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Artificial Intelligence and Digital Transformation as Drivers of Economic Transformation in Kenya's Manufacturing Sector

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Abstract: *Artificial Intelligence (AI) and digital transformation are reshaping global manufacturing, serving as transformative drivers of productivity, competitiveness, and sustainable development. In Kenya, where manufacturing is central to the Bottom-up Economic Transformation Agenda (BETA), the integration of AI with complementary digital technologies such as the Internet of Things (IoT), cloud computing, and big data analytics presents new opportunities for sectoral modernization. This paper examines how AI and digital transformation influence economic transformation through employment creation within Kenya's manufacturing sector. Using mediation regression analysis based on Hayes' Model 4, the study tests the mediating role of firm operational efficiency in the relationship between AI, digital transformation and employment outcomes. The findings reveal that while automation and AI adoption can displace routine and low-skilled labour, they simultaneously improve operational efficiency, generate high-skilled employment opportunities, foster innovation, and enhance sector-wide competitiveness. These dual disruptive and transformative effects underscore the importance of proactive policy frameworks, workforce reskilling, and inclusive innovation ecosystems. With strategic alignment, AI and digital transformation can reposition Kenya's manufacturing sector as a catalyst for inclusive economic growth and sustainable development.*

Key Words: Artificial Intelligence, Digital Transformation, Manufacturing, Economic Transformation, Employment Creation, Sustainable Development

I. Introduction

The manufacturing industry in Kenya has long been recognized as a crucial driver of economic growth and employment, accounting for 15.9% of wage employment in the private sector in 2023 (Kenya National Bureau of Statistics (KNBS, 2024). However, despite its potential, the sector's contribution to the country's Gross Domestic Product (GDP) has in the last 10 years, shown a declining trend, plummeting from 10.0% in 2014 to 7.8% in 2023, a decrease from the previous decade's consistent levels around 10% (KNBS, 2018; KNBS, 2024). In 2014, the sector accounted for 10.0% of GDP, but this figure steadily decreased to 9.4% in 2015, 9.3% in 2016, and 7.2% in 2017 (KNBS, 2018). This improved in 2018, at 8.4%, then steadily dropped again to 7.9% in 2019, 7.6% in 2020, and 7.4% in 2021. With the 2020 and 2021 decline largely attributed to the global economic downturn caused by the COVID-19 pandemic, the sector showed slight recovery in 2022, contributing 7.8%. It however slightly decreased again to 7.6% in 2023 (KNBS, 2024).

A comparatively better trend, albeit dismal, has been observed in the sector's wage employment, exhibiting gradual growth with some fluctuations. In 2014, the sector accounted for about 20.0% of wage employment (KNBS, 2019). This share slightly increased over the years, reaching 20.3% in 2015 and 20.4% in 2016. The trend continued with 20.2% in 2017, 2018, 2019 and 2020 (KNBS, 2021). The share slightly increased to 20.7% in 2020. However, it notably plummeted to 15.8% in 2021 and 15.9% in 2022. It stagnated at 15.9% in 2023 (KNBS, 2023).

The observed decline reflects the sector's struggle with persistent challenges, including high production costs, inadequate infrastructure, and competition from cheaper imports, which have limited its growth potential (Kenya Association of Manufacturers (KAM), 2024). Despite government initiatives such as the Big Four Agenda, which prioritizes manufacturing as a key pillar for economic development, the sector has yet to achieve the targeted 15% contribution to GDP as outlined in the Vision 2030 development plan (Government of Kenya, 2018), highlighting the need for renewed focus and strategic interventions. In recent years, digital transformation has emerged as a potential solution to these challenges, offering opportunities to enhance efficiency, innovation, and competitiveness (Martínez-Peláez et al., 2023). Integrating advanced technologies such as automation, artificial intelligence (AI), data analytics and the Internet of Things (IoT), manufacturers can significantly enhance operational efficiency, reduce production costs, and improve product quality (Aldoseri et al., 2024).

Globally, manufacturing firms have increasingly adopted digital transformation technologies to enhance efficiency, productivity, and competitiveness (Baldwin et al., 2019). For example, General Electric (GE) employs AI and IoT in its "Brilliant Manufacturing" initiative, optimizing production processes and reducing downtime. Siemens uses AI and IoT in its "Digital Factory" to enhance efficiency and flexibility, while Tesla's Gigafactories leverage automation and robotics for mass production of electric vehicles. In Japan, Toyota integrates data analytics and cloud computing in its "Smart Factory" initiatives to optimize supply chains (SYSPRO, 2023). In Sub-Saharan Africa, firms like Nigeria's Dangote Cement have adopted automation and data analytics to improve production efficiency, although the region faces challenges such as limited digital infrastructure (World Bank, 2020; SYSPRO, 2023).

