Digital Colonialism as an Economic Strategy: Engineered Inequality

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Abstract. While the systemic biases and discriminatory outcomes of AI are increasingly well-documented, this article argues that these dynamics also facilitate a subtler, less examined form of neo-colonialism that disproportionately affects Africa due to enduring historical and structural power imbalances in the global digital ecosystem. A pertinent question, however, is whether unethical biases are deliberate or unintended. This paper examines the intrinsic algorithmic biases that disproportionately marginalize communities in Africa, critically analyzing whether these computational systems replicate and reinforce entrenched historical power asymmetries, and to what extent this occurs intentionally, through the lens of postcolonial theory. Through an analysis of ownership structures, capital flows, and policy decisions in AI development and deployment, this paper demonstrates that digital discrimination reflects both structural reproduction of inequality and increasingly deliberate institutional choices. While some bias emerges from inherited systemic patterns, the systematic elimination of equity safeguards and declining of inclusive AI commitments by actors with full knowledge of consequences reveals that exclusion has become a foreseeable outcome of deliberate policy decisions within technological ecosystems that reflect and reproduce colonial-era hierarchies of power and knowledge.

Keywords: AI, AI in Africa, algorithmic bias, digital discrimination, colonialism

1 Introduction

The South Korean economist Ha-Joon Chang asserts: “Economics has become like Catholic theology in medieval Europe. It has become the language of the rulers... they are not going to let you speak it unless you belong to the priesthood or are from an extremely privileged background.” [1] In essence, Chang's statement highlights how the exclusivity of economics can perpetuate systemic biases and discrimination, limiting the field's ability to serve the broader public interest. The insularity and complexity of contemporary economics serve as barriers to democratic deliberation and social change just as Latin and theology became exclusionary. If artificial intelligence (AI) is central to the current economic system, then the biases embedded in AI algorithms will perpetuate exclusion. This paper demonstrates the exclusionary nature of AI systems by providing a case study on racial bias, revealing how algorithmic decisions can systematically disadvantage certain groups. Racial bias refers to the systematic and often unintended discrimination that occurs when AI systems produce outcomes that disadvantage individuals or groups [2]. Based on existing capital and ownership structures, an argument is then made that this bias may not be incidental but rather a deliberate tool to perpetuate new and pervasive forms of colonialism.

2 AI, the Global Economy and Neo-Colonial Models

AI has emerged as a transformative force in the global economy. Its applications have revolutionized entire industries and offered unprecedented opportunities for innovation and human advancement. There are compelling arguments that it has now become the central driver of the global economy. AI is projected to contribute $15.7 trillion to global GDP by 2030 [3]. However, with the current status quo, this projection is expected to have a significantly smaller impact on Africa. Collectively Africa, Oceania, and some less developed Asian markets could grow by just $1.2 trillion or 5.6% GDP growth [4]. Marwala [5] argues that Africa is increasingly viewed as a passive actor because it is not innovating on the scale of the US or China, for example. This assertion provides a context for understanding why the continent has been forced into a dependency role which is counter to the developmental needs of the continent.

This disparity is not only economic but structural. Inequity in this regard is not just confined to delayed adoption or a lack of infrastructure but also reflects deeper structural inequalities that shape the development, deployment, governance and even impact of these technologies [6] [7]. AI carries deeply problematic undercurrents of systemic bias that lead to digital discrimination resulting in a new form of colonialism that disproportionately and negatively impacts Africa because of a persistence of historical power imbalances. While bias, in its simplest sense, denotes a tendency or inclination within data that can produce either favorable or unfavorable outcomes depending on its context, this paper specifically examines biases that result in unfair or unethical consequences. Although the primary focus of this paper is racial bias in particular, it acknowledges that bias can intersect with other factors, such as gender and class and thus cannot be viewed in a silo. Menon [8] asserts that the assumed neutrality of AI systems is a misrepresentation as there are both overt and covert biases embedded in the algorithms that inform these systems. In terms of racial bias, she argues that Africa and the African diaspora are disproportionately impacted by this misrepresentation. These biases thus create new and pervasive colonial pathways resulting in the “algorithmic colonization of Africa” [9]. Such harms are not abstract and range from biased facial recognition systems to data extraction practices that replicate exploitative economic models [10]. The import of this argument is that power and influence exerted by the West is reminiscent of historical patterns of colonialism. The implications for Africa cannot be underplayed as it strips citizens of autonomy, can be exploitative and could erode local cultures and identities [9]. There is an argument to be made that this new form of colonization has led to developmental challenges in Africa, which if unchallenged will persist [9]. Within digital spaces, challenges to sovereignty, economic exploitation and cultural imposition take place [8]. Given the current power dynamics and concentration of AI, Priya and Arockiasamy [11] caution that developing countries may become dependent on AI technologies developed elsewhere thus perpetuating a cycle of technological and economic subordination. This could be further exacerbated by the prioritization of Western values and norms in these systems. The emerging challenges of algorithmic bias could undermine the very principles of autonomy and justice. This debate draws parallels between historical colonization practices and the current digital landscape which is controlled and powered by the West.

