources through which AI systems are designed, trained, deployed, and governed. Existing scholarship indicates that Global South countries frequently encounter AI through imported platforms, externally developed standards, extractive data practices, and technologically dependent infrastructures. The paper further examines algorithmic coloniality, data extraction, labour asymmetries, linguistic exclusion, digital infrastructure gaps, and unequal participation in AI governance. It argues that AI may simultaneously reproduce existing global inequalities and create opportunities for developmental transformation. A more equitable AI order therefore requires stronger technological sovereignty, locally relevant datasets, inclusive research ecosystems, South–South cooperation, accountable governance, and greater participation of Global South actors in defining the norms and objectives of AI development.

Keywords: *Artificial Intelligence; Global Inequality; Algorithmic Power; Global North; Global South; Algorithmic Coloniality; Digital Colonialism; Data Inequality; AI Governance; Technological Sovereignty; Digital Divide; Data Extraction; Algorithmic Bias;*

1. Introduction

Artificial Intelligence (AI) has evolved from a specialized computational technology into a major infrastructure shaping economic production, public administration, healthcare, education, financial services, communication, and political decision-making. The increasing use of algorithmic systems has consequently transformed the distribution of information, opportunities, resources, and institutional authority. However, the global expansion of AI has not occurred under conditions of equal technological capacity. Advanced computational infrastructure, research institutions, investment capital, proprietary datasets, intellectual property, and highly skilled technical labour remain disproportionately concentrated in technologically advanced economies. As a result, AI should be examined not only as an instrument of innovation and economic growth but also as a structure through which existing global inequalities may be reproduced and intensified.

The conventional understanding of the digital divide primarily emphasizes differences in access to computers, internet connectivity, digital devices, and information and communication technologies. Although these disparities remain significant, the emergence of AI introduces a

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more complex form of technological inequality. Contemporary algorithmic systems depend on access to large-scale datasets, computing infrastructure, cloud platforms, specialized expertise, semiconductor technologies, and financial resources. Consequently, countries may possess substantial levels of digital connectivity while remaining dependent on external actors for the development and control of advanced AI systems. Heeks argues that digital inequality in the Global South can no longer be understood exclusively through exclusion from digital systems because participation itself may produce unequal outcomes when more powerful actors capture a disproportionate share of the value generated by digital activities [1].

The distribution of AI capabilities therefore represents an important dimension of the contemporary Global North–South divide. Countries with advanced AI ecosystems possess greater capacity to develop foundational models, control digital platforms, attract investment, generate intellectual property, and establish technological standards. In contrast, many developing countries participate primarily as consumers of externally developed technologies, providers of data and digital labour, or markets for algorithmic products. Such asymmetry creates a structural distinction between those who design and govern algorithmic systems and those whose social and economic activities become increasingly subject to them. AI-related inequality is consequently not simply an issue of unequal access to technology; it is increasingly an issue of unequal control over the technological infrastructures and knowledge systems that determine how technology operates.

Data constitute a particularly important source of this asymmetry. The expansion of data-driven technologies has increased the ability of governments and corporations to classify populations, predict behaviour, allocate resources, and influence decision-making. Taylor conceptualizes this challenge through the idea of data justice, emphasizing that individuals and communities must be considered in terms of how they become visible, represented, classified, and treated through the data they generate [2]. In the context of AI, these concerns become more significant because data are not merely stored information but a fundamental input into machine-learning systems. Unequal control over data can therefore translate into unequal control over algorithmic knowledge, commercial value, and institutional decision-making.

The geographical concentration of AI research and infrastructure also has implications for technological sovereignty. The ability to develop AI independently requires more than access to finished software applications. It involves domestic research institutions, computing resources, skilled personnel, datasets, investment, semiconductor access, regulatory capacity, and intellectual-property capabilities. When these resources are externally controlled, countries may become dependent on foreign platforms and infrastructures even when AI adoption is extensive. Such dependency can restrict domestic innovation and reduce the capacity of governments and institutions to determine how AI should be developed according to local social, cultural, linguistic, economic, and developmental priorities.

The relationship between AI and historical structures of power has increasingly attracted attention through decolonial scholarship. Mohamed, Png, and Isaac argue that AI should be examined through postcolonial and decolonial perspectives because technological systems are embedded within broader intellectual, political, economic, and social structures of power [3]. This perspective is particularly relevant to the Global North–South divide because many AI systems are developed using datasets, assumptions, categories, languages, and institutional priorities that do not adequately represent the diversity of Global South populations. Algorithmic systems can therefore reproduce forms of epistemic and cultural inequality even when their technical performance appears efficient.