In Kenya, the manufacturing sector has historically been characterized by labour-intensive processes, outdated technology, and limited integration into global value chains. In the current administration's Bottom-up Economic Transformation Agenda (BETA) however, manufacturing and digital transformation hold central roles as enablers of socio-economic transformation through driving employment creation, attracting investment, and boosting foreign exchange earnings (Parliamentary Service Commission, 2023). Implemented by the Fourth Medium Term Plan (MTP IV) 2023-2027, BETA is geared towards economic turnaround and inclusive growth through a value chain approach. To this end, BETA targets sectors with high impact to drive economic recovery, key among which, manufacturing. The Digital Superhighway pillar of BETA is particularly foundational to manufacturing, as it aims to enhance digital infrastructure across Kenya, providing the backbone for widespread digital transformation in key sectors, including manufacturing (Republic of Kenya, 2023). In the private sector, several large manufacturers (100 employees and above) have already adopted digital systems into their operations in a bid to boost competitiveness and enhance efficiencies while cutting costs and wastage (Igadwah, 2022). This adoption has especially accelerated on the realization of the depth and scope of business disruptions caused by Covid-19 pandemic. For instance, Bidco Africa are beginning to utilize automation and data analytics to streamline operations and improve decision-making (SYSPRO, 2021).

The extent to which digital transformation can drive industrialization for economic transformation and employment creation in Kenya's manufacturing sector however remains underexplored. While several studies have explored the general impact of digitalization on economic growth (OECD, 2019; UNCTAD, 2020), there is a gap in the literature regarding its specific influence on economic transformation and employment creation with reference to the manufacturing sector in Kenya. This research is thus motivated by the need to understand the role of digital transformation in advancing Kenya's industrialization agenda and its impact on economic transformation and employment creation. Understanding this relationship is critical for policymakers, industry stakeholders, and development partners aiming to leverage digital technologies for economic transformation and job creation.

This study differentiates itself by focusing specifically on the manufacturing industry in Kenya, providing an in-depth analysis of how digital transformation can drive economic transformation and employment creation within this sector. Unlike previous studies that often take a broad approach, this research zeroes in on the manufacturing context, addressing the unique challenges and opportunities present in Kenya. More specifically, it set out to determine the effect of digital transformation on economic transformation, focusing on the manufacturing share of GDP; evaluate the effect of digital transformation on employment creation in the manufacturing sector; and assess the mediating role of economic transformation on the relationship between digital transformation and employment creation within the country's manufacturing sector.

II. Materials and Methods

The study was conducted between 29th August and 16th September, 2024 and employed the cross-sectional research design. This design was particularly suitable for capturing data from manufacturing firms across various metrics: Digital technologies and leadership as indicators of digital transformation; Firm performance as an indicator of economic transformation; and employment growth rate as indicator of employment creation. Utilizing this approach enabledthe study examine existing relationships between digital transformation and key performance indicators, making it effective for identifying trends and correlations without requiring longitudinal data (Kumar,2018). According to KAM (2024), manufacturers are are grouped into 14 sectors, which are further broken down into Sub-sectors. The main sectors include: Agriculture/Agro-processing, Automotive, Building, Mining and Construction, Chemical & Allied, Energy, Electrical and Electronics, Food and Beverages, Leather and Footwear, Metal and Allied, Paper, Pharmaceutical and Medical Equipment, Plastics and Rubber, Textile and Apparels Sector, Timber and Services and Consultants. The accessible population comprised KAM membership, who total 1128 (KAM, 2023). KAM is the representative organization for manufacturing value-add industries in Kenya, drawing countrywide membership across the 14 manufacturing sectors. The study focused on Nairobi County, as a majority approximately 60% of KAM members (682) are based in Nairobi, therefore providing a larger representative pool of the different sub-sectors in manufacturing. To arrive at the desired sample size, the Yamane (1967) formula was employed:

$$n = \frac{N}{1 + N(e)^2}$$

Where:

n = Required sample

N = Total population = 682

e = Margin of error, set at 0.1 (90% confidence level)

