Effect of Artificial Intelligence on Manufacturing and Industrialisation in Africa:

Automation Disruption, Employment Threats, and Industrial Policy Responses

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ABSTRACT

This study examines the effect of artificial intelligence on manufacturing and industrialisation in Africa, focusing on how AI-driven automation is disrupting industrial employment, threatening the labour-intensive manufacturing pathway that historically enabled structural transformation in East Asia, and reshaping the industrial policy choices available to African economies. The study adopts a mixed-methods design combining systematic documentary analysis, comparative policy mapping, and secondary quantitative data from major international and regional institutions. Guided by Structural Transformation Theory and the Technology-Organisation-Environment Framework, the study identifies six major disruption domains: automation of labour-intensive tasks, concentration of productivity gains in foreign-owned firms, displacement of workers without adequate reskilling or protection, widening technology capability gaps, disruption of supply chains through AI-enabled reshoring and nearshoring, and the closure of Africa's traditional industrialisation pathway.

Findings show that AI and automation contributed to a manufacturing employment decline of 6 to 19 percent across the formal sectors of the five focus countries between 2020 and 2023, while fewer than 8 percent of African manufacturing firms adopted AI-assisted production technologies. This creates what the study terms the African Manufacturing AI Paradox: AI is disrupting jobs before delivering broad productivity or capability gains. The study's main contribution is to identify and theorise this paradox as a structural challenge to African industrialisation. It proposes a seven-Policy Priority industrial policy framework to govern AI adoption in ways that support employment, local capability development, and long-term industrial transformation.

Keywords: artificial intelligence; manufacturing Africa; industrialisation; structural transformation; automation; employment disruption; industrial policy; technology transfer; reshoring; African Continental Free Trade Area

1. INTRODUCTION

Manufacturing has historically been the engine of structural economic transformation. The development experiences of South Korea, Taiwan, China, Vietnam, and other East and South-East Asian economies demonstrate a consistent pathway from agricultural subsistence to industrial productivity to services-led growth, with labour-intensive manufacturing serving as the critical bridge through which large numbers of low-skilled rural workers moved into formal industrial employment, acquired capabilities, generated savings, and supported the domestic demand that sustained economic growth [1]. This industrialisation pathway was made possible by a specific combination of factors: abundant low-cost labour, preferential trade arrangements that provided access to global markets for manufactured exports, foreign direct investment that brought technology and management knowledge, and government industrial policies that supported capability development. Africa has been positioning itself to follow a variant of this pathway for decades, with numerous industrial policies, special economic zones, and investment promotion programmes designed to attract labour-intensive manufacturing investment.

Artificial intelligence is disrupting this pathway in a manner that is structurally distinct from any previous technological disruption in manufacturing. Previous waves of manufacturing automation, from mechanisation in the nineteenth century to assembly-line production in the twentieth century to computer-controlled manufacturing in the 1980s and 1990s, were primarily capital-labour substitutions that increased the productivity of manufacturing workers rather than eliminating the need for them at the task level. AI-driven automation is qualitatively different: it is substituting for the cognitive dimensions of manufacturing work, including quality inspection, process monitoring, predictive maintenance, production planning, and supply chain coordination, at the same time as robotics and cobots are substituting for the physical dimensions [2]. The combination of cognitive and physical automation is eliminating not just individual tasks but entire categories of manufacturing employment, including the entry-level assembly and quality control roles through which African manufacturing workers historically built their industrial capabilities.

The consequence for Africa is a specific and previously uncharacterised structural challenge that this paper identifies as the African manufacturing AI paradox: AI is disrupting Africa's manufacturing employment base before it has generated the productivity and capability gains that would justify and compensate for the displacement, because the disruption is driven primarily by global technology trends and multinational firm decisions rather than by deliberate African industrial strategy. African manufacturing workers are losing jobs to AI automation at factories owned by multinational corporations implementing global automation strategies, while African manufacturing firms lack the capital, capabilities, and data infrastructure to adopt AI tools that would make them competitive. The result is a double disadvantage: employment loss without productivity gain, and technological disruption without capability development.

This paper examines four research questions. First, what manufacturing employment disruptions is AI generating across the five focus countries, and what is the scale of displacement relative to the manufacturing sector's contribution to structural transformation? Second, what is the technology capability gap between AI-adopting multinational manufacturers and locally owned African manufacturing firms, and how is it widening? Third, how is AI-enabled reshoring and supply chain reconfiguration affecting African manufacturing integration into global value chains? Fourth, what industrial policy framework is required to govern AI adoption in African manufacturing in a manner that supports rather than subverts the continent's industrialisation objectives?

The paper proceeds as follows. Section 2 presents the background and policy landscape. Section 3 establishes the theoretical framework. Section 4 describes the methodology. Section 5 examines AI applications, benefits, risks, and regulatory challenges. Section 6 presents findings and discussion. Section 7 proposes policy recommendations. Section 8 concludes.

2. BACKGROUND AND POLICY LANDSCAPE

A. African Manufacturing and the Industrialisation Imperative

Manufacturing's contribution to African GDP has stagnated or declined across much of the continent over the past two decades, a pattern described by economists as premature deindustrialisation: the movement of labour out of manufacturing into services before the productivity gains of industrialisation have been fully captured [3]. The United Nations Industrial Development Organisation documents that manufacturing's share of GDP across sub-Saharan Africa declined from 14 percent in 2000 to 11 percent in 2022, against a global average of 16 percent and a Chinese average of 26 percent [4]. This trajectory contradicts the structural transformation model and leaves African economies in a services-dominated structure that lacks the productivity gains, technology diffusion, and export earnings that manufacturing-led development generates.

The African Continental Free Trade Area, which entered into operation in 2021 and represents a market of 1.4 billion people and a combined GDP of 3.4 trillion USD, has created new momentum for African manufacturing by expanding the domestic market for African manufactured goods and creating incentives for regional value chain development [5]. The AfCFTA industrial protocol, adopted in 2023, specifically targets the development of African manufacturing capacity and the deepening of regional industrial linkages. AI technology and its governance are directly relevant to this agenda: whether AI enables or subverts African manufacturing development will substantially determine whether the AfCFTA delivers its industrial transformation promise.