While the rhetoric around bias is usually centered around divisions between the Global North and the Global South, there is merit in honing into Africa specifically. While Kloß [12] and Levander and Mignolo [13] argue that the Global South is a political and ideological construct that emerges in response to global inequalities and power struggles, there are significant disparities within this grouping. Prashad [14] and Kloß [12] thus caution against viewing the Global South as a homogeneous entity. The degrees of separation are apparent in understandings of AI power dynamics. AI power concentration lies in the West and in China to a slightly lesser extent. Recent estimations, however, indicate that China is quickly closing the gap, particularly following the launch of DeepSeek’s generative model in January 2025. Lee [15] states: “Previously I think it was a six to nine month gap and behind in everything. And now I think that's probably three months behind in some of the core technologies, but actually ahead in some specific areas.” This indicates that the Global South cannot be viewed as a single unit as there are differing levels of AI development and deployment with areas in Asia emerging as significant global competitors. Africa thus emerges as a unique case study in any exploration about algorithmic bias. Africa has been referred to as the center of the Global South but as Yeats writes in ‘The Second Coming’, “Things fall apart; the center cannot hold.” [16] While Africa is positioned as the center, there are forces both external and internal that threaten to make real the fate Yeats describes as “mere anarchy is loosed upon the world” This has proved an accurate sentiment in the case of Africa’s AI development and deployment. Tran [17] argues: “While there are questions about whether some countries—such as China or Russia—should be considered parts of the Global South (GS), it is obvious that Africa is at the center of the group. Different aspects of Africa—its potential, its reality, and its efforts to realize its potential— embody the challenges and the prospects of the GS in general. More specifically, the difficulties Africa faces, how it will deal with them, its progress or lack of progress, and the changes it would like to see in the current international economic and financial system to help it overcome the obstacles to development, help make clear what the GS is all about." The position adopted is that Africa is central to the Global South, encapsulating both the challenges and prospects faced as its experiences reflect broader issues of development and economic growth. The continent's efforts to overcome its difficulties and navigate the international economic system provide insight into the core concerns and aspirations of the Global South as a whole. An example of this is Africa's marginalization during the global COVID-19 vaccine rollout. While wealthier nations in the Global North hoarded vaccine doses, African countries were left to rely on donations or delayed shipments. This experience prompted calls for greater health sovereignty as African nations called for patent waivers. In this way, African nations were able to articulate Global South concerns around equity and access [18].

Africa's vulnerability globally and within the Global South thus raises an important question with regards to whether these biases within algorithms are deliberate or unintended. There is an argument to be made that existing uneven power structures enable bias and thus discrimination. While overt malice may not always be present, the persistence of unequal global power structures suggests that bias is not simply accidental, it is enabled and perpetuated by those who hold power. Control of AI is confined to a few large tech companies prompting the question, who controls the development and deployment of AI and consequently, who benefits from its value [19]? Menon [8] calls for the critical examination of AI's technological and power structures to prevent perpetuating historical inequalities. Although somewhat dated considering the rapid proliferation of AI and the extraordinary jump in adoption during the COVID-19 period, the Center for Security and Emerging Technology (CSET) provides valuable information on capital concentration and there seems to be little change in this regard [20]. As of 2019, the United States led the global AI investment market, attracting $25.2 billion (64% of global AI investment) across 1,412 transactions, with total global AI equity investment reaching $40 billion across 3,100 transactions. While China's AI investment surged between 2015 and 2017, it declined to near-2015 levels by 2019 attributed primarily to overexpansion in previous years [21]. In the same period, AI investment in Western Europe, Israel, India, Japan, and Singapore grew rapidly. More recently, a 2024 Ascendix report found that the US dominates AI startup funding with an estimated 5,509 AI startups, which attracted $47 billion in non-governmental funding in 2022. China follows with 1,446 AI startups and $95 billion in private AI investments that year. China is certainly seeing a rebound since its 2019 slump. As Morgan