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Algorithmic power is also manifested through labour relations. The development and operation of AI systems involve extensive human labour, including data annotation, content moderation, platform work, data collection, and other forms of digital production. Much of this labour is geographically dispersed and may be performed in lower-income countries while the higher-value stages of AI development remain concentrated in technologically advanced economies. The resulting structure can produce an unequal distribution of value in which workers contribute essential inputs to AI systems without obtaining a proportionate share of the economic benefits generated from them. The concept of adverse digital incorporation provides a useful framework for understanding this phenomenon because it emphasizes situations in which participation in digital systems does not necessarily eliminate inequality and can instead enable powerful actors to extract disproportionate value from less-powerful participants [1].

AI can nevertheless provide substantial developmental opportunities for the Global South. Applications in agriculture, healthcare, education, disaster management, financial services, environmental monitoring, and public administration may improve productivity and expand access to essential services. The central issue is therefore not whether developing countries should adopt AI, but under what institutional, economic, and political conditions AI can contribute to inclusive development. Without appropriate governance and domestic capabilities, AI adoption may deepen technological dependency; with adequate investment and institutional capacity, it may support technological leapfrogging and strengthen developmental autonomy.

Against this background, the present paper examines AI as a form of algorithmic power and analyses its relationship with global inequality. Particular attention is given to disparities in computational infrastructure, data ownership, research capacity, digital labour, linguistic representation, technological sovereignty, and AI governance. The paper argues that the Global North–South AI divide should be understood as a structural inequality involving not merely access to AI technologies but the ownership, production, control, and governance of algorithmic systems. Addressing this divide consequently requires a shift from technology transfer and passive adoption toward capacity building, equitable knowledge production, local technological development, data justice, and meaningful participation of Global South actors in international AI governance.

2. Literature Review

2.1 Digital Inequality and the Global South

Early scholarship on technological inequality largely conceptualized the problem through the digital divide, focusing on unequal access to information and communication technologies. This perspective established that differences in connectivity, hardware, affordability, digital skills, and technological infrastructure could reproduce existing socioeconomic inequalities. However, increasing digital participation has complicated the assumption that inclusion necessarily produces equitable outcomes. Heeks demonstrates that digital systems in the Global South can generate inequality even among populations that are already digitally included. His concept of "adverse digital incorporation" emphasizes relationships in which technologically or economically advantaged actors extract disproportionate value from the work or resources of disadvantaged groups [1]. This framework is particularly relevant to AI because participation in AI-enabled systems may expose individuals and economies to new forms of dependency without providing equivalent control over the technologies involved.

The shift from access-based inequality toward structural digital inequality is important for understanding contemporary AI. AI systems require substantially greater resources than conventional digital technologies, including large datasets, advanced computing infrastructure,

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specialized technical expertise, and considerable financial investment. Consequently, the AI divide may be substantially more concentrated than the conventional digital divide. A country may have widespread internet access and substantial digital adoption while remaining dependent on foreign companies for foundational models, cloud computing, AI hardware, and algorithmic infrastructure. This creates a distinction between digital participation and technological autonomy.

2.2 Data, Classification, and Data Justice

Data have become a central resource in contemporary algorithmic economies. The increasing collection and processing of digital information enables institutions to classify individuals, predict behaviour, assess risk, and make decisions at unprecedented scale. Taylor argues that the expansion of data-driven systems requires a concept of data justice because technological systems determine how individuals become visible, represented, classified, and treated [2]. Her framework emphasizes visibility, engagement with technology, and discrimination as interconnected dimensions of justice.

The concept of data justice provides an important foundation for understanding AI-related inequality. Machine-learning systems depend heavily on the availability and quality of training data. When populations, languages, occupations, cultural practices, or socioeconomic conditions are inadequately represented in datasets, AI systems may perform unevenly across different groups. At the international level, this creates an additional asymmetry because data generated by populations in the Global South may contribute to commercially valuable AI systems whose ownership and economic benefits are concentrated elsewhere. Data therefore function simultaneously as an informational resource, an economic asset, and a source of algorithmic power.

2.3 Algorithmic Bias and Structural Inequality

Research on algorithmic bias has challenged the assumption that computational systems are inherently objective. Algorithms are designed within social institutions and trained on data reflecting existing social conditions. Consequently, discriminatory patterns can enter AI systems through data selection, classification methods, model design, deployment environments, and institutional decision-making. Algorithmic discrimination should therefore be understood as a sociotechnical phenomenon rather than merely a programming error.

The relevance of this literature extends beyond inequalities within individual countries. Global AI systems may also reproduce geographical and cultural biases because their training datasets and development environments are concentrated in particular regions. Languages, cultural practices, legal systems, and social conditions that receive limited representation may consequently be inadequately recognized by AI systems. This produces an international dimension of algorithmic bias in which populations in the Global South can be subjected to technologies designed primarily around assumptions developed elsewhere.

2.4 Decolonial Perspectives on Artificial Intelligence

Decolonial scholarship provides a particularly important theoretical contribution to the study of AI and global inequality. Mohamed, Png, and Isaac argue that AI should be understood through the historical structures of power that shape knowledge production, technological development, and social organization [3]. Their analysis challenges the assumption that technological systems can be separated from the political and cultural contexts in which they are created.