The five focus countries represent distinct manufacturing contexts. South Africa has the most developed manufacturing sector, contributing approximately 13 percent of GDP, with significant automotive, chemical, food processing, and metals manufacturing activity. Nigeria's manufacturing sector contributes approximately 9 percent of GDP, dominated by food and beverage processing, cement, and consumer goods, with significant informal manufacturing activity not captured in official statistics. Kenya has a growing manufacturing sector contributing approximately 8 percent of GDP, with agro-processing, textiles, and construction materials as principal subsectors. Ghana's manufacturing contributes approximately 10 percent of GDP, with aluminium processing, food manufacturing, and consumer goods as major activities. Egypt has the most diversified manufacturing base among the five focus countries, contributing approximately 16 percent of GDP, with textiles, chemicals, food processing, automotive assembly, and construction materials as significant subsectors.

B. AI Adoption in African Manufacturing: Current State

AI adoption in African manufacturing is characterised by a sharp divide between large, foreign-owned manufacturers implementing global automation strategies and locally owned small and medium manufacturing enterprises operating with minimal AI capability. The World Bank Enterprise Survey 2023 documents that fewer than 8 percent of African manufacturing firms have adopted any form of AI-assisted production technology, with adoption rates highest among foreign-affiliated firms (31 percent) and lowest among locally owned SMEs (below 3 percent) [6]. This adoption gap reflects differences in capital availability, technical capability, data infrastructure, and the strategic imperatives of global versus local manufacturing operations.

In the automotive sector, which represents one of Africa's most significant manufacturing investments, AI adoption is driven by global original equipment manufacturers implementing uniform production technologies across their global facility networks. Toyota, Volkswagen, BMW, and Ford all operate AI-assisted production systems at their South African plants, implementing the same automation technologies used in their European and Asian facilities regardless of local labour market conditions [7]. In the textile and apparel sector, which represents Africa's most significant opportunity for labour-intensive export manufacturing, AI-powered quality inspection, inventory management, and predictive maintenance are being adopted by globally connected manufacturers, while locally owned garment manufacturers continue to rely predominantly on manual production processes.

C. Current Policy and Regulatory Environment

The policy environment governing AI in African manufacturing is characterised by industrial policies that were designed without reference to AI disruption, investment frameworks that have not incorporated AI-specific conditions, and labour legislation that does not address the specific circumstances of AI-driven displacement. Table 1 maps the key policy instruments relevant to AI in manufacturing across the five focus jurisdictions and at the continental level.

Table 1

Policy and Regulatory Landscape: AI in Manufacturing and Industrialisation in Africa

Policy Instrument	Jurisdiction	Type	AI Manufacturing-Specific	Key Provisions and Governance Gaps
UNIDO Framework for Industrial Policy in the Digital Age (2021)	International	Framework	Partial	Addresses digital technologies including AI in industrial policy. Emphasises capability development and technology transfer. Non-binding. Limited African adoption.
African Continental Free Trade Area Industrial Protocol (2023)	African Union	Protocol	No	Targets African manufacturing development and regional value chains. No AI-specific provisions. No technology transfer obligations. No AI employment protection clauses.
African Union Agenda 2063: First Ten-Year Implementation Plan (2022)	African Union	Strategy	No	Targets industrialisation as a continental priority. No AI-specific provisions in manufacturing chapters. Technology development referenced generically.
South Africa: Industrial Policy Action Plan (2022-2025)	South Africa	Policy	Partial	References Fourth Industrial Revolution technologies including AI. No binding AI technology transfer obligations on investors. No AI employment impact assessment requirements.
Nigeria: National Industrial Revolution Plan (2022-2025)	Nigeria	Plan	No	Targets manufacturing growth. No AI provisions. No automation impact assessment requirements. Labour displacement from automation not addressed.
Kenya: Big Four Agenda Manufacturing Policy Priority and MSEA Act (2020)	Kenya	Policy	No	Targets manufacturing growth and SME development. No AI-specific provisions. Investment incentives do not condition AI adoption on local employment or technology transfer.
Ghana: National Industrial Policy (2021)	Ghana	Policy	No	Targets value-added manufacturing. No AI provisions. Special economic zones do not require technology transfer or AI employment standards from investors.
Egypt: Industrial Development Strategy 2030	Egypt	Strategy	Partial	References advanced manufacturing technologies. Partial provisions for technology localisation in defence and aerospace. No binding AI employment protection or technology transfer requirements.
All jurisdictions: AI Employment Transition Frameworks	All five	Legislation	No	No African jurisdiction has enacted legislation or policy specifically addressing the retraining, social protection, or transition rights of manufacturing workers displaced by AI

	automation. This represents a critical and universal governance gap.

Note: Sources: UNIDO [8]; African Union Commission [5, 9]; DTIC South Africa [10]; Federal Ministry of Industry Nigeria [11]; Ministry of Industrialisation Kenya [12]; Ministry of Trade Ghana [13]; Ministry of Trade and Industry Egypt [14].

D. Policy Gaps and Governance Challenges

The regulatory mapping in Table 1 reveals five critical governance gaps. First, no African industrial policy framework conditions investment incentives, including tax holidays, special economic zone privileges, or import duty exemptions, on AI technology transfer obligations that would build local manufacturing capability alongside productivity gains. This means that multinational manufacturers can access Africa's investment incentives while implementing global AI automation strategies that do not benefit African industrial capability development. Second, no African jurisdiction has enacted legislation or policy specifically addressing the employment transition rights of manufacturing workers displaced by AI automation, leaving displaced workers dependent on general unemployment insurance systems that were designed for cyclical rather than structural displacement. Third, AI employment impact assessments, which would require manufacturers to evaluate and disclose the employment consequences of planned AI adoption before implementation, are absent from all five focus countries' regulatory frameworks. Fourth, no African manufacturing investment framework specifically requires AI capability transfer as a condition of investment approval, meaning that foreign manufacturers can operate AI-enabled factories in Africa while keeping the AI design, training, and optimisation functions outside the continent. Fifth, no continental mechanism exists for coordinating African industrial AI policy across the AfCFTA framework to prevent regulatory competition that drives a race to the bottom in employment and technology transfer standards.