Stanley [22] phrased it, “a sleeping giant awakens”. This is driven by strong government support and a focus on efficiency and cost-effectiveness. Despite challenges from US restrictions, China is pursuing AI self-sufficiency within five years and adopting open-source models The UK ranks third, with its AI market projected to reach $1 trillion by 2035. OpenAI leads global AI funding with $11.3 billion, followed by Anthropic at $7.7B and Databricks at $4B. These firms receive significant backing from tech giants such as Microsoft, Google, and Amazon. Corporate capital spending on AI infrastructure is immense, with Google, Microsoft, Meta, and Amazon investing $52.9 billion in the second quarter of 2024. This has increased significantly in 2025. The combined profits of these companies surged to $92.17 billion in the second quarter of 2025. Infrastructure investments are also projected to total $350 billion by the end of this year [23]. With the likes of DeepSeek and humanoid robots emerging, China could very well be considered back in the race. It is projected that China’s core AI market could reach $140 billion by 2030. AI could therefore contribute an extra 0.2–0.3 percentage point to annual GDP growth over the next few years.

While these statistics provide insight into the concentration of power globally, there are further insights into the racial makeup of these companies that indicate why bias is ingrained in these systems. Research from 2022 [24] found that only 25% of AI solution developers, on average, come from racial or ethnic minority groups while 29% of organizations have no minority employees working on AI solutions at all. Despite these damning figures, only a third of these companies have targeted programs to increase this number. Even then, these programs are disproportionately targeted at improving just gender diversity while largely overlooking ethnic diversity. This suggests that bias, and racial bias in particular, may not be accidental or incidental. Existing power structures don't just enable bias, but potentially manufacture it systematically. For example, three major facial-analysis programs were found to have significant skin-tone and gender biases, with error rates under 1% for light-skinned men but up to nearly 47% for darker-skinned women [25]. The study by MIT and Stanford researchers [25] demonstrates how training data dominated by white, male faces skews AI accuracy. Their findings raise concerns about systemic discrimination in commercial AI systems. The study concludes that existing power structures not only overlook marginalized groups but embed their exclusion into supposedly objective technologies. This bias thus isn’t merely a technical flaw but rather a consequence of systemic decisions about whose data is collected and valued and whose experiences are rendered invisible in technological design. These outcomes reflect global hierarchies of race, gender, geography, and capital. Bias is thus not incidental but institutionalized. As this paper demonstrates, ownership and control become crucial indicators of potential deliberate discrimination. As control of AI development is centralized in Western (primarily US) and Chinese tech ecosystems, these companies have minimal representation from or accountability to African contexts. As the ownership metrics and investment figures show, the US and