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From this perspective, algorithmic systems may reproduce colonial patterns when knowledge, data, labour, and resources are extracted from less-powerful populations while decision-making authority remains concentrated among technologically dominant institutions. Decolonial AI therefore involves more than improving the technical fairness of algorithms. It requires examination of who defines technological objectives, whose knowledge is included, whose languages are represented, who owns the infrastructure, and who has the authority to determine acceptable forms of AI deployment [3].

This literature is especially relevant to the Global North–South divide because the dominant AI ecosystem remains highly concentrated in technologically advanced countries and multinational corporations. The resulting asymmetry can create a form of technological dependency in which developing countries adopt systems without possessing equivalent capacity to modify, audit, govern, or replace them. Decolonial approaches consequently broaden the discussion from algorithmic fairness toward questions of technological sovereignty, epistemic diversity, and institutional power.

2.5 AI, Digital Labour, and Unequal Value Creation

Another important strand of literature concerns the labour required to construct and maintain digital and AI systems. Although AI is frequently presented as an autonomous technological capability, its development depends on extensive human activities such as data collection, annotation, content moderation, quality assessment, and platform-based work. These activities are frequently distributed across international production networks.

The concept of adverse digital incorporation is useful in this context because it highlights how participation in digital economies can coexist with unequal value distribution [1]. Workers and communities may provide essential inputs to digital systems while receiving only a small proportion of the economic value generated by those systems. In AI supply chains, this problem can occur when lower-value and labour-intensive activities are geographically displaced toward lower-income regions while high-value activities such as model development, intellectual-property ownership, platform control, and commercialization remain concentrated elsewhere. This creates a form of algorithmic economic inequality that cannot be captured through measures of technology access alone. Understanding the AI divide therefore requires examination of the entire value chain, including data production, labour, computing, model development, deployment, ownership, and commercialization.

2.6 Research Gap

The existing literature establishes several important dimensions of digital and algorithmic inequality, but these perspectives are frequently examined separately. Digital-divide research emphasizes access and participation; data-justice scholarship emphasizes representation and discrimination; decolonial scholarship focuses on historical power and knowledge structures; and digital-development research examines unequal incorporation and value extraction [1]–[3]. A more integrated framework is required to explain how these dimensions interact within the emerging global AI economy. The principal gap concerns the relationship between **algorithmic capability and international structural power**. AI inequality is not adequately explained by differences in access to AI applications because the deeper issue concerns who controls the resources required to create, train, deploy, and govern advanced AI systems. Computational infrastructure, data, research capacity, intellectual property, technical expertise, digital labour, and regulatory influence operate together to determine the distribution of algorithmic power. Accordingly, this paper extends the existing literature by treating the Global North–South AI divide as a multidimensional structural phenomenon. It connects digital inequality, data justice, algorithmic power, technological dependency, digital labour, and

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decolonial theory to explain how AI may reproduce global economic and political inequalities while simultaneously offering opportunities for developmental transformation. This integrated perspective provides the basis for examining not only who has access to AI, but also **who produces it, who owns it, who governs it, whose knowledge it represents, and who captures the value generated by it**.

3. Dimensions of the Global AI Divide

3.1 Computational and Digital Infrastructure

Artificial Intelligence is substantially more infrastructure-intensive than conventional digital technologies. The development of advanced AI requires high-performance computing, graphics processing units, cloud platforms, high-capacity data storage, reliable electricity, high-speed networks, and specialized technical expertise. These resources are unevenly distributed across the international system, creating a significant structural advantage for technologically advanced economies. Countries possessing extensive computational infrastructure can develop and deploy increasingly sophisticated models, while countries lacking such infrastructure often remain dependent on foreign cloud providers, platforms, and technological suppliers.

This disparity is particularly important because computational capacity is becoming a strategic resource comparable to other critical technological infrastructures. The concentration of advanced computing facilities and AI research laboratories in a limited number of countries allows technologically dominant economies and corporations to determine the direction of AI innovation. Developing countries may consequently experience AI primarily through imported applications rather than through domestic technological production. Such dependency limits their ability to independently determine model architecture, training priorities, data governance, security standards, and deployment conditions [3], [6].