These governance gaps reflect industrial policies that were designed for an era in which manufacturing technology was primarily physical and incremental rather than digital and discontinuous. Closing them requires not merely the addition of AI-specific clauses to existing industrial policies but the fundamental redesign of African industrial policy around the realities of an AI-transformed manufacturing economy.

3. THEORETICAL AND ANALYTICAL FRAMEWORK

A. Structural Transformation Theory

Structural Transformation Theory, foundationally developed by Lewis [15] and Kuznets [16] and extended for the contemporary African context by McMillan, Rodrik, and Verduzco-Gallo [3] and Page [17], provides the macroeconomic framework for understanding AI's impact on African industrialisation. The theory holds that economic development occurs through the movement of labour and capital from lower-productivity agricultural and informal activities to higher-productivity industrial activities, with manufacturing serving as the principal vehicle for this productivity-enhancing structural transformation. The theory predicts that countries that successfully develop manufacturing sectors generate not only immediate productivity and income gains but also dynamic learning effects, technology spillovers, and institutional capabilities that support long-run development.

Applied to AI's impact on African manufacturing, Structural Transformation Theory generates three analytical propositions that this paper tests empirically. First, if AI automation eliminates the labour-intensive manufacturing roles that constitute Africa's primary comparative advantage in attracting industrial investment, the structural transformation pathway from agriculture to manufacturing employment is blocked, trapping African workers in lower-productivity activities and foreclosing the learning and capability development that manufacturing employment generates [3]. Second, if AI productivity gains in manufacturing accrue primarily to capital-owning multinational corporations rather than to African workers and locally owned firms, structural transformation will not generate the income growth and demand linkages in the African economy that the theory predicts as development consequences of industrialisation. Third, if AI enables global manufacturers to reshore production to high-income countries by reducing the labour cost advantage that made African locations attractive, the development window during which Africa could attract labour-intensive manufacturing investment will close before the continent has achieved the income levels at which labour scarcity would naturally support the transition to capital-intensive production. This third proposition, which this paper calls the foreclosure of the industrialisation pathway, is the most consequential implication of AI for African development and has not been adequately addressed in the African industrial policy literature.

B. The Technology-Organisation-Environment Framework

The Technology-Organisation-Environment Framework, developed by Tornatzky and Fleischer [18] and extensively applied to technology adoption in industrial firms by Oliveira and Martins [19] and adapted for developing economy manufacturing contexts by Awa, Ukoha, and Emecheta [20], provides the analytical framework for understanding the firm-level determinants of AI adoption in African manufacturing. The framework holds that technology adoption decisions are shaped by three categories of factor: technology factors, including the relative advantage of the technology and its compatibility with existing systems; organisation factors, including firm size, technical capability, and financial resources; and environment factors, including competitive pressure, industry structure, and regulatory context. The framework predicts that AI adoption will be concentrated among larger, better-resourced, and more internationally connected firms, because these firms experience greater competitive pressure from global AI adoption, have greater financial resources for AI investment, and have existing IT infrastructure that makes AI integration more compatible.

Applied to African manufacturing, the Technology-Organisation-Environment Framework explains the sharp AI adoption divide between large multinational manufacturers and locally owned SMEs documented in Section 2B, and it generates specific predictions about the conditions under which AI adoption could be broadened to include African SMEs. The framework predicts that without deliberate policy intervention to address the organisation and environment barriers facing African manufacturing SMEs, market forces alone will not produce broad-based AI adoption: the competitive pressure driving AI adoption operates primarily through global value chain relationships that African SMEs do not have, the financial resources required for AI investment are unavailable to most African manufacturing SMEs, and the technical capability prerequisites are absent from a manufacturing sector that has not historically invested in digital infrastructure.

The integration of Structural Transformation Theory and the Technology-Organisation-Environment Framework enables this paper to examine AI's impact on African manufacturing at two levels simultaneously: the macroeconomic level, where Structural Transformation Theory establishes the development stakes of AI disruption for African industrialisation, and the firm level, where the Technology-Organisation-Environment Framework explains why the AI adoption gap between multinational and locally owned manufacturers is structural rather than transitional. This dual-framework approach distinguishes the analysis from prior work that has examined AI in African manufacturing either through a macroeconomic lens [3, 17] or through a firm-level technology adoption lens [6] without integrating both perspectives into a unified policy analysis.

4. METHODOLOGY

A. Research Design and Approach

This study employs a mixed-methods research design combining qualitative documentary and policy analysis with secondary quantitative data analysis, following the explanatory sequential mixed-methods model of Creswell and Creswell [21]. The design is appropriate because the research questions require both an empirical characterisation of the scale and pace of AI-driven manufacturing employment change, the technology adoption gap between multinational and locally owned manufacturers, and the reshoring effects of AI on African manufacturing integration, which is a quantitative inquiry, and an interpretive analysis of the policy frameworks, structural barriers, and industrial governance gaps that shape these dynamics, which is a qualitative inquiry.

B. Data Sources and Collection

Three categories of secondary data sources are employed. The first category comprises quantitative datasets from authoritative international institutions. Manufacturing sector data were drawn from the UNIDO Industrial Statistics Database 2023 [4], the World Bank Manufacturing Value Added Data 2023 [22], and national statistical office manufacturing reports from all five focus countries. AI adoption data were drawn from the World Bank Enterprise Survey 2023 [6], the McKinsey Global Institute reports on AI and manufacturing [23], and the World Economic Forum Future of Jobs Report 2023 [24]. Employment data were drawn from the ILO World Employment and Social Outlook 2023 [25] and national labour ministry reports. Global value chain and reshoring data were drawn from the OECD Trade in Value Added Database 2022 [26] and the Kearney Reshoring Index 2023 [27].

The second category comprises policy documents including national industrial policies, investment promotion frameworks, special economic zone regulations, labour legislation relevant to automation-driven displacement, and AfCFTA industrial protocol documentation. The third category comprises peer-reviewed academic literature published between 2020 and 2026, identified through systematic Scopus, Web of Science, and Google Scholar searches using the terms artificial intelligence manufacturing Africa, automation industrialisation Africa, AI employment displacement manufacturing, reshoring AI Africa, and structural transformation AI. Of 89 articles identified, 56 met the inclusion criteria.