China constitute the twin poles of AI innovation and infrastructure. These powers hold data, talent, computing power as well as the geopolitical leverage to shape global AI trajectories. Africa could thus be considered enslaved by these AI powers as it sits on the periphery and the receiving end of AI. The outsider phenomenon amplifies Africa's marginalization, where its people are subject to external systems and biases without meaningful participation or agency in the creation or oversight of these transformative technologies. The lack of diverse development teams inherently embeds particular worldviews and assumptions. While there is little information on the exact makeup of these teams, the 2025 turnaround on diversity, equity, and inclusion (DEI), which the White House [26] has termed “shameless discrimination” is certainly an indictment. Furendal [19] argues that the prevailing private ownership model also poses systemic challenges that cannot be effectively addressed through regulation alone, indicating a pressing need for alternative ownership models to ensure more equitable control. This very clarion call stands in opposition to current policies. The scrapping of DEI by the Trump administration does not bode well for shifting dynamics in the US. This could stand in direct opposition to the argument for localized systems considering where capital flows stem from. A Forbes report [27] found that as of 24 March 2025, at least 39 major companies have rolled back or eliminated their DEI initiatives. The technology thus creates value for developers and owners and those that look like them and not necessarily for those experiencing its effects. Calvin and Leung [28] suggest that the current strategies employed by AI developers can lead to exclusionary practices. For example, while many AI companies are patenting their technologies to protect against infringement lawsuits and to maintain a competitive edge, they also share research to attract talent and customers. This dual approach raises concerns about how open they are willing to be. Furthermore, the presence of ‘patent trolls’ or entities that hold patents solely for litigation purposes without producing any products can create an environment where companies may become more secretive about their innovations to avoid lawsuits. In January 2025, the White House [29] also released an executive order aimed at reinforcing the United States' leadership in AI by ensuring its development remains free from ideological bias and regulatory barriers. Then, in February, both the US and the UK declined signing a ‘Statement on Inclusive and Sustainable AI’ at the Paris AI Action Summit. At the summit vice president JD Vance [30] declared that the US’s priority is competitiveness, adding: “The AI future is not going to be won by hand-wringing about safety.” Consequently, there are concerns that AI companies supplying the US government may face pressure to remove safety measures if they are seen as supporting DEI or hindering innovation, which could lead to fewer safeguards in AI products. Bishop [31] argues: “All signs suggest the Trump administration favors a reduction in the ethical regulation of AI. The executive orders may be interpreted as allowing or encouraging the free expression and generation of even discriminatory and harmful views on subjects such as women, race, LGBTQIA+ individuals and immigrants.”

These examples reflect broader concerns about the alignment of unaccountable technological power with state interests. The growing influence of tech executives in shaping both public policy and military applications represents surveillance capitalism's capture of democratic institutions [32]. In this scenario, private economic interests increasingly determine public technological trajectories. As governments eliminate safety frameworks while simultaneously expanding military AI investments, it raises concerns about authoritarian applications of AI [33]. These applications erode democratic norms as power is centralized through opaque corporate-state partnerships that operate beyond meaningful public oversight [34].

A fitting example of the potential dangers of this approach is the chatbot Tay that was launched by Microsoft in 2016 to learn human speech patterns through Twitter interactions [35]. However, it was shut down within 24 hours after generating racist, sexist, and anti-Semitic tweets. In response, Microsoft [36] released a statement stating: “Looking ahead, we face some difficult – and yet exciting – research challenges in AI design. AI systems feed off of both positive and negative interactions with people. In that sense, the challenges are just as much social as they are technical. We will do everything possible to limit technical exploits but also know we cannot fully predict all possible human interactive misuses without learning from mistakes.” Zemčík [37] asks if the failure of Tay was inherently malicious, flawed, and ineffective, or whether our judgment is influenced by cognitive shortcuts and biases. The author argued that the chatbot “held up a mirror to people about how things were in reality—as if it had a mind of its own.” Neff and Nagy [38] assert that Tay’s responses reflected “social relationships and the state of humanity”. This example seems to have been less of a warning than a case study in unregulated and unchecked AI. This year, Elon Musk's AI chatbot, Grok 3, has made unfiltered, controversial remarks on politics, free speech, and social issues, particularly in India. In response, it declared [39]: “some slam me for bias, others cheer." Grok also reinforced the white genocide narrative in South Africa by perpetuating far right and white propaganda that had no empirical basis. The generative model has gone so far as to term itself ‘Mecha-Hitler’. In the aftermath, its developer, xAI, secured a $200 million contract with the U.S. Department of Defense. Zemčík [37] concludes that AI can both mitigate and introduce cognitive biases, but it is important to note that these systems lack morality, emotions, and consequences for their actions even as users attribute human-like accountability to them. Vorsino [40] postulates that Tay is located in web 2.0, which is influenced by neoliberal, racialized, and gendered frameworks that define its structure.