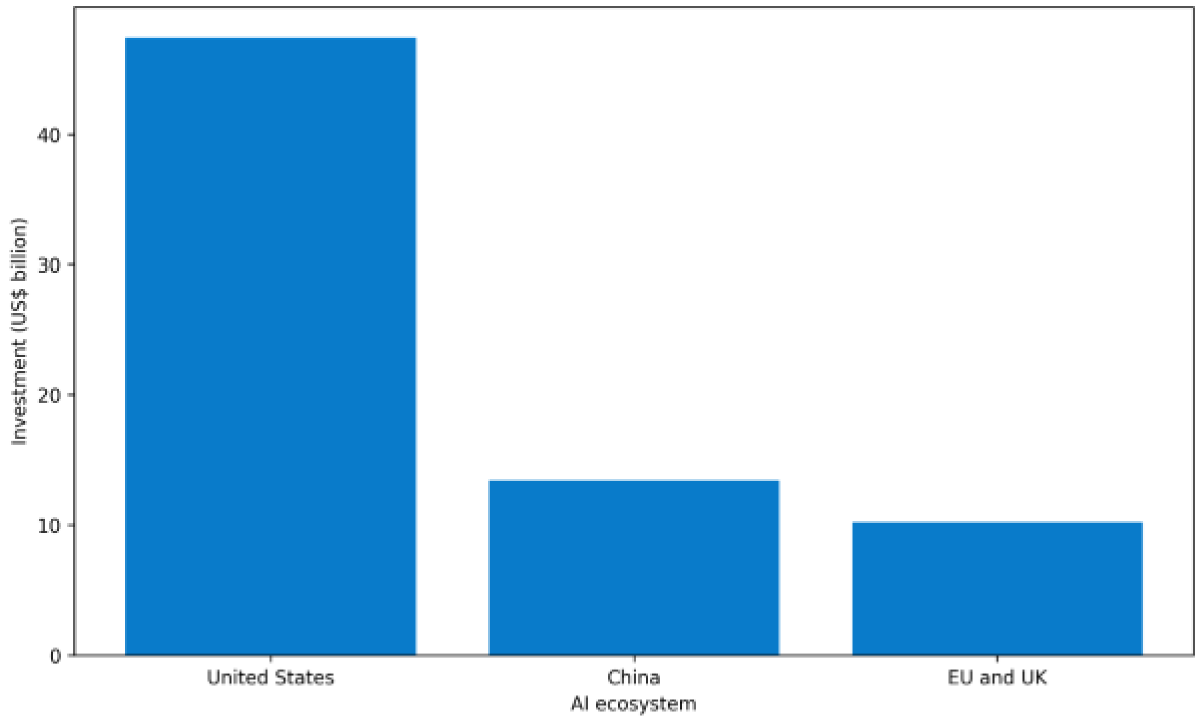

Figure 1. Private investment in artificial intelligence by major AI ecosystems in 2022.

3.2 Data Ownership and Extraction

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Data constitute one of the principal productive resources of AI. Large-scale datasets enable machine-learning systems to identify patterns, generate predictions, automate classifications, and improve performance. However, the geographical production of data does not necessarily correspond to ownership of the resulting technological and economic value. Individuals, communities, businesses, and governments in developing countries generate substantial quantities of digital data, while the infrastructure required to aggregate, process, analyse, and commercialize these data may be controlled by external corporations. This asymmetry creates a form of data extraction in which populations become sources of commercially valuable information without acquiring proportional control over its subsequent uses. Data justice scholarship demonstrates that the consequences extend beyond privacy because data systems influence visibility, representation, participation, and discrimination [2]. In AI, these concerns become more consequential because datasets can be transformed into predictive models and automated decision-making systems whose effects extend across entire populations.

3.3 AI Research, Human Capital, and Innovation Capacity

AI innovation is strongly associated with research universities, specialized laboratories, venture capital, intellectual property, high-skilled labour, and access to advanced computing. These resources remain disproportionately concentrated in a relatively small group of technologically advanced economies. The resulting concentration creates cumulative advantages: countries with stronger AI ecosystems attract researchers and investment, generate more intellectual property, establish research networks, and subsequently become more attractive destinations for additional capital and talent. For many Global South countries, limited research financing and institutional capacity are compounded by the migration of highly trained researchers toward better-funded international laboratories. This creates a cycle in which countries with weaker AI ecosystems struggle to build the human and institutional capabilities necessary to become technologically independent. AI development therefore has the potential to intensify existing inequalities in scientific and technological capacity rather than simply reflecting them.