C. Analytical Methods

Qualitative analysis employed policy mapping, gap analysis, and thematic analysis following Braun and Clarke [28] procedures. Quantitative analysis employed descriptive statistical methods to characterise manufacturing employment trends, AI adoption rates by firm type and country, productivity differentials between AI-adopting and non-adopting manufacturers, and reshoring indices for manufacturing categories relevant to African exports. A manufacturing AI disruption index was constructed for each focus country aggregating employment change, AI adoption differential, and global value chain integration measures. All quantitative data are presented in the accompanying supplementary dataset.

D. Limitations

Three limitations are acknowledged. First, consistent and comparable data on AI-specific manufacturing automation, as distinct from broader automation and technology adoption, is not systematically collected by statistical offices in any of the five focus countries, requiring inference from proxy indicators including robot density, enterprise survey technology adoption data, and sectoral employment trends. Second, the five-country focus does not capture the distinct manufacturing contexts of Ethiopia, Rwanda, Mauritius, or Morocco, each of which represents an important dimension of the African manufacturing AI landscape. Third, the rapid pace of AI technology development means that specific automation capabilities described may evolve significantly during the period between data collection and publication.

5. ARTIFICIAL INTELLIGENCE IN AFRICAN MANUFACTURING AND INDUSTRIALISATION: APPLICATIONS AND POLICY IMPLICATIONS

A. Current AI Applications in African Manufacturing

Artificial intelligence is deployed across seven functional domains in African manufacturing, with a consistent pattern of concentration in large, foreign-affiliated manufacturing operations and near-absence in locally owned SMEs.

The first domain is AI-powered quality control and inspection. Computer vision systems using deep learning algorithms for defect detection, dimensional measurement, and surface quality inspection are deployed across the automotive, electronics, and food processing manufacturing sectors in South Africa, Egypt, and Kenya. Volkswagen and BMW's South African plants use AI vision systems for paint defect detection and body panel alignment inspection that have replaced teams of manual quality inspectors [7]. Egypt's automotive assembly operations, including those of Nissan, Geely, and Dongfeng, similarly deploy AI quality inspection systems implemented as part of global production standards. The quality and consistency improvements generated by AI inspection are genuine and significant, but the employment displacement they produce falls disproportionately on lower-skilled production workers who have limited alternative employment options.

The second domain is AI-driven predictive maintenance. Machine learning models trained on sensor data from production equipment predict component failure before it occurs, enabling maintenance interventions that prevent unplanned downtime. This application is particularly significant in capital-intensive manufacturing sectors including cement, chemicals, and metals, where unplanned equipment failure imposes large production losses. LaFargeHolcim, Dangote Cement, and other major African cement manufacturers have deployed AI predictive maintenance systems, with documented reductions in unplanned downtime of 20 to 35 percent [29]. While these systems primarily affect maintenance scheduling rather than eliminating maintenance employment, they do reduce the number of maintenance technicians required per unit of equipment, contributing to a longer-term reduction in maintenance workforce demand.

The third domain is AI-assisted production planning and scheduling. Machine learning optimisation algorithms for production scheduling, inventory management, and supply chain coordination are deployed by the largest African manufacturers across all five focus countries. These systems replace the planning and coordination functions previously performed by production planning teams, eliminating mid-level manufacturing management roles while improving overall production efficiency.

The fourth domain is collaborative robotics and AI-guided assembly. Cobot systems combining physical robotic arms with AI vision and force-sensing capabilities are being introduced in labour-intensive assembly operations in South Africa's automotive sector and Egypt's electronics manufacturing. Unlike conventional industrial robots that require safety cages and separation from human workers, cobots are designed to work alongside humans, performing the most repetitive and ergonomically stressful assembly tasks while human workers handle more variable and judgment-intensive operations. In practice, cobot deployment in African factories often reduces assembly team sizes rather than creating genuine human-robot collaboration [30].

The fifth domain is AI-powered process optimisation in continuous manufacturing. Reinforcement learning algorithms for process control optimisation are deployed in chemical, petrochemical, and food processing operations, continuously adjusting process parameters to optimise yield, energy efficiency, and product consistency. This application has generated significant efficiency gains in South African and Egyptian chemical manufacturing but creates negligible direct employment, as continuous manufacturing processes have always been capital-intensive and operator requirements are already minimal.

The sixth domain is AI-enabled supply chain management. AI platforms for demand forecasting, supplier selection, procurement optimisation, and logistics coordination are used by the largest African manufacturers and by the African subsidiaries of multinational corporations. These systems are particularly relevant to African manufacturing's integration into global value chains, and their adoption by multinational firms has implications for the sourcing decisions, quality standards, and compliance requirements facing African supplier firms.

The seventh domain is AI-assisted product design and development. Generative design algorithms and AI-powered simulation tools for product development are used by South African automotive component manufacturers, Egyptian industrial equipment producers, and Kenyan agro-processing equipment manufacturers. These tools accelerate design cycles and reduce prototyping costs, enabling more rapid product innovation, but they require technical capabilities and computing infrastructure that are beyond the reach of most African manufacturing SMEs.

B. Benefits and Opportunities

AI adoption in African manufacturing generates four categories of documented benefit. First, quality and competitiveness improvements: AI quality inspection and process optimisation systems have generated documented quality improvements in South African automotive component manufacturing that have supported the retention and expansion of global OEM supply contracts [7]. Egypt's AI-adopting textile manufacturers have similarly documented reductions in defect rates that have strengthened their competitive position in export markets [14]. These quality gains are directly relevant to African manufacturing's ability to meet the standards required for participation in global value chains.

Second, productivity gains for AI-adopting firms: the World Bank Enterprise Survey documents that AI-adopting African manufacturers report productivity improvements of 18 to 35 percent compared with non-adopting competitors in the same sector [6]. These productivity gains are significant, but their concentration in large, predominantly foreign-owned firms means that they are not generating broad-based industrial productivity growth in the African economy.

Third, safety improvements: AI-assisted monitoring of hazardous manufacturing processes, AI-powered safety inspection systems, and AI-driven ergonomic assessment tools have reduced workplace accident rates in AI-adopting South African mining and chemical manufacturing operations by an estimated 22 to 41 percent [10]. This benefit is genuinely positive for manufacturing workers and is less contested than employment displacement impacts.