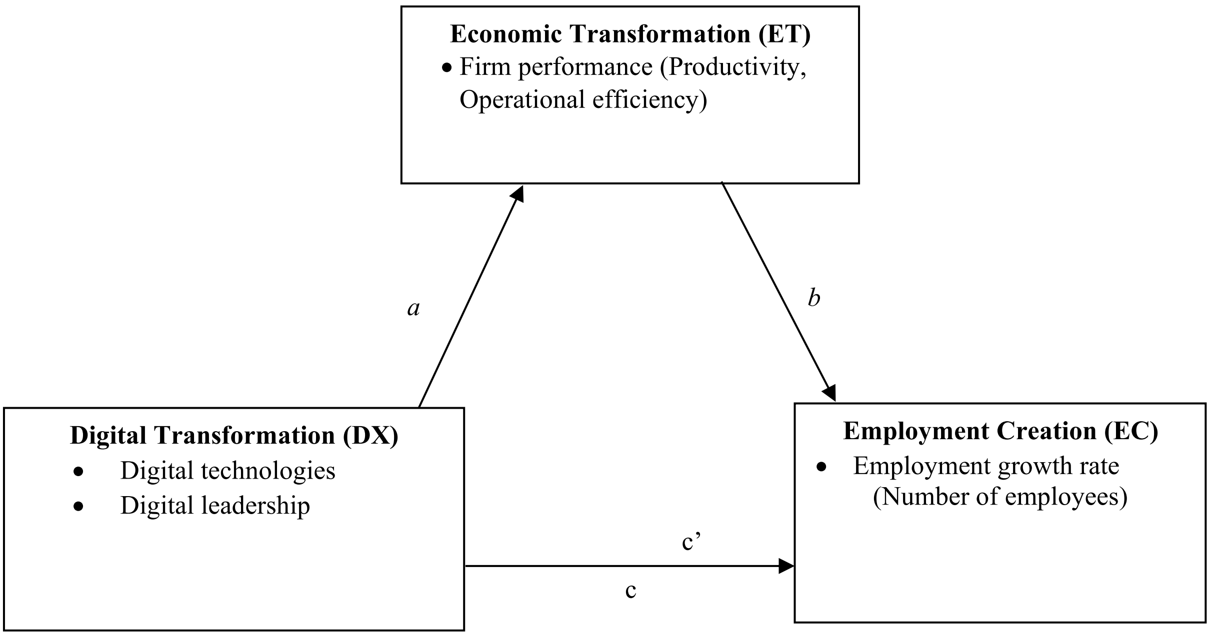
Therefore;

$$n = \frac{682}{1+682(0.1)^2}$$

n= 87

A sample of 87 was thus reached, sampled based on the systematic random sampling technique. As per Saunders et al. (2019), systematic random sampling is a probability sampling technique where sample elements are selected from a larger population at a regular interval after choosing a random starting point. In this regard, every 5th firm was selected. The sampling frame was obtained from KAM.

The study relied on quantitative data, collected from both primary and secondary sources. Primary data was gathered from sampled manufacturing firms through structured questionnaires, while secondary data was sourced from reputable publications such as the KNBS Economic Surveys, industry reports from KAM, and other relevant economic and industrial reports. The independent variable, digital transformation, was measured by the level of investment in digital infrastructure by manufacturing firms; while the mediating variable, Economic Transformation, was measured by the manufacturing sector's share of GDP over the 10-year period. The dependent variable, Employment Creation, was measured by the employment growth rate within the manufacturing sector. The study employed quantitative data analysis techniques, specifically using mediation regression analysis with Hayes' Model 4. This model (Figure a) is well-suited for examining indirect effects and is commonly used to test mediation hypotheses, making it ideal for exploring the complex relationships among digital transformation, economic transformation, and employment creation (Hayes, 2017).