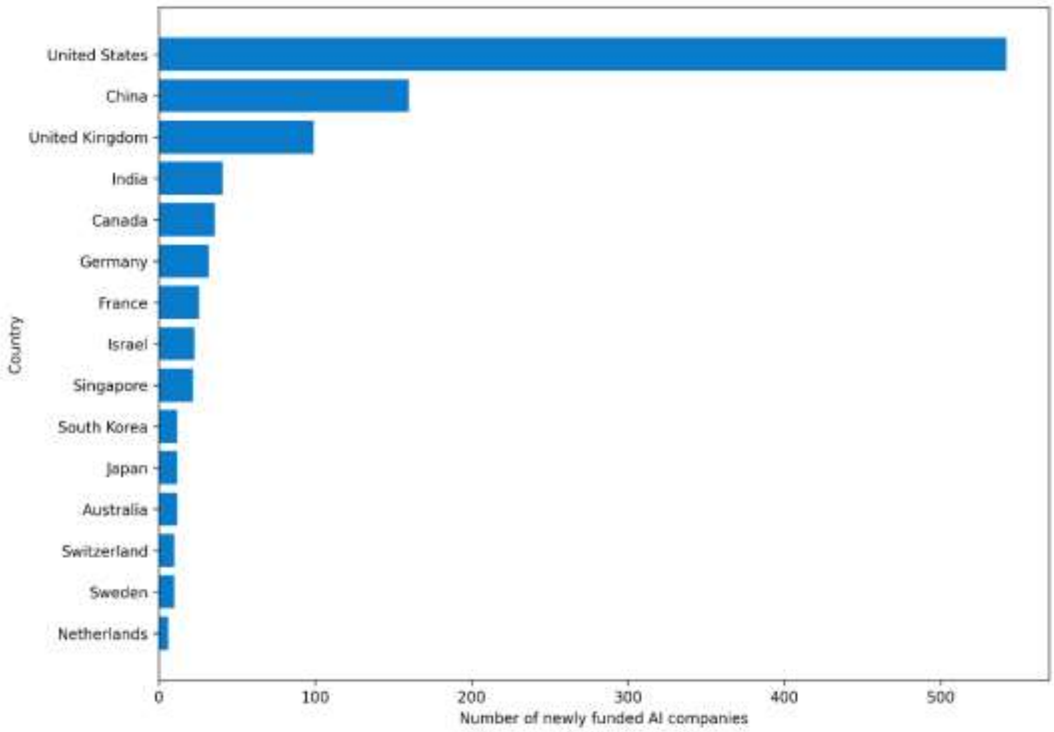

Figure 2. Geographical distribution of newly funded AI companies in 2022.

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3.4 Language, Culture, and Epistemic Inequality

The representational capacity of AI systems is uneven across languages and cultures. Major AI models have historically benefited from disproportionately large quantities of digitally available material in dominant languages, particularly English. Languages with smaller digital footprints may receive substantially less representation in training datasets, benchmarks, language resources, and commercial AI applications. This can produce differences in system performance and accessibility across linguistic communities.

The issue is not merely technical accuracy. Language embodies cultural knowledge, social relationships, historical experience, and locally specific forms of meaning. Underrepresentation of Global South languages and knowledge systems can consequently produce epistemic inequality. Decolonial scholarship argues that technological systems should be examined in relation to whose knowledge is recognized as authoritative and whose perspectives are excluded [3]. AI systems developed primarily around Northern datasets and assumptions may therefore reproduce a hierarchy of knowledge even when they are deployed globally.

3.5 Digital Labour and Unequal Distribution of Value

AI development depends on extensive human labour that remains relatively invisible in narratives portraying AI as autonomous intelligence. Data annotation, image classification, transcription, content moderation, data cleaning, evaluation, and other activities are necessary for producing usable AI systems. These activities can be outsourced to workers in lower-income economies where labour costs are comparatively low.

This international division of labour creates an asymmetry between the location of labour and the location of value capture. Workers may perform essential tasks while the ownership of platforms, algorithms, intellectual property, and commercial applications remains concentrated elsewhere. The concept of adverse digital incorporation provides a useful explanation because participation in the digital economy does not automatically result in equitable development; disadvantaged participants can become integrated into systems under conditions that primarily benefit more powerful actors [1].

3.6 Unequal Access to AI Benefits

AI has considerable potential to improve agricultural forecasting, disease diagnosis, educational access, financial services, environmental monitoring, disaster response, and public administration. However, access to these benefits depends on infrastructure, affordability, institutional capacity, skilled personnel, data availability, and appropriate regulation. Consequently, the countries most capable of exploiting AI may also be those already possessing stronger technological and economic foundations.

The resulting pattern can create a cumulative advantage. Wealthier economies use AI to increase productivity and innovation, generating additional resources for further technological investment, while countries with limited capacity may experience slower adoption or dependence on externally developed systems. AI can therefore function simultaneously as a mechanism of technological advancement and a mechanism for reproducing developmental inequality.

Table 1. Principal Dimensions of the Global AI Divide

Dimension	Global North Advantage	Major Global South Constraint	Inequality Outcome

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Computing infrastructure	Greater access to advanced computing and cloud capacity	Limited high-performance computing and capital	Dependence on external infrastructure
Data	Large-scale aggregation and processing capacity	Limited control over data ecosystems	Unequal data-derived value
Research capacity	Concentrated laboratories, funding and expertise	Lower research investment and talent migration	Persistent innovation gap
Intellectual property	Strong ownership of AI technologies and platforms	Dependence on imported technologies	Technological dependency
Language resources	Extensive digital resources for dominant languages	Underrepresented local and indigenous languages	Linguistic and epistemic exclusion
Digital labour	Concentration of high-value AI employment	Outsourcing of lower-value tasks	Unequal value distribution
Venture capital	Greater availability of AI investment	Limited domestic AI financing	Uneven commercialization
Governance capacity	Greater influence over standards and regulation	Lower representation in global rule-making	Governance asymmetry
AI applications	Greater ability to integrate AI into institutions	Infrastructure and affordability constraints	Unequal developmental benefits

4. Algorithmic Power and Mechanisms of Inequality

4.1 Algorithmic Power as a Form of Institutional Power

Algorithmic systems increasingly perform functions traditionally undertaken by human institutions. They rank individuals, classify information, assess risk, recommend decisions, allocate resources, detect suspicious behaviour, and determine eligibility for services. This expansion means that algorithms increasingly participate in the distribution of social and economic opportunities.