Fourth, AfCFTA value chain integration: AI supply chain management tools have the potential to facilitate African manufacturers' participation in regional value chains under the AfCFTA by improving supply chain transparency, reducing logistics costs, and enabling more effective matching of African suppliers with regional buyers. Several AfCFTA pilot projects for regional supply chain development are incorporating AI tools for supplier discovery and compliance monitoring [5].

C. Risks, Harms, and Ethical Considerations

Against these documented benefits, AI adoption in African manufacturing generates six categories of serious risk, harm, and structural threat that are the central focus of this paper's analysis.

The first and most structurally significant risk is the foreclosure of the labour-intensive industrialisation pathway. The development model through which East Asian economies achieved structural transformation depended on the ability to attract labour-intensive manufacturing investment by offering competitive labour costs, and then to use the income, skills, and institutional development generated by manufacturing employment to gradually upgrade to more capital-intensive and technology-intensive production. AI automation is rendering this pathway progressively less viable by reducing the labour cost advantage that made African locations attractive for labour-intensive manufacturing. When AI vision systems can replace teams of quality inspectors and cobots can replace assembly workers at capital costs that are declining rapidly, the relative attractiveness of African locations, based on lower labour costs, diminishes [3, 17]. This does not mean that African manufacturing is impossible in an AI world, but it does mean that the specific development pathway through which manufacturing employment drove structural transformation in East Asia is no longer available in the same form. The paper names this the foreclosure of the industrialisation pathway and argues that it constitutes the most consequential long-run implication of AI for African development.

The second risk category is the manufacturing AI paradox documented in this paper's abstract: AI is disrupting Africa's manufacturing employment base before generating the productivity and capability gains that would justify the displacement. This paradox arises because the employment disruption is driven by multinational firms implementing global automation strategies, while the productivity gains and technology capabilities generated by AI adoption remain within the multinational firm's global technology system rather than diffusing into the African economy. African workers bear the displacement cost; African economies do not capture the productivity benefit.

The third risk category is the widening of the technology capability gap. As multinational manufacturers deploy increasingly sophisticated AI production systems, the gap between the AI capabilities embedded in foreign-owned African factories and the technological capabilities of locally owned African manufacturing SMEs is widening. This capability gap has direct implications for supply chain linkages: as multinational manufacturers adopt AI quality management and supply chain optimisation systems, they impose new digital compliance requirements on their supplier networks that locally owned African suppliers often cannot meet, leading to supplier exclusion rather than local sourcing [31].

The fourth risk category is AI-enabled reshoring and nearshoring. Global manufacturing corporations are using AI automation to reconsider the geographic distribution of their production. When AI-powered robots and cobots reduce the labour cost component of manufacturing to a small share of total cost, the labour cost advantage of African locations diminishes relative to the logistical, quality, and intellectual property advantages of producing in proximity to the primary market. The Kearney Reshoring Index 2023 documents a multi-year trend of manufacturing reshoring to the United States, Western Europe, and East Asia among global corporations implementing AI automation [27]. For Africa, this reshoring trend represents a contraction of the manufacturing investment opportunities that the continent has been working to attract.

The fifth risk category is the displacement of manufacturing workers without adequate social protection. African social protection systems, including unemployment insurance, retraining programmes, and labour transition support, were designed for frictional and cyclical unemployment rather than for the structural displacement generated by AI automation. When AI automation eliminates entire categories of manufacturing employment rather than temporarily reducing demand for specific skills, the assumption embedded in African social protection systems, that workers who lose manufacturing jobs will find comparable manufacturing employment elsewhere after a period of job search, does not hold [25]. The absence of AI-specific employment transition frameworks in all five focus countries means that manufacturing workers displaced by AI automation face this structural challenge without dedicated support.

The sixth risk category is the gender dimension of manufacturing AI displacement. Women are disproportionately represented in the manufacturing roles most susceptible to AI automation, including garment assembly, food processing, and electronics manufacturing quality control [32]. In countries where women's formal manufacturing employment represents one of the primary mechanisms through which women have achieved financial independence and escape from household poverty, AI-driven displacement from manufacturing employment has specific gender dimensions that are not addressed by any of the five focus countries' AI or industrial policies.

D. Sector-Specific Regulatory Challenges

Four regulatory challenges are specific to the governance of AI in African manufacturing. First, the investment promotion frameworks that govern manufacturing investment in all five focus countries have been designed primarily to attract investment volume rather than to shape the quality, technology content, and employment characteristics of that investment. Incorporating AI technology transfer obligations and employment impact requirements into these frameworks requires a fundamental reorientation of investment promotion philosophy that may encounter resistance from investment promotion agencies and finance ministries that prioritise investment quantity over investment quality. Second, the labour legislation of all five focus countries addresses dismissal procedures, redundancy compensation, and retraining obligations in terms that were designed for individual employment contract termination rather than for the systemic displacement of entire job categories by technology. Third, the AfCFTA industrial protocol, while creating the institutional architecture for continental industrial coordination, does not yet contain AI-specific provisions and its negotiating process is insufficiently engaged with the specific implications of AI for African manufacturing competitiveness. Fourth, the monitoring and evaluation frameworks of national industrial development authorities do not include AI adoption tracking, technology transfer measurement, or AI employment impact assessment metrics, making it impossible to assess whether AI adoption in manufacturing is serving African industrial development objectives or undermining them.

6. FINDINGS AND DISCUSSION

A. Key Findings

Finding 1: The African manufacturing AI paradox is empirically confirmed. Analysis of manufacturing employment data from the five focus countries confirms that formal manufacturing employment declined by between 6 and 19 percent between 2020 and 2023 across the focus countries, with the sharpest declines concentrated in quality control, assembly, and production planning roles that correspond to the manufacturing functions most susceptible to AI automation [25]. Simultaneously, the World Bank Enterprise Survey 2023 confirms that fewer than 8 percent of African manufacturing firms overall, and fewer than 3 percent of locally owned manufacturing SMEs, have adopted any form of AI-assisted production technology [6]. The combination of employment decline and minimal local AI adoption confirms the paradox: the employment disruption is being driven primarily by multinational firms implementing global automation strategies rather than by broad-based AI adoption among African manufacturers. African manufacturing workers are bearing the displacement cost of a technological transition that African manufacturing firms are not driving and from which African manufacturing capabilities are not benefiting.

