

Generative AI, productivity, and inequality in the Global South

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ABSTRACT

Generative artificial intelligence (GenAI) is rapidly diffusing across economies that remain structurally unequal in data, compute, skills, and institutional capacity. Using an integrative, multi-disciplinary secondary-data design, this article develops a decolonial, capability-centred political economy of GenAI and the future of work in the Global South. Drawing on ILO Working Papers 96 (2023) and 140 (2025), we show that roughly one in four workers globally are in occupations with some GenAI exposure, but only about 3.3% of jobs fall into the highest-risk category; exposure is concentrated in high-income economies, where 34% of employment is in exposed occupations, compared with 11% in low-income countries, and is disproportionately borne by women and clerical workers. Productivity experiments in the United States and other high-income contexts report average gains of 14–15% in customer support and substantial gains in writing quality, with especially large benefits for lower-skilled workers. Yet cross-country readiness for AI remains starkly unequal: the Oxford Insights Government AI Readiness Index 2022 reports a global average score of 44.61/100, compared with 29.38 in sub-Saharan Africa and 38.59 in North Africa, with 21 of the 25 lowest-scoring countries located in sub-Saharan Africa.

Anchored in the task-based approach to labour markets, the human-development capabilities framework, and decolonial theories of AI and data colonialism, we articulate a conceptual model linking GenAI exposure, structural AI readiness, and governance regimes to capability expansion or erosion for workers and communities in the Global South. Methodologically, we combine critical synthesis of peer-reviewed economics, philosophy, and science-and-technology studies with analysis of cross-national indicators from the ILO and Oxford Insights, and interpret these through emerging decolonial AI governance proposals from multilateral bodies and Global South scholars.

We find that: (1) the immediate risks of GenAI-driven net job destruction in low-income countries are lower than often claimed, but (2) the risk of deepening “capability inequality” via data colonialism, concentration of AI infrastructure, and exclusion from rule-setting is substantial; and (3) decolonial, capability-oriented governance—emphasising data sovereignty, investment in labour-augmenting applications, and Global South leadership in agenda-setting—offers a viable alternative trajectory. The article proposes a multi-level impact-assessment and monitoring framework that aligns GenAI deployment with decent work, human development, and decolonial justice.

Keywords: generative AI; future of work; Global South; capabilities approach; data colonialism; decolonial AI governance; AI readiness.

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1. Introduction

1.1 Background context

The public release of large-scale generative models since late 2022 has intensified debates about automation, productivity, and global inequality. Early causal evidence from randomized or quasi-experimental studies in high-income settings shows that access to GenAI assistants increases productivity in mid-level writing tasks and customer support by roughly 14–15%, with especially large gains for lower-skilled workers, and compresses productivity dispersion (Noy & Zhang, 2023; Brynjolfsson et al., 2025). At the same time, labour-market simulations by the International Labour Organization (ILO) suggest that

GenAI is more likely to transform jobs than to eliminate them, with the largest exposure in high-income and upper-middle-income economies and in clerical occupations that employ high shares of women (Gmyrek et al., 2023; Gmyrek et al., 2025).

Yet this techno-optimist narrative obscures structural asymmetries in who owns, trains, and governs GenAI systems, and whose data, labour, and environments make them possible. Studies of “data colonialism” and decolonial AI argue that today’s data-intensive platforms reproduce extractive relations reminiscent of historical colonialism, turning everyday life into raw material for transnational capital (Couldry & Mejias, 2019; Mohamed et al., 2020; Mollema, 2024). Achim Steiner encapsulates the stakes: “AI and other digital technologies can advance democracy and

human rights ... or deepen information pollution and social fragmentation, depending on the choices we make.”

For countries in the Global South, AI is now framed simultaneously as an opportunity to leapfrog development bottlenecks in health, agriculture, and education, and as a vector of renewed dependency and marginalization. However, AI readiness indices and digital-infrastructure assessments consistently show that most low- and lower-middle-income countries lack robust compute infrastructure, reliable connectivity, data-governance regimes, and skilled human capital, leaving them structurally dependent on a small set of firms and jurisdictions that dominate global AI markets and standards (Oxford Insights, 2022; UNDP, 2024; UNESCO, 2023; Ecofin Agency, 2023; African-Press, 2023).