Algorithmic power therefore extends beyond the technical operation of software. It involves the authority to define categories, determine relevant data, establish evaluation criteria, and translate computational predictions into institutional decisions. Noble's analysis of algorithmic systems demonstrates how seemingly neutral technological processes can reproduce social hierarchies and discriminatory representations [7]. In the international context, the question becomes whose assumptions are embedded within globally deployed AI systems and whose interests influence their design.

4.2 Algorithmic Bias and Automated Discrimination

Bias can enter AI systems through training datasets, data collection practices, model objectives, classification systems, deployment environments, and institutional decision-making. Historical

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inequalities represented in datasets can consequently be reproduced by automated systems. Benjamin's analysis of the "New Jim Code" demonstrates how technological systems can reproduce racialized inequalities while appearing objective or technologically neutral [5]. Noble similarly shows that algorithmic classification can reinforce social stereotypes and unequal representations [7].

For Global South populations, algorithmic discrimination may occur when systems developed using datasets from other geographical and cultural contexts are deployed without adequate local validation. Such systems may incorrectly classify individuals, misunderstand local languages, produce inappropriate recommendations, or reproduce assumptions that do not correspond to local social conditions. The problem therefore involves both conventional algorithmic bias and the broader issue of contextual mismatch.

4.3 Platform Concentration and Corporate Power

The contemporary AI ecosystem is characterized by substantial concentration of technological capabilities among large corporations and research institutions. Control over computational infrastructure, proprietary datasets, cloud platforms, foundational models, application programming interfaces, and intellectual property gives these organizations considerable influence over the direction of AI development.

Corporate concentration can create dependency even when AI services are widely available. A country may have access to advanced AI applications without possessing the ability to independently reproduce or modify the underlying technology. This distinction between **access and control** is fundamental to understanding algorithmic inequality. Access allows participation in an existing technological system; control provides the ability to determine how that system evolves.

4.4 Data Extraction and Global Value Chains

AI-related value chains frequently separate the production of raw inputs from the ownership of high-value technological outputs. Individuals generate behavioural data, workers perform data-processing activities, and communities provide social and cultural information, while corporations may transform these resources into commercially valuable models and services.

This structure resembles broader patterns of unequal global value distribution. The critical difference is that data can be continuously generated and extracted at enormous scale. Consequently, data-intensive business models can produce persistent asymmetries between those who contribute informational resources and those who possess the technical infrastructure to monetize them. Data colonialism provides a useful analytical framework for interpreting this process because it connects contemporary data extraction with longer historical patterns of resource appropriation and unequal power [3], [4].

4.5 Technological Dependency and Sovereignty

Technological sovereignty refers to the capacity of states and societies to make meaningful decisions concerning critical technologies without excessive dependence on external actors. In AI, sovereignty involves access to computing, domestic expertise, data infrastructure, research institutions, open technological resources, and effective regulatory capabilities.

Technological dependency becomes problematic when governments or organizations cannot adequately audit, modify, replace, or negotiate the systems upon which they depend. This dependency may also constrain policy choices because the technological standards established by dominant firms and countries can become de facto global standards. Developing countries

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therefore face a strategic challenge: adopting foreign AI systems may produce immediate efficiency gains but can simultaneously deepen long-term technological dependence.

4.6 AI Governance and Unequal Political Representation

The governance of AI increasingly involves international standards, ethical frameworks, technical norms, trade arrangements, intellectual-property rules, privacy regulations, and human-rights principles. However, technological capacity influences the ability of states and institutions to participate effectively in these processes.

Global South participation in AI governance is essential because AI systems operate across jurisdictions and affect populations with substantially different social, economic, and legal conditions. Png emphasizes the importance of greater participation of Global South stakeholders in AI governance and argues that governance frameworks should not be shaped exclusively by institutions from technologically dominant countries [10]. Without broader participation, global AI standards may inadvertently reflect the interests and assumptions of the countries and corporations with the greatest technological resources.