Finding 2: The technology capability gap between multinational and locally owned manufacturers is structural and widening. The AI adoption differential documented in Section 2B, with multinational manufacturers adopting AI at rates of 31 percent compared with below 3 percent for locally owned SMEs, represents not merely a difference in technology adoption timing but a structural divergence in manufacturing capability that is inconsistent with the technology learning and diffusion processes that Structural Transformation Theory identifies as essential to industrial development [3]. This finding identifies a specific mechanism through which AI adoption in African manufacturing is failing to generate the technology spillovers and capability development that would support long-run industrialisation, extending prior literature on technology transfer in African manufacturing [17] by demonstrating that AI creates a new and more rapid form of capability divergence than previous manufacturing technology transitions.

Finding 3: No African industrial policy framework specifically addresses AI employment transition obligations. The review of industrial policies, labour legislation, and investment frameworks across all five focus countries confirms that no jurisdiction has enacted legislation or policy specifically requiring manufacturers to fund, facilitate, or participate in AI employment transition programmes for displaced workers [10, 11, 12, 13, 14]. This finding identifies the most urgent and specific governance gap in African manufacturing AI governance: the workers most immediately harmed by AI automation, those who are currently losing manufacturing jobs to AI-enabled displacement, have no policy framework dedicated to their transition.

Finding 4: AI-enabled reshoring is measurable and directionally threatening to African manufacturing integration. Analysis of global reshoring trend data from the Kearney Reshoring Index 2023 and OECD Trade in Value Added data confirms a measurable trend of manufacturing activity returning from developing-country locations to high-income-country locations in sectors where AI automation has substantially reduced the labour cost component [26, 27]. For Africa, the most exposed manufacturing sectors are textiles and apparel, electronics assembly, and basic consumer goods manufacturing, precisely the sectors that Africa's industrial strategies have identified as priority targets for attracting labour-intensive manufacturing investment. This finding provides the most direct empirical evidence of the industrialisation pathway foreclosure risk identified as this paper's central analytical contribution.

Finding 5: Gender-disaggregated data on AI manufacturing displacement is absent from all five focus jurisdictions. The review of national labour statistics, manufacturing employment records, and industrial policy monitoring systems across all five focus countries confirms that none publishes gender-disaggregated data on manufacturing employment changes attributable to automation or AI adoption [32]. This data gap means that the specific gender consequences of AI manufacturing displacement, which theory predicts will be concentrated among women in assembly, quality control, and processing roles, cannot be empirically documented or policy-targeted.

B. Comparative Analysis

The comparative analysis across the five focus countries reveals important variations in both AI manufacturing adoption and industrial policy sophistication. South Africa presents the most advanced manufacturing AI adoption, the most significant employment displacement, and the most developed industrial policy infrastructure, including the Industrial Policy Action Plan and the Special Economic Zones Act, but even South Africa's industrial policy has not been updated to address AI-specific technology transfer or employment transition obligations. Egypt presents the most diversified manufacturing sector and has the most advanced AI manufacturing adoption among the five focus countries in sectors beyond automotive, including textiles, food processing, and pharmaceuticals, and Egypt's Industrial

Development Strategy 2030 is the most technologically ambitious among the focus countries, though it lacks binding AI employment protections. Nigeria and Ghana face the most acute manufacturing AI paradox dynamics: both have industrial policies that target manufacturing growth, and both are experiencing manufacturing employment pressure from AI adoption in foreign-affiliated firms, without any policy framework addressing the resulting displacement. Kenya's manufacturing sector is in a transitional position: its AI adoption rate in manufacturing is lower than South Africa's or Egypt's, but its agritech and fintech ecosystems are generating AI manufacturing capability in food processing and agro-processing that represents a genuine African manufacturing innovation story.

This comparative analysis supports the conclusion that the manufacturing AI paradox operates across all five focus countries regardless of manufacturing sector sophistication or industrial policy maturity, demonstrating its structural character. It also identifies South Africa's industrial policy infrastructure and Egypt's technological ambition as the most developed foundations on which AI-specific industrial governance could be built, and it identifies Kenya's agro-processing AI innovation as the most replicable model of locally owned African manufacturing AI adoption.

C. Discussion

The findings of this study confirm and extend prior literature on manufacturing and structural transformation in Africa [3, 17] in three important respects. They confirm Structural Transformation Theory's prediction that AI automation threatens to block the labour-intensive industrialisation pathway by reducing the labour cost advantage that makes African locations attractive for manufacturing investment, providing the first systematic empirical evidence of this effect across five African manufacturing economies. They extend the Technology-Organisation-Environment Framework by demonstrating that the organisation and environment barriers to AI adoption are more severe for African manufacturing SMEs than for manufacturing firms in the high-income-country contexts where the framework was originally applied, requiring more substantial policy intervention to overcome. And they introduce the African manufacturing AI paradox as a named, empirically characterised, and theoretically grounded concept that enables more precise industrial policy targeting than the general observation that AI is disrupting manufacturing employment.

The most consequential implication of the findings for policy is that the industrial development window for Africa may be narrowing due to AI automation. If AI continues to reduce the labour cost advantage that makes African manufacturing locations attractive for investment, the period during which Africa can attract labour-intensive manufacturing investment and use it as a development vehicle is finite. The urgency of this conclusion argues for immediate industrial policy reform that incorporates AI technology transfer obligations, employment transition frameworks, and manufacturing capability development investments into Africa's industrial governance architecture, rather than deferring these reforms until the employment disruption becomes politically unmanageable.

7. POLICY RECOMMENDATIONS

The policy recommendations of this study are grounded directly in the five findings presented in Section 6 and structured around a seven-Policy Priority industrial policy framework designed to address the African manufacturing AI paradox identified as this paper's primary contribution to knowledge. The framework operates simultaneously at the firm level, through technology transfer obligations and AI capability development support; at the worker level, through employment transition funds and gender-responsive transition programmes; at the industry level, through investment incentive conditions and employment impact assessment requirements; and at the continental level, through AfCFTA AI manufacturing standards. Each Policy Priority is elaborated below.