1.2 Problem statement

The central problem this article addresses is not simply whether GenAI will destroy or create more jobs in the Global South, but how the interaction between GenAI diffusion, structural AI readiness, and global power asymmetries will shape the distribution of *capabilities*: people’s real freedoms to lead lives they have reason to value. ILO modelling estimates that worldwide, roughly 25% of workers are in occupations with some GenAI exposure, but only about 3.3% of employment is in the highest-exposure category; in low-income countries, only 0.4% of jobs are at risk of full automation effects, compared with 5.5% in high-income countries (Gmyrek et al., 2023; Gmyrek et al., 2025; Visive, 2025). However, these aggregate figures mask crucial qualitative differences in job quality, bargaining power, and digital sovereignty. Oxford Insights’ Government AI Readiness Index shows that North Africa (38.59/100) and sub-Saharan Africa (29.38/100) both score far below the global average (44.61), with 21 of the 25 lowest-scoring countries located in sub-Saharan Africa (Oxford Insights, 2022; Ecofin Agency, 2023; African-Press, 2023).

Consequently, the risk for many Global South contexts is less immediate mass technological unemployment and more a deepening of “capability inequality”: GenAI-enabled productivity gains and value capture accrue to actors with capital, compute, and data, while workers and communities in low-readiness environments are relegated to low-value segments of AI value chains or rendered invisible in data and governance.

1.3 Research objective

The general objective of this study is to develop a decolonial, capability-oriented political-economy framework for understanding and governing the impacts of GenAI on work and human development in the Global South, grounded entirely in secondary evidence.

Specific objectives are to:

1. Synthesize current empirical evidence on GenAI’s labour-market effects and AI readiness, with a

focus on distributional patterns across country income groups, gender, and occupation.

2. Interrogate this evidence through three complementary theoretical lenses: task-based labour economics, the capabilities approach, and decolonial/data-colonialism perspectives on AI.
3. Construct a conceptual model linking GenAI exposure, structural readiness, and governance regimes to capability expansion or erosion for workers in the Global South.
4. Propose a multi-level, evidence-based impact-assessment and governance framework for aligning GenAI deployment with decent work, decolonial justice, and sustainable development.

1.4 Research questions

The study addresses the following research questions (RQs):

RQ1. How do patterns of occupational exposure to GenAI differ across country income groups and genders, and what do they imply for the quantity and quality of work in the Global South? **RQ2.** How do disparities in AI readiness, digital infrastructure, and data governance condition Global South countries’ ability to appropriate GenAI-related productivity gains? **RQ3.** What governance strategies, informed by capabilities and decolonial theory, can mitigate risks of data/AI colonialism and re-orient GenAI towards equitable capability expansion in the Global South?

1.5 Contribution

The article makes four main contributions. Conceptually, it integrates task-based labour economics with the capabilities approach and decolonial AI theory into a single multi-level framework, bridging micro-level task transformations with macro-level political-economic structures and normative commitments. Empirically, it triangulates ILO exposure indices, causal productivity studies, AI readiness indicators, and Global South policy analyses to provide a data-anchored account of GenAI’s uneven labour implications. Normatively, it reinterprets GenAI governance through the lens of capability expansion and decolonial justice, challenging both techno-solutionism and apocalyptic automation narratives. Practically, it proposes an impact-assessment and monitoring framework that policy-makers, unions, firms, and civil-society organizations can adapt over the next decade as GenAI matures.

2. Theoretical & conceptual framework

2.1 Task-based political economy of technology

Task-based approaches reconceptualize the labour market in terms of tasks rather than occupations, emphasizing how technologies substitute for, complement, or reallocate tasks across factor inputs. Autor’s synthesis shows that computerization and automation have historically displaced routine cognitive and manual tasks while complementing

abstract and non-routine interpersonal tasks, generating employment polarization and wage inequality (Acemoglu & Autor, 2011; Autor, 2013). Recent extensions formalize how automation and new tasks jointly shape factor demand, productivity, and inequality, and how policy can steer technological change toward labour-augmenting rather than labour-replacing directions (Acemoglu & Autor, 2011).