There is thus justified concern about how the economic power amassed by large AI companies can translate into political influence, which could undermine democratic processes as seen in the example of Grok 3’s political leanings [19]. This is demonstrated by the potential for AI companies to lobby lawmakers, influence legislation in their favor, and limit the capability of citizens to effect collective decisions [19]. Bias could thus be considered a feature, not a bug, of current technological ecosystems. Increasingly so, it demonstrates how colonial-era power dynamics are technologically reproduced. Moreover, as these ownership structures indicate, there is also disparity within the Global South. Ballim and Breckenridge [41] ask a crucial question: “African people, firms and societies have produced, have been monopolized and discounted by metropolitan corporations with the energetic assistance of local elites. Will the growing power of the centers of AI in the United States and China – and the global monopoly power of a small number of firms secured by AI – produce a new era of data-driven extraversion and dependency?”

There is also an acknowledgement from the US that China is a formidable player in AI innovation and thus a significant strategic competitor, according to the Final Report of the National Security Commission on Artificial Intelligence [42]. Intriguingly, China, the other “AI superpower” was a signatory to the ‘Statement on Inclusive and Sustainable AI’. However, China’s largely inward AI policies, which are focused primarily on domestic development and national security may hinder hopes for inclusivity. Although written in 2018, Kai Fu-Lee’s [43] AI Superpowers: China, Silicon Valley, and the New World Order makes the argument: “The West may have sparked the fire of deep learning, but China will be the biggest beneficiary of the heat the AI fire is generating.” The US report makes an argument for the US to partner with historical allies of the United States, such as nations in Europe (e.g., the United Kingdom, Germany, and France) and partners in Asia (such as Japan, South Korea, and Australia) to work together on AI standards, research, and security. The report also highlights the potential for cooperation with emerging AI powers that share democratic values, including countries such as India and Canada as these nations are seen as vital partners in the global AI landscape. There is unsurprisingly no mention of any African nations, indicating that power is indeed located elsewhere. Moreover, China's growing technological presence in Africa has also sparked concerns about digital neo-colonialism, which allows for the exertion of control and influence over African nations [44]. A potential future could thus be a Chinese-led AI landscape.

Although China has a rather comprehensive set of AI regulations that advocate for inclusivity and transparency, there are also accompanying criticisms. Discussions on Chinese AI governance often overlook the substance and policymaking process of its regulations. Commentary typically falls into two extremes: dismissing the regulations as insignificant or using them for political leverage. Critics argue that since Xi Jinping and the CCP can override their own rules, these regulations hold little real importance [45]. In a global context, despite technological prowess and advancement, this once again indicates the glaring divide between the Global North and the Global South. This concentration of AI power, with Africa systematically excluded from its development and governance, raises fundamental questions of technological sovereignty and postcolonial power relations

3 A Postcolonial Framework

Menon [8] and Marwala [5] make the argument for inclusive and localized datasets to reimagine the resulting power imbalance. However, the ownership structures and capital flows in AI development and deployment stand in direct opposition to this goal. Despite having over 2,400 AI companies, Africa attracted only $4 million in AI funding across five deals in Q2 2024, compared to $23.2 billion raised globally. This means less than 1% of global AI investment flows into Africa [46].

Western-developed AI is fundamentally misaligned with African contexts and interests thus reproducing power imbalances by maintaining technological dependency. Africa has been portrayed as a ‘passive observer’ in technological development, which is an ideologically flawed narrative. Colonial interruption has systematically excluded African scholars, artisans, and scientists from developing indigenous technological solutions. The perceived technological lag is actually a result of colonial disruption, not inherent African inability. Postcolonial theory provides a crucial framework for understanding these power differentials as the concept of the ‘other’ helps interpret how algorithmic bias continues colonial-era discrimination [8]. The technology represents a new form of discrimination that operates subtly across all societal spheres. Without addressing these systemic biases, Africa’s socio-economic development will remain constrained. Nkrumah [47] cautioned that neocolonialism would represent the ultimate phase of imperialism and that it would hinder progress and reverse development. The policies put in place surrounding AI and the emerging inequities in the Global South make a compelling argument for a neocolonial bend. Priya and Arockiasamy [11] state that a: “sort of humiliation and underestimation on Blacks is continued in the Postcolonial condition too. The Western domination perpetuates through AI tools.”