Table 2

Summary of Policy Recommendations

Priority	Recommendation	Target Actor(s)	Timeline
HIGH	Amend investment promotion frameworks in all five focus jurisdictions to condition AI-related manufacturing investment incentives on technology transfer obligations, requiring foreign AI manufacturing investors to establish local AI capability development programmes, train local engineers, and source AI system components locally where feasible.	Industry Ministries; Investment Promotion Authorities	Short-term: 1 to 2 years
HIGH	Establish dedicated manufacturing worker AI transition funds in all five focus jurisdictions, financed through a levy on AI-adopting manufacturers proportional to the employment reduction generated by AI adoption, providing retraining, income support, and employment placement services for displaced workers.	Labour Ministries; Industry Ministries; Employer Federations	Short-term: 1 to 2 years
HIGH	Mandate AI employment impact assessments for all manufacturers employing more than 50 workers before implementing AI automation that will result in workforce reductions, requiring disclosure of the projected employment impact and the planned worker transition measures.	Labour Ministries; Industry Ministries	Short-term: 1 to 2 years
HIGH	Condition AI manufacturing investment incentives on local employment retention thresholds, requiring AI-adopting manufacturers receiving government incentives to maintain minimum employment levels or demonstrate equivalent local economic value creation through supply chain development.	Investment Promotion Authorities; Finance Ministries	Short-term: 1 to 2 years
MEDIUM	Establish public AI manufacturing capability development programmes targeting locally owned manufacturing SMEs, providing subsidised access to AI tools, technical training, and data infrastructure support to reduce the technology capability gap between multinational and local manufacturers.	Industry Ministries; Development Finance Institutions; AfDB	Medium-term: 3 to 5 years
MEDIUM	Develop gender-responsive AI manufacturing employment transition programmes that specifically address the disproportionate displacement of women from manufacturing assembly, quality control, and processing roles, including targeted retraining and alternative employment pathways for affected women workers.	Labour Ministries; Gender Ministries; Employer Federations	Medium-term: 3 to 5 years
MEDIUM	Incorporate AI technology transfer and employment standards into the AfCFTA industrial protocol, establishing continental minimum standards for AI manufacturing investment that prevent a regulatory race to the bottom in employment and technology transfer requirements across member states.	African Union Commission; AfCFTA Secretariat; Trade Ministries	Medium-term: 3 to 5 years
LOW	Establish a continental manufacturing AI governance architecture under the AfCFTA and African Union, including a shared AI manufacturing technology assessment function, a continental manufacturing employment monitoring system, and a pan-African manufacturing AI capability development fund financed by the African Development Bank.	African Union Commission; AfCFTA Secretariat; AfDB	Long-term: 5 or more years

Note: Source: Authors' analysis based on findings of this study and policy mapping in Table 1. Timelines are indicative.

Policy Priority 1. AI Technology Transfer Obligations in Investment Frameworks

Industry ministries and investment promotion authorities in all five focus jurisdictions must amend their manufacturing investment frameworks to condition access to AI-related investment incentives, including tax holidays, customs duty exemptions, and special economic zone privileges, on binding AI technology transfer obligations. These obligations must require foreign AI manufacturing investors to establish local AI capability development programmes that train a defined minimum number of African engineers, data scientists, and AI system operators; to source AI system components, training data services, and AI maintenance from local providers where technically feasible; and to locate AI research and development functions in Africa rather than exclusively in the home country of the investing firm. The evidence base is Finding 2, which documents the structural and widening technology capability gap between multinational and locally owned manufacturers, and Structural Transformation Theory's emphasis on technology spillovers as an essential dimension of manufacturing-led industrial development [3].

Policy Priority 2. Manufacturing Worker AI Transition Funds

Labour ministries and industry ministries must jointly establish dedicated manufacturing worker AI transition funds in all five focus jurisdictions, financed through a levy on AI-adopting manufacturers set at a percentage of the wage savings generated by AI-driven workforce reductions. These funds must provide displaced manufacturing workers with three categories of support: income replacement at a meaningful level for a defined transition period, enabling workers to support their families while retraining; access to retraining programmes specifically designed for AI-era manufacturing and service employment, including technical skills in AI-adjacent manufacturing roles, digital literacy, and vocational certification; and employment placement services that actively connect retrained workers with growing employment sectors. The evidence base is Finding 3, which documents the complete absence of AI employment transition frameworks across all five focus jurisdictions, and Finding 1, which documents manufacturing employment declines of 6 to 19 percent over the 2020 to 2023 period.

Policy Priority 3. Mandatory AI Employment Impact Assessments

Labour ministries must enact regulations requiring all manufacturers employing more than 50 workers to conduct and publish AI employment impact assessments before implementing any AI automation that will result in workforce reductions above a defined threshold. These assessments must quantify the projected employment impact of the planned automation; document the specific roles that will be displaced and the demographic characteristics of the affected workers, including gender and age; and specify the worker transition measures the employer will implement to support displaced workers. Assessments must be submitted to the relevant labour authority before automation implementation, and a mandatory consultation period with worker representatives must follow. This Policy Priority provides the data foundation for the manufacturing worker AI transition funds in Policy Priority 2 and the gender-responsive programme in Policy Priority 6.

Policy Priority 4. AI Investment Incentives Conditioned on Local Employment

Investment promotion authorities must establish minimum local employment retention thresholds as conditions of AI manufacturing investment incentive packages, requiring manufacturers who receive government incentives while adopting AI automation to maintain minimum employment levels relative to pre-automation baselines, or to demonstrate equivalent local economic value creation through supply chain localisation, local procurement, or community investment programmes. This Policy Priority addresses the core of the manufacturing AI paradox by ensuring that the public resources invested in manufacturing attraction through incentive programmes generate commensurate employment and economic returns for African communities rather than subsidising corporate automation strategies that generate productivity gains and profits that are largely repatriated.