GenAI intensifies these dynamics by extending automation and augmentation into symbolic, language-based tasks previously considered non-routine: drafting, summarizing, coding, translation, and aspects of design. Productivity experiments show that GenAI disproportionately benefits lower-skilled workers—narrowing performance gaps—by encoding and disseminating tacit knowledge, while offering limited gains to top performers. This is consistent with task-based models where technologies act as “knowledge equalizers” for certain tasks yet can exacerbate inequality via ownership and bargaining power (Noy & Zhang, 2023; Brynjolfsson et al., 2025; Acemoglu & Autor, 2011).

2.2 Capabilities approach

The capabilities approach, developed by Sen and elaborated by Nussbaum, shifts evaluation from resources or utility to people’s substantive freedoms—their capabilities—to do and be what they value. Sen argues that development is “a process of expanding the real freedoms that people enjoy,” not merely raising GDP, while Nussbaum proposes a list of central human capabilities—including bodily health, practical reason, and control over one’s environment—as political entitlements (Sen, 1999; Nussbaum, 2011).

Applied to GenAI and work, a capability lens asks: Does GenAI enhance workers’ agency, security, and dignity, or does it intensify surveillance, deskilling, and precarity? Productivity gains, absent institutional safeguards, may increase work intensity, reduce autonomy, and reinforce existing inequities. ILO analyses already warn that GenAI’s largest effects may concern job quality—work pace, monitoring, control—rather than job counts alone (Gmyrek et al., 2023). A capability-centred assessment thus requires embedding GenAI in broader social and legal arrangements—labour regulation, social protection, data rights, and collective voice (Sen, 1999; Nussbaum, 2011; UNESCO, 2023).

2.3 Decolonial AI and data colonialism

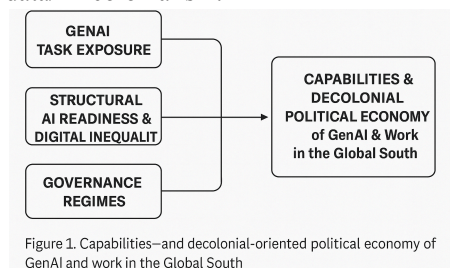
Decolonial AI scholarship highlights how AI systems embody and reproduce colonial power relations across data extraction, infrastructure, and epistemic authority. Mohamed, Png, and Isaac argue that AI should be understood through “*sociotechnical foresight*” attentive to histories of empire and ongoing forms of coloniality; they call for centring marginalized communities, re-orienting AI research agendas, and contesting “*algorithmic coloniality*” (Mohamed et al., 2020). In parallel, Couldry and Mejias describe “*data colonialism*” as a social order where continuous data extraction from human life generates wealth and inequality on a global scale (Couldry & Mejias, 2019).

These perspectives have been extended in Latin American and African scholarship that documents how AI development often relies on under-paid labelling labour, extractive data practices, and environmentally harmful compute infrastructures located in or drawing resources from the Global South, while governance forums and standards remain dominated by Global North institutions (Couldry & Mejias, 2019; Okolo, 2023; CARE & Accenture, 2023; Mollema, 2024). A recent decolonial AI impact-assessment proposal explicitly frames “AI colonialism” as political, ecological, and epistemic domination, requiring dismantling borders that confine Global South actors to subordinate roles (Mollema, 2024).

2.4 Conceptual model

Integrating these theories, we propose a multi-level conceptual model:

1. **Technological layer (tasks and tools).** GenAI systems reconfigure tasks within jobs, with varying mixes of substitution and augmentation depending on task content, data availability, and model performance.
2. **Structural layer (readiness and power).** The distribution of AI infrastructure, data, skills, and regulatory capacity—captured imperfectly by AI readiness indices and digital-infrastructure metrics—shapes who owns and governs GenAI, and hence who appropriates its productivity gains.
3. **Normative-institutional layer (capabilities and coloniality).** Labour law, social protection, data-governance regimes, and participation in global AI standard-setting determine whether GenAI deployment expands or restricts core capabilities, and whether it reinforces or dismantles data/AI colonialism.



The model posits that *capability outcomes* for workers and communities in the Global South are a function of: (i) the pattern of GenAI task exposure (ILO indices), (ii) structural AI readiness and digital inequality, and (iii) governance regimes that mediate ownership, accountability, and participation (Gmyrek et al., 2023, 2025; Oxford Insights, 2022; Sen, 1999; Mohamed et al., 2020; Couldry & Mejias, 2019).