There is an argument to be made for decolonial justice-centered alternatives. In this regard, Menon [8] highlights the need for interventions such as policy development, ethical charters, diverse datasets, and regulatory oversight bodies to address digital discrimination through a postcolonial lens. The shift, however, globally in terms of AI governance etc. remains in question and challenges the very notion of an effective postcolonial strategy. Calvin and Leung [29] suggest AI companies adopt patent pools where companies might share their patents to reduce litigation risks and promote innovation. If structured correctly, this could mitigate some exclusionary practices by allowing broader access to technology.

Munyua [48] demonstrates that successful multistakeholder engagement in internet governance is possible in African contexts by documenting Kenya's inclusive ICT policy development process from 2003-2006. However, this success has not translated to broader continental coordination. The 2021 crisis at the African Network Information Center (AFRINIC), the regional internet registry responsible for IP address allocation across Africa, revealed systemic governance failures. Despite AFRINIC's mandate to promote meaningful state participation in internet governance, African governments remained largely absent from its governance structures, even though they had access to mechanisms like the Africa Government Working Group (AfGWG) and membership in ICANN's Governmental Advisory Committee (GAC) [49].

This disengagement from regional internet infrastructure governance reflects deeper institutional failures. In the multistakeholder model of global internet governance, governments play a vital role in upholding the public interest, particularly in areas such as cybersecurity, development, and cross-border data regulation [50]. In Africa, this role has often been either neglected or distorted by attempts at centralized control [49]. While Western dominance of global internet governance structures creates structural imbalances, the failure of African governments to engage consistently has compounded these challenges. This dual dynamic of external power asymmetries combined with internal governmental inertia enables Western influence to persist largely unchallenged [51].

Effective participation in internet governance requires structure, continuity, capacity and sustained political will [52]. Without these elements, governance vacuums are filled by either private interests or external actors. Moving forward requires structured engagement with clear boundaries, capacity building to ensure policymakers across sectors understand internet governance issues, continental coordination mechanisms, and a focus on public interest as the guiding principle for government involvement [50].

4 From Historical to Digital Colonialism: A Conceptual Framework

To understand whether AI bias is deliberate requires an understanding of colonialism and how it continues to operate today. Colonialism is not merely a historical period that ended with formal independence but an ongoing structural system that still shapes global power relations [53]. The colonial process, concentrated primarily in the 19th and 20th centuries, involved Western powers dominating and exploiting territories while imposing Western constructs and standards on non-Western societies. Yet, the deeper legacy lies in the coloniality of power or the enduring hierarchies that persist in how knowledge is valued, whose labor is exploited and where wealth accumulates [53]. Colonialism restructured economies to serve colonial interests by ensuring that wealth and resources flowed outward while colonized populations were locked into positions of dependency [54] [55]. In this process, it devalued indigenous knowledge systems by positioning Western epistemologies as universal and objective while dismissing other ways of knowing as backward or irrelevant [56] [57]. These patterns didn't disappear with independence but rather embedded themselves in economic relationships and knowledge hierarchies that shape the contemporary world.

As this paper demonstrates, contemporary AI development operates within and reinforces these colonial structures. African user data flows to Western servers, generating billions in value captured by foreign corporations, while the continent receives less than 1% of global AI investment despite hosting 2,400 AI companies [46]. This mirrors historical patterns where African resources enriched distant centers of power. Algorithmic systems designed in Silicon Valley and Beijing determine creditworthiness or employment decisions, for instance. It could thus be argued that governance is imposed from the outside where it has been optimized for other contexts and populations. African institutions increasingly depend on technologies they didn't build and cannot modify to include contextually appropriate dimensions [9]. Training datasets systematically exclude or misrepresent African knowledge systems and languages thus positioning Western data and norms as the universal standard against which all others are measured and often found deficient [8]. The coloniality of power persists as Western constructs are imposed as technological standards, wealth flows outward and structural dependency deepens [53].

A critical question emerges: are these patterns inevitable consequences of how technology develops or do they reflect choices made by those with power? Systemic bias operates through normalized practices and inherited inequalities. Galtung [58] argues that this is a form of structural violence where harm occurs without requiring intention. Training data captures patterns of discrimination already present in historical records or hiring decisions, for instance. Development teams lack diversity because educational pipelines reflect longstanding barriers to access in STEM fields. Market concentration perpetuates itself as established players leverage network effects and accumulated resources to maintain dominance. These dynamics explain some bias as structural rather than intentional.