Policy Priority 5. Public AI Manufacturing Capability Development

Industry ministries and development finance institutions, with African Development Bank financing, must establish public AI manufacturing capability development programmes specifically targeting locally owned manufacturing SMEs. These programmes should provide subsidised access to AI tools including cloud-based machine vision platforms, AI quality management systems, and predictive maintenance tools; technical training in AI system operation, maintenance, and optimisation delivered in forms accessible to manufacturing SME managers and workers with limited prior digital experience; data infrastructure support including connectivity subsidies and IoT sensor installation grants; and peer learning networks connecting AI-adopting African manufacturing SMEs with each other and with AI manufacturing research capabilities at African universities and technical institutes. This Policy Priority is the supply-side complement to the demand-side incentive conditions in Policy Priority 4.

Policy Priority 6. Gender-Responsive Manufacturing AI Transition

Labour ministries and gender ministries must develop gender-responsive AI manufacturing employment transition programmes that specifically address the disproportionate displacement of women from manufacturing assembly, quality control, food processing, and garment production roles by AI automation. These programmes must include targeted retraining in AI-adjacent manufacturing skills that represent genuine employment pathways for women with manufacturing backgrounds; income support designed for the specific economic circumstances of women manufacturing workers, who are more likely to be sole household providers and less likely to have formal savings; childcare support during retraining periods that addresses the primary barrier to women's participation in retraining programmes; and active employment placement services with employers committed to hiring retrained women manufacturing workers. The evidence base is Finding 5, which documents the complete absence of gender-disaggregated AI manufacturing displacement data and gender-specific transition provisions across all five focus jurisdictions.

Policy Priority 7. Continental AI Manufacturing Governance under AfCFTA

The African Union Commission and the AfCFTA Secretariat must incorporate AI manufacturing standards into the AfCFTA industrial protocol, establishing continental minimum requirements for AI technology transfer, employment protection, and local capability development that apply to all manufacturing investment across AfCFTA member states. These continental standards must prevent a regulatory race to the bottom in which individual countries undercut each other's employment and technology transfer requirements to attract manufacturing investment. Simultaneously, the African Development Bank must establish a pan-African manufacturing AI capability development fund to finance the public programmes in Policy Priority 5 at continental scale, enabling African manufacturing SMEs across the continent to access AI tools and capabilities that would be beyond the reach of any individual country's public budget. This fund should target specifically the African manufacturing sectors with the greatest AfCFTA regional value chain potential, including agro-processing, textiles and apparel, construction materials, and pharmaceutical manufacturing.

8. CONCLUSION

This paper has examined the effect of artificial intelligence on manufacturing and industrialisation in Africa through the analytical lenses of Structural Transformation Theory and the Technology-Organization-Environment Framework, employing a mixed-methods research design grounded in comprehensive secondary data analysis and systematic policy mapping across five major African manufacturing economies. The study has demonstrated that AI adoption in African manufacturing is generating documented productivity and quality improvements in large, predominantly foreign-owned manufacturing operations, while simultaneously producing six categories of serious disruption for African industrial development: the foreclosure of the labour-intensive industrialisation pathway, the African manufacturing AI paradox of employment disruption without capability gain, the widening technology capability gap between multinational and local manufacturers, AI-enabled reshoring and nearshoring that threatens Africa's manufacturing investment attractiveness, manufacturing worker displacement without adequate social protection, and gendered displacement concentrated among women manufacturing workers.

The central finding and primary contribution of this study to knowledge is the identification, empirical characterisation, and theoretical grounding of the African manufacturing AI paradox: the structural condition in which AI is disrupting Africa's manufacturing employment base before generating the productivity and capability gains that would justify the displacement, because the disruption is driven primarily by multinational firm global automation strategies rather than by African industrial strategy. Analysis of manufacturing employment data confirms declines of 6 to 19 percent in formal manufacturing employment across the five focus countries between 2020 and 2023, while AI adoption among locally owned manufacturers remains below 3 percent. This paradox has not been previously named or systematically characterised across multiple African manufacturing economies in the published literature.

The paper proposes a seven-Policy Priority industrial policy framework: AI technology transfer obligations, manufacturing worker transition funds, mandatory AI employment impact assessments, AI investment incentives conditioned on local employment, public AI manufacturing capability development, gender-responsive transition programmes, and continental AI manufacturing governance under the AfCFTA. These recommendations are grounded in the specific evidence of this study, calibrated to the institutional realities of African industrial governance, and directed at named actors with defined implementation timelines.

The paper's contribution to knowledge is threefold. It provides the first systematic comparative characterisation of the African manufacturing AI paradox across five major economies. It demonstrates, through the integration of Structural Transformation Theory and the Technology-Organisation-Environment Framework, that the paradox is structurally produced by the design of AI manufacturing adoption and cannot be resolved without deliberate industrial policy intervention. And it proposes a theoretically grounded, institutionally realistic policy framework that industry ministers, labour ministers, investment promotion authorities, and development partners can adopt as the basis for AI-responsive industrial governance.

Future research should develop standardised AI manufacturing adoption metrics that disaggregate AI technology adoption by firm ownership type, size, and nationality; conduct primary firm-level research on the technology capability barriers facing African manufacturing SMEs; evaluate the effectiveness of specific technology transfer obligation designs in generating genuine local capability development; and extend the geographic scope to include Ethiopia, Morocco, and Rwanda, which represent important dimensions of the African manufacturing landscape not captured in the five-country focus. The governance of AI in African manufacturing is among the most consequential industrial policy challenges of the current decade, with direct implications for Africa's ability to use manufacturing as the engine of structural economic transformation.

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10. DECLARATIONS

Author contributions. All authors contributed to the conceptualization, documentary analysis, comparative regulatory mapping and drafting of this study. E.U.N. led the research design and supervised the work. All authors

reviewed and approved the final manuscript.

Competing interests. The authors are affiliated with Veristzon Global Research Lab, A research Partner organisation with the International Institute of Artificial Intelligence and Research (IIAR), which publishes this journal.The manuscript was subject to the journal's standard peer review process.

Funding. This research received no external funding.

Data availability. This study draws on publicly available secondary data from the sources listed in the references. No new data were generated.

Use of AI tools. AI assistance was used for language editing. All analysis, interpretation and

conclusions are the authors' own