Table 2. Mechanisms Through Which Algorithmic Power Can Reinforce Global Inequality

Mechanism	Primary Source of Power	Effect on Global South	Long-Term Implication
Computational concentration	Advanced computing and cloud infrastructure	External technological dependence	Reduced technological autonomy
Data extraction	Control over data aggregation and processing	Loss of economic and informational value	Persistent data dependency
Algorithmic classification	Proprietary models and decision systems	Contextual and representational bias	Institutional inequality
Platform concentration	Control over digital platforms	Limited bargaining power	Corporate dependency
Intellectual property	Patents, proprietary models and software	High adoption and licensing costs	Innovation constraints
Digital labour outsourcing	Labour-cost differentials	Low-value employment concentration	Unequal value capture
Knowledge concentration	Research institutions and expert networks	Limited domestic knowledge production	Persistent innovation gap
Standard-setting	Regulatory and technological influence	Limited representation	Asymmetric AI governance
Linguistic dominance	Large datasets in dominant languages	Poor performance for local languages	Cultural and epistemic exclusion

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5. Global South Perspectives and Pathways Toward Algorithmic Equity

5.1 Technological Sovereignty

Reducing the global AI divide requires strengthening domestic technological capabilities rather than relying exclusively on imported AI applications. Public investment in computing infrastructure, digital networks, research institutions, open-source technologies, and skilled human resources can provide the foundations for greater technological autonomy.

Technological sovereignty does not necessarily imply complete technological self-sufficiency. Rather, it involves sufficient domestic capability to evaluate, negotiate, adapt, audit, and govern critical technologies. Strategic partnerships can therefore coexist with sovereignty when countries retain meaningful control over essential technological decisions.

5.2 Locally Grounded and Inclusive AI

AI systems should be developed around local languages, cultural contexts, institutional conditions, and developmental priorities. Greater investment in regional-language datasets and locally generated knowledge can improve system performance while reducing epistemic exclusion.

Community participation is also important. AI systems affecting welfare, healthcare, education, agriculture, employment, and public administration should incorporate the perspectives of the populations that use and experience them. Such participation can reduce the gap between technological design and social requirements.

5.3 Strengthening AI Research and Human Capital

Universities and public research institutions should constitute central components of national AI strategies. Investment in AI education, interdisciplinary research, computing facilities, research grants, and international collaboration can help establish sustainable innovation ecosystems.

Capacity building should extend beyond highly specialized AI engineering. Legal scholars, social scientists, economists, ethicists, policymakers, linguists, and domain specialists are necessary for developing AI systems that are technically capable and socially appropriate. A multidisciplinary research ecosystem can also improve the ability of Global South institutions to participate in international AI governance.

5.4 South–South Cooperation

South–South cooperation provides an important alternative to exclusive dependence on North–South technology transfer. Developing countries often share comparable challenges involving linguistic diversity, infrastructure constraints, agricultural development, public-service delivery, informal economies, and resource limitations.

Collaborative development of datasets, AI models, research programmes, computing infrastructure, regulatory approaches, and educational resources could reduce duplicated costs and improve bargaining power. Such cooperation could also facilitate AI systems designed around developmental conditions that differ from those of technologically advanced economies.

5.5 Inclusive AI Governance

AI governance should include meaningful representation from developing countries, civil society, academic institutions, labour organizations, and affected communities. Governance

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mechanisms should address transparency, accountability, privacy, discrimination, labour rights, data ownership, environmental impacts, and equitable distribution of AI benefits.

The objective should not be to prevent AI adoption but to ensure that adoption occurs under conditions that protect public interests. A governance framework centred exclusively on innovation and competitiveness risks overlooking structural inequalities, whereas a framework combining innovation with rights, accountability, and distributive justice can better support inclusive development [6], [10], [11].

5.6 Decolonising AI Knowledge and Practice

Decolonising AI requires questioning assumptions about whose knowledge, languages, values, and developmental priorities shape technological systems. It involves greater inclusion of researchers and institutions from historically underrepresented regions in AI research, evaluation, standard-setting, and governance.

The objective is not simply to insert additional datasets from the Global South into existing AI architectures. More fundamentally, it requires recognizing that technological priorities themselves are socially and politically constructed. Decolonial approaches therefore advocate greater participation in determining what AI should accomplish, for whom it should be developed, and under what conditions it should be deployed [3], [8].

Table 3. Strategic Pathways for Reducing the Global AI Divide

Priority	**Key Intervention**	**Expected Outcome**
Computing capacity	Public and regional AI infrastructure	Reduced infrastructure dependency
Data sovereignty	Strong data governance and local data institutions	Greater control over data value
Human capital	AI education and interdisciplinary training	Expanded domestic expertise
Research	Public funding for AI research	Stronger innovation ecosystems
Local languages	Regional-language datasets and models	Greater linguistic inclusion
Digital labour	Fair wages and labour protections	More equitable value distribution
Open technologies	Open-source models and shared infrastructure	Lower barriers to innovation
South–South cooperation	Joint research and infrastructure programmes	Greater collective bargaining capacity
Governance	Inclusive national and international regulation	Improved accountability
Technological sovereignty	Domestic capacity to audit and adapt AI	Greater policy autonomy

6. Discussion

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6.1 AI as Both a Product and Producer of Inequality

The evidence reviewed indicates that AI does not create global inequality independently of existing economic and political structures. Instead, AI inherits inequalities in capital, infrastructure, education, research capacity, data ownership, and political influence. These inequalities subsequently influence who can develop and benefit from AI. AI can then reinforce the same disparities by increasing productivity and technological capabilities more rapidly in already advantaged economies.