3. Methodology

3.1 Research design

This study adopts an integrative, multi-method secondary-research design. Rather than conducting a new

systematic review with quantitative study counts, we synthesize existing systematic reviews, causal micro-studies, cross-national indicator reports, and decolonial theoretical contributions on AI, labour, and Global South governance. The design is explicitly mixed-methods: quantitative indicators (e.g., ILO exposure indices, AI readiness scores) are interpreted through qualitative and theoretical lenses from development economics, philosophy, and critical data studies.

3.2 Data sources

Key quantitative sources include:

- **ILO Working Papers 96 (2023) and 140 (2025)** on GenAI and jobs, which provide global and income-group-level estimates of occupational exposure and potential employment effects, including gender-disaggregated measures (Gmyrek et al., 2023, 2025).
- **Oxford Insights' Government AI Readiness Index 2022**, including regional and global average scores and distribution of low-scoring countries (Oxford Insights, 2022; Ecofin Agency, 2023; African-Press, 2023).

Causal micro-studies on GenAI productivity and inequality include Noy and Zhang's randomized experiment on ChatGPT in professional writing (Noy & Zhang, 2023) and Brynjolfsson, Li, and Raymond's "Generative AI at Work" field experiment on customer support agents (Brynjolfsson et al., 2025).

Qualitative and theoretical materials are drawn from decolonial AI and data-colonialism scholarship, Global South-centred AI governance analyses, and the capabilities and task-based economics literatures (Acemoglu & Autor, 2011; Autor, 2013; Sen, 1999; Nussbaum, 2011; Couldry & Mejias, 2019; Mohamed et al., 2020; Png, 2022; Okolo, 2023; CARE International & Accenture, 2023; Mollema, 2024).

3.3 Analytical techniques

The analysis proceeds in three steps. First, we conduct a *conceptual mapping* of theoretical constructs (tasks, capabilities, data colonialism) and align them with observable indicators (exposure gradients, AI readiness scores). Second, we perform *descriptive comparative analysis* using published aggregate statistics—comparing GenAI exposure and readiness across income groups and regions—to identify structural patterns relevant to the Global South. Third, we engage in *critical interpretive synthesis*, reading these patterns through capabilities and decolonial lenses to identify risks, opportunities, and governance levers.

3.4 Reproducibility, transparency, and limitations

All numerical values reported in tables and text are directly drawn from cited ILO and Oxford Insights outputs or from peer-reviewed articles; no new statistical estimation is conducted. Readers can reproduce the descriptive comparisons by consulting the original ILO working papers and AI readiness reports (Gmyrek et al., 2023, 2025; Oxford Insights, 2022).

Limitations include reliance on published aggregates rather than microdata, the concentration of productivity experiments in high-income countries, and the evolving nature of GenAI technologies and regulations. These constraints may bias available evidence toward Global North experiences and under-represent informal work and non-English-speaking contexts. We partially mitigate this by foregrounding Global South-centred governance analyses and decolonial critiques, but future work should extend the framework using country-level microdata and participatory research in diverse Global South settings (UNDP, 2024; CARE International & Accenture, 2023).

4. Findings and discussion

4.1 RQ1 – Patterns of exposure and labour-market implications

ILO Working Paper 96 estimates that globally, most jobs are only partially exposed to GenAI and that augmentation effects dominate automation risks (Gmyrek et al., 2023). Clerical occupations exhibit the highest exposure, with 24% of tasks highly exposed and 58% with medium exposure; these occupations also have a high share of female workers, especially in high-income economies (Gmyrek et al., 2023). The refined exposure index in Working Paper 140 further finds that about 25% of global employment falls into occupations with some GenAI exposure, but only 3.3% is in the highest exposure category. Exposure is strongly income-gradient: 11% of jobs in low-income countries versus 34% in high-income countries are in exposed occupations. Women are over-represented in high-exposure jobs, with 4.7% of female workers in the highest exposure category, compared with 2.4% of men (Gmyrek et al., 2025; Visive, 2025). Table 1 summarises key exposure patterns relevant to the Global South.