However, deliberate bias emerges when institutional actors make policy decisions with foreseeable discriminatory consequences while possessing both knowledge and power to choose otherwise. Consider that 64% of global AI investment concentrates in the United States [20] within firms where only 25% of developers come from racial minorities and 29% of organizations employ no minority AI developers at all [24]. Initially this appears structural as it could be argued that this is the outcome of historical patterns. Yet, when these same firms systematically eliminate diversity initiatives [26], when governments issue executive orders removing equity protections from AI development and when nations explicitly decline signing commitments to inclusive AI, we witness active choices to maintain exclusionary patterns [26] [39]. The difference between structural and deliberate is dependent on conscious policy decisions that predictably perpetuate exclusion.

Some scholars argue AI's geographic concentration reflects natural market dynamics. Porter [59] and Audretsch and Feldman [60] demonstrate that innovation clusters emerge through knowledge spillovers and agglomeration economies. In other words, physical proximity enables collaboration and rapid iteration. This suggests concentration may be economically efficient rather than discriminatory. Others contend algorithmic bias represents technical complexity or what Selbst et al. [61] term “abstraction traps”. This refers to well-intentioned systems that produce harmful outcomes through design limitations rather than malice.

While these explanations certainly have merit, they cannot account for the policy environment. Historical power asymmetries determined which regions developed enabling institutions in the first place [62] indicating that ‘natural’ clustering reflects inherited advantage rather than pure merit. More importantly, efficiency arguments fail to explain why 39 major companies eliminated diversity initiatives within months [26] or why governments actively dismantled safety frameworks while expanding military AI investments [29]. When institutional actors with full awareness systematically remove equity safeguards, we move beyond unintended consequences to deliberate choices.

The concentration of AI capital and power thus reflects not merely market forces but political decisions about whose innovation merits funding and whose knowledge systems count as valid. This analysis employs policy analysis and political economy frameworks to trace how ownership structures, capital flows, and policy decisions reveal power holders actively maintaining exclusionary systems while possessing both knowledge of consequences and capacity for different choices.

5 Conclusion and Limitations

It is acknowledged that this context is continually changing. While this critique looks at the period in the first half of 2025, a limitation may very well be the fast-shifting nature of both AI, policy and geopolitics. Many of these changes could not have been anticipated just a year prior. Methodologically, this analysis traces patterns through policy documents, investment data, and institutional decisions. While this approach cannot definitively prove individual motivations, it reveals institutional patterns where actors with knowledge and power make choices with foreseeable discriminatory consequences. Additional limitations include restricted access to internal corporate decision-making processes and the time lag between policy implementation and measurable outcomes.

The ascendancy of AI in the global economy has surfaced new fissures of inequality that astoundingly mirror historical patterns of exclusion and power inequalities crucially along lines of race. This paper argues that the ostensibly neutral architectures of AI often reproduce and encode racialized hierarchies, functioning almost as deliberate tools to deepen existing hierarchies of capital, race and power. The evidence demonstrates how exclusion operates through capital concentration in

Western firms lacking diversity, the systematic elimination of equity safeguards via DEI rollbacks and safety framework removals, and the creation of structural dependencies as African institutions rely on AI technologies they neither control nor can modify for local contexts.

The question is whether the persistent marginalization of Africa in AI development and governance is accidental. The evidence suggests it reflects broader patterns of digital colonialism that position the continent as a passive recipient. While some algorithmic bias emerges from structural reproduction of existing inequalities, the pattern of deliberate policy choices by institutional actors with full awareness of consequences reveals intentionality [26] [27] [29] [30].

Unless these exclusionary practices are confronted head on through deliberate and intentional shifts in ownership models, regulatory frameworks and capacity-building initiatives, AI will be fundamentally compromised for the Global South – and Africa in particular. The current trajectory of AI carries the inherent risks of further entrenching a new wave of imperialism. There is thus an urgent need for Africa to assert its agency or fall into the trap of yet again a period of engineered inequality.

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