This produces a cumulative relationship between technological capacity and economic power. Countries with greater resources can invest more heavily in AI, while AI-generated productivity gains provide additional resources for subsequent technological investment. Without deliberate redistributive and capacity-building measures, this cycle may widen the North–South divide.

6.2 From Digital Access to Algorithmic Control

The traditional digital divide is increasingly insufficient for analysing AI inequality. Internet connectivity and access to digital devices remain important, but AI introduces deeper questions concerning ownership, control, computational capacity, data, intellectual property, and governance.

The distinction can be summarized as follows:

Digital divide: Who can access technology?

AI divide: Who can develop, train, own, control, audit, govern, and economically benefit from technology?

The second question represents a considerably deeper form of inequality because it concerns the underlying architecture of technological power rather than only access to its outputs.

6.3 AI Is Not Technologically Neutral

The literature on algorithmic bias, digital inequality, and decolonial AI challenges the idea that AI systems operate independently of social values [3], [5], [7]. Data reflect social histories; algorithms embody design choices; models reflect training environments; and deployment decisions reflect institutional priorities.

Consequently, improving computational accuracy alone cannot guarantee equitable outcomes. A technically accurate system can still produce socially undesirable outcomes if the underlying objective, dataset, institutional context, or distribution of benefits is unequal. AI governance must therefore incorporate both technical evaluation and political-economic analysis.

6.4 Developmental Potential and Risks

AI presents genuine opportunities for developing countries. It can support precision agriculture, multilingual education, healthcare diagnostics, climate-risk assessment, financial inclusion, infrastructure management, and disaster preparedness. The ability to deploy AI without reproducing the entire technological trajectory of earlier industrial economies may provide opportunities for technological leapfrogging.

However, technological leapfrogging is not automatic. If AI applications depend entirely on external platforms, proprietary infrastructure, foreign data centres, and imported expertise, adoption may increase technological dependency. The developmental value of AI therefore depends on the institutional conditions under which it is introduced.

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6.5 Toward a More Equitable AI Order

A more equitable AI order requires a shift from **AI access** toward **AI capability and control**. Global South countries need opportunities to develop local research ecosystems, participate in technological design, negotiate data arrangements, protect digital labour, and influence international standards.

The objective should not be to establish an artificial technological separation between the Global North and Global South. Instead, international cooperation should facilitate equitable knowledge exchange, shared infrastructure, open research, responsible technology transfer, and reciprocal partnerships. Such an approach can convert AI from an instrument of technological dependency into a platform for shared development.

6.6 Integrated Analytical Framework

The relationship between AI and global inequality can be conceptualized through six interconnected layers: **resources → capabilities → production → deployment → governance → value distribution**. Unequal access to resources produces unequal technological capabilities; unequal capabilities influence who produces AI; production patterns shape deployment; deployment is influenced by governance; and governance determines, in part, how economic and social value is distributed.

This framework demonstrates why isolated interventions are unlikely to eliminate the AI divide. Improving connectivity without increasing computational capacity, strengthening research without addressing data sovereignty, or promoting AI adoption without improving governance may leave the underlying structure unchanged. A comprehensive strategy must therefore address the entire AI ecosystem.

Table 4. Integrated Framework for Analysing AI and Global Inequality

Layer	Central Question	Major Inequality
Resources	Who controls capital, data, computing and infrastructure?	Resource inequality
Capabilities	Who possesses technical and research expertise?	Knowledge inequality
Production	Who develops models, platforms and applications?	Innovation inequality
Deployment	Who receives useful and affordable AI applications?	Access and application inequality
Governance	Who establishes AI rules and standards?	Political inequality
Value distribution	Who captures economic and social benefits?	Distributional inequality

7. Conclusion

Artificial Intelligence is becoming a major source of global technological power, but its benefits and governing capabilities remain unequally distributed. The Global North–South AI divide extends beyond internet access to computing infrastructure, data ownership, research capacity, intellectual property, digital labour, linguistic representation, and regulatory influence. AI can reproduce existing inequalities when technological control remains

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concentrated among powerful states and corporations. However, it can also support inclusive development when countries build domestic capabilities, protect data and labour rights, develop local-language systems, strengthen research institutions, and participate meaningfully in AI governance. Achieving algorithmic equity therefore requires transforming Global South countries from predominantly technology consumers into active producers, co-designers, owners, and governors of AI technologies.

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