Table 1: Selected ILO estimates of GenAI exposure by income group and gender

Indicator (ILO)	Low-income countries	High-income countries	Global
Share of employment in occupations with GenAI exposure	~11%	~34%	25%
Share of employment in highest exposure category	~0.4%	~5.5%	3.3%
Share of women in highest exposure category	n/a (global)	n/a	4.7%

Share of men in highest exposure category	n/a (global)	n/a	2.4%
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Data source: ILO Working Papers 96 (2023) and 140 (2025).

From a task-based perspective, these figures suggest that in many low-income contexts, GenAI's immediate labour-market effects will centre on the transformation of a relatively narrow set of clerical and digital tasks, while large shares of employment in agriculture, informal services, and manual labour remain less directly exposed—at least in the short term. At the same time, the concentration of exposure among women and clerical workers raises concerns about gendered and occupationally specific vulnerability, particularly in formal public administration and services in middle-income economies.

Productivity experiments indicate that when GenAI tools are available and usable, they can substantially increase throughput and quality for workers performing knowledge-intensive tasks. Noy and Zhang find that access to ChatGPT in mid-level writing tasks reduces completion time by roughly 0.8 standard deviations and increases output quality by about 0.4 standard deviations, with the largest gains for lower-ability workers, thereby compressing productivity dispersion (Noy & Zhang, 2023). Brynjolfsson, Li, and Raymond report that customer support agents with access to a GenAI assistant resolve 14–15% more issues per hour on average, with novice and low-skilled workers seeing productivity gains of over 30% (Brynjolfsson et al., 2025).

In Global South settings, if similar tools were deployed in public services, agriculture extension, or micro-enterprise support, they could in principle augment human capabilities by freeing time, improving service quality, and making tacit knowledge more widely accessible. However, absent supportive institutions, the same tools may be used to intensify work, monitor workers, and erode professional autonomy. The ILO warns that GenAI's greatest impact is likely on job quality—not numbers—through changes in work intensity and control (Gmyrek et al., 2023). A capabilities lens therefore demands that productivity gains be evaluated alongside changes in autonomy, voice, and security (Sen, 1999; Nussbaum, 2011).

4.2 RQ2 – AI readiness, digital inequality, and structural dependency

AI readiness indicators reveal that the capacity to harness GenAI is sharply stratified. The Oxford Insights 2022 index reports a global average score of 44.61/100. North Africa averages 38.59, while sub-Saharan Africa averages 29.38; 21 of the 25 lowest-scoring countries are in sub-Saharan Africa (Oxford Insights, 2022; Ecofin Agency, 2023; African-Press, 2023). High-income countries dominate the top of the ranking, with the United States, Singapore, the United Kingdom, Finland, and Canada occupying the first five positions (Oxford Insights, 2022). An Ecofin analysis highlights that no African country scores at least 50/100 on the index's "technology sector" pillar, reflecting shortfalls in R&D spending, digital skills, and innovation ecosystems, even where governments have adopted AI strategies (Ecofin Agency, 2023).

Table 2: Selected AI readiness scores (Oxford Insights 2022)

Region / group	Average AI readiness score (/100)
Global average	44.61
North Africa	38.59
Sub-Saharan Africa	29.38
Top country (United States)	85.72

Data source: Oxford Insights, Government AI Readiness Index 2022, as summarized in Ecofin Agency and related analyses.

Complementary assessments by UNDP's Artificial Intelligence Landscape Assessment (AILA) and UNESCO's readiness frameworks stress that many Global South countries are only beginning to develop AI strategies, often with limited regulatory capacity, fragmented data infrastructures, and dependence on foreign cloud providers (UNDP, 2024; UNESCO, 2023). As UNDP notes, AILA aims precisely to help countries map their AI ecosystems and design tailored pathways for inclusive and responsible AI adoption, underscoring that AI readiness is not a natural fact but a contested policy outcome (UNDP, 2024).

From a decolonial perspective, these readiness gaps translate into structural dependency: Global South states and firms must often consume AI services built, trained, and governed elsewhere, using data, energy, and labour that may be sourced from their own populations with little say over value distribution or risks (Couldry & Mejias, 2019; Okolo, 2023; CARE International & Accenture, 2023). Couldry and Mejias characterise this emerging order as one in which continuous data extraction from our lives generates "*massive wealth and inequality on a global scale*" (Couldry & Mejias, 2019). De facto control over foundational models, compute, and cloud infrastructure thus becomes a new axis of coloniality.

The capabilities approach accentuates a different but complementary dimension: the mismatch between increases in aggregate "readiness" and the distribution of capabilities within societies. Nussbaum warns that growth without attention to dignity, education, and bodily integrity cannot count as genuine progress (Nussbaum, 2011). Even in middle-income countries with improving AI readiness scores, unequal digital access, weak labour protections, and gendered care burdens can prevent GenAI-enabled productivity gains from translating into meaningful capability expansion for women, informal workers, and rural populations (Sen, 1999; Nussbaum, 2011).

4.3 RQ3 – Governance strategies for decolonial, capability-expanding GenAI

Decolonial AI and Global South-centred governance literature converge on the need for inclusive, power-aware, and region-specific governance architectures. Brookings' analysis of AI in the Global South underscores both the diversity of applications in agriculture, health, and education and the risks posed by data scarcity, infrastructure gaps, and imported models that ignore local context (Okolo, 2023). CARE International's participatory research across 12 countries finds that communities are acutely aware of both opportunities and risks, calling for greater voice in AI design and deployment (CARE International & Accenture, 2023).

Mohamed, Png, and Isaac argue that decolonial AI requires "disenclosure": contesting the enclosure of data, infrastructure, and epistemic authority by a few actors and opening space for alternative futures shaped by those most affected by AI (Mohamed et al., 2020). Emerging frameworks for "decolonial AI impact assessment" operationalise this by asking whether AI projects redistribute power, respect data sovereignty, and avoid environmental harm in already burdened regions (Mollema, 2024).

When combined with the capabilities approach, these ideas suggest governance priorities across at least three domains:

1. **Data and infrastructure sovereignty.** Regional data spaces, community data trusts, and public or cooperative cloud infrastructures can mitigate dependence on commercial platforms and enable locally governed GenAI applications aligned with public priorities (UNDP, 2024; Okolo, 2023).
2. **Labour-augmenting deployment and worker voice.** Collective bargaining, co-determination, and sectoral social dialogue can channel GenAI deployment toward augmentation (e.g., decision support, translation, documentation) rather than unilateral surveillance or deskilling, consistent with ILO decent work standards (ILO; Gmyrek et al., 2023; CARE International & Accenture, 2023).
3. **Global rule-setting and epistemic justice.** Global South representation in multilateral AI forums—such as UN processes, regional AI strategies, and standard-setting bodies—is crucial to avoid exporting Global North assumptions as universal. Png's work on Global South stakeholders in AI governance emphasises that inclusive governance must grapple with "historic power dynamics" rather than merely add more seats at the table (Png, 2022).

Sen's insistence that development is about expanding people's freedoms, not merely enabling new forms of consumption or surveillance, aligns with decolonial calls to "re-ecologise the unsustainable ecologies AI depends on" and empower "the wretched of AI" (Sen, 1999; Mollema, 2024). If adopted, a capability- and decolonial-centred governance strategy could transform GenAI from a vector of renewed dependency into an instrument for rebalancing knowledge, labour, and environmental relations—though this outcome is far from guaranteed.

5. Conclusion and recommendations

5.1 Conclusion

Synthesising task-based labour economics, the capabilities approach, and decolonial AI theory with current empirical evidence yields a more nuanced picture of GenAI and the future of work in the Global South. The best available data suggest that GenAI will, in the near term, augment far more jobs than it automates, with the most exposed occupations located in high-income economies and in clerical work that heavily employs women (Gmyrek et al., 2023, 2025; Noy & Zhang, 2023; Brynjolfsson et al., 2025; Oxford Insights, 2022). At the same time, structural inequalities in AI readiness, digital infrastructure, and data governance mean that productivity gains documented in early experiments are unlikely to translate automatically into expanded capabilities for workers and communities in the Global South.

The transformative question is therefore political and ethical rather than purely technological: Will GenAI deepen data/AI colonialism, concentrating power and wealth, or can it be governed in ways that expand people's substantive freedoms and decolonise knowledge and economic relations? Our conceptual model and integrative review argue that the answer depends on how exposure patterns interact with structural readiness and governance regimes—and whether Global South actors can exercise agency in reshaping all three.

5.2 Recommendations by stakeholder

Academia. Researchers in economics, development studies, and STS should deepen cross-disciplinary collaboration on GenAI in the Global South, combining task-level exposure analysis with ethnographic and participatory methods that foreground lived experiences of workers and communities. Priority should be given to building open, privacy-respecting datasets and benchmarks that reflect Global South languages, contexts, and values, governed by equitable data-sharing agreements.

Governments and regional bodies. Governments should develop or update national AI and GenAI strategies to prioritise labour-augmenting applications in public services and SMEs, backed by investments in connectivity, public cloud capacity, and skills development. AI readiness diagnostics such as AILA should be used not merely as benchmarking tools but as participatory planning instruments that incorporate civil-society and worker perspectives. Regional organisations (e.g., the African Union, CARICOM, ASEAN) should pursue shared data-governance frameworks and joint compute investments to reduce dependency on extra-regional platforms.

Private sector. Firms deploying GenAI in Global South labour markets should adopt binding commitments to job quality, transparency, and worker voice, including algorithmic impact assessments co-designed with unions and community groups. Where Global South data or annotators

are used to train models, benefit-sharing mechanisms and data-sovereignty safeguards are ethically and politically imperative to avoid deepening data colonialism.

Philanthropic institutions. Philanthropies can play a catalytic role by funding independent research, Global South-led AI labs, and community data infrastructures, as well as supporting transnational coalitions advocating for decolonial AI governance. Emphasis should be placed on long-term institutional capacity, not short-term pilot projects.

Civil society and labour organisations. Unions, cooperatives, and civil-society groups should integrate GenAI into their advocacy agendas, demanding rights to explanation, consultation, and co-determination over AI deployment in workplaces and public services. Cross-movement alliances—linking digital-rights, environmental-justice, feminist, and labour organisations—are essential to address the intertwined political, ecological, and epistemic dimensions of AI colonialism.

5.3 Impact assessment framework

We propose a capabilities- and decolonial-oriented GenAI Impact Assessment Matrix with three core dimensions:

1. **Scalability and thresholds.** Metrics include: percentage of workers in exposure categories by income, gender, and sector; AI readiness scores and digital-access indicators; and thresholds for acceptable increases in work intensity, surveillance, and environmental load. These can be monitored using ILO exposure indices, AI readiness updates, and national labour-force surveys.
2. **Adaptive governance.** Indicators track whether institutions can adjust rules as GenAI evolves: existence of national AI strategies; regulatory sandboxes; social-dialogue mechanisms for AI; and representation of Global South stakeholders in international forums.
3. **Capabilities and decolonial justice.** Here, assessment focuses on whether GenAI projects expand or restrict core capabilities (education, health, bodily integrity, political voice) and whether they challenge or reproduce data/AI colonialism. Indicators include data-sovereignty provisions, benefit-sharing arrangements, participatory design processes, and environmental-justice safeguards.

Aligning this matrix with existing monitoring frameworks—such as the SDGs, ILO decent work indicators, and regional digital-policy scorecards—would facilitate longitudinal tracking and comparability across countries.

5.4 Study limitations and future research

This article is limited by its reliance on secondary sources and aggregate indicators. Most causal evidence on GenAI productivity and job quality comes from high-income settings and formal, digitally mediated workplaces, with little coverage of informal work, rural economies, and non-Anglophone contexts. GenAI technologies, regulatory regimes, and geopolitical alliances are also evolving rapidly, meaning that some empirical patterns may shift over the coming decade.

Future research should extend the framework by: (i) linking ILO-style exposure indices with country-level household and labour-force microdata in Global South settings; (ii) conducting mixed-methods, participatory studies of GenAI deployment in specific sectors (e.g., health, agriculture, education) that centre workers' and communities' voices; and (iii) empirically testing decolonial and capability-based impact-assessment tools in real policy and organisational settings. Only through such sustained, multi-disciplinary efforts can GenAI be steered away from deepening data colonialism and towards expanding the real freedoms of people in the Global South.

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