Fi 1: Hayes Model 4
Source: Hayes (2017)

Where:
DX is Digital Transformation
ET is Economic Transformation (Mediating Variable (M))
EC is Employment Creation
a is the beta coefficient for the direct effect of DX on ET (Model II)
b is the beta coefficient for the direct effect of ET on EC (Model III)
c is the beta coefficient for the direct effect of DX on EC (Model I)
c′ is the beta coefficient for the indirect effect of DX on EC through ET (Model III)

The following regression models were employed:

$EC = \alpha_1 + cDX + \varepsilon_1$……………………………………………………………… Model I (Direct Effect)
$ET = \alpha_2 + aDX + \varepsilon_2$……………………………………………………………… Model II (Direct effect)
$EC = \alpha_3 + c'DX + bET + \varepsilon_3$……………………………………………………Model III (Indirect effect)

III. Results

The reliability of the research instruments was assessed using Cronbach's Alpha, a widely accepted measure for evaluating internal consistency. According to Nunnally (1978), a Cronbach Alpha threshold of 0.7 or higher indicates acceptable reliability. As shown in Table 1, all scales exceeded the 0.7 threshold, Digital Transformation (0.7), Economic Transformation (0.787), and Employment Creation (0.764), demonstrating that the instruments used in the study were reliable for measuring the constructs. These values suggest strong internal consistency, affirming the reliability of the data collection tools.

Table 1: Instrument Reliability

Scale	Cronbach Alpha	No. of Items	Verdict
Digital Transformation	0.7	13	Reliable
Economic Transformation	0.787	10	Reliable
Employment Creation	0.764	8	Reliable

3.1 Digital Transformation and Employment Creation

The study first set out to evaluate the effect of digital transformation on employment creation in the manufacturing sector. A linear regression model was thus adopted, producing three outputs: Model summary, Analysis of Variance (ANOVA), and Coefficients. The Model Summary (Table 1) shows that the regression model explains 7% of the variance in employment creation, as indicated by the R-Square value of 0.070. Although this indicates that digital transformation has a relatively low explanatory power in predicting employment creation, it is still statistically significant.

Table 1: Model Summary (Model 1)

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.265[a]	.070	.056	3.46570

a. Predictors: (Constant), Digital Transformation

The ANOVA (Table 2) confirms the significance of the model, with an F-value of 4.822 and a p-value of 0.032, which is below the 0.05 threshold. This suggests that digital transformation has a statistically significant impact on employment creation, although the effect is modest.

Table 2: ANOVA (Model 1)

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	57.912	1	57.912	4.822	.032[b]
	Residual	768.709	64	12.011		
	Total	826.621	65			

a. Dependent Variable: Employment Creation
b. Predictors: (Constant), Digital Transformation

Finally, the Coefficients table (Table 3) reveals that digital transformation has a negative effect on employment creation, with an unstandardized coefficient of -.265 and a p-value of 0.032. This means that for every unit increase in digital transformation, employment creation decreases by .265 units. The effect was also statistically significant, implying that digital transformation has a negative and significant effect on employment creation (β = -.265, SE = 4.112, t = -2.196, $p < .05$). The result reflects automation replacing certain jobs, especially in labour-intensive manufacturing sectors.

Table 3: Coefficients (Model 1)

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	43.238	4.112		10.515	.000
	Digital Transformation	-.167	.076	-.265	-2.196	.032

a. Dependent Variable: Employment Creation

The model can be fitted as follows: Employment creation = 43.238 + *c*Digital Transformation (-.265)

3.2 Digital Transformation and Economic Transformation

The study also sought to determine the effect of digital transformation on economic transformation, focusing on firm performance as an indicator for economic transformation. A linear regression model was similarly adopted, producing three outputs: Model summary, ANOVA, and Coefficients. In the Model Summary (Table 4), the R-Square value of 0.079 indicates that digital transformation explains 7.9% of the variance in economic transformation, specifically in terms of the manufacturing share of GDP. While the model has a low explanatory power, the Adjusted R-Square of 0.064 suggests that the relationship between digital transformation and economic transformation is still meaningful, though not robust.

Table 4: Model Summary (Model 2)

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.280[a]	.079	.064	4.08289

a. Predictors: (Constant), Digital Transformation

In the ANOVA (Table 5), the F-value of 5.463 and a p-value of 0.023 indicate that the regression model is statistically significant. This suggests that digital transformation has a significant impact on economic transformation, reinforcing the idea that digital technologies play a role in shaping the manufacturing sector's contribution to GDP.

Table 5: ANOVA (Model 2)

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	91.062	1	91.062	5.463	.023[b]
	Residual	1066.877	64	16.670		
	Total	1157.939	65			

a. Dependent Variable: Economic Transformation

b. Predictors: (Constant), Digital Transformation

The Coefficients table (Table 6) shows that digital transformation has a negative effect on economic transformation, with an unstandardized coefficient of -0.280 and a p-value of 0.023. This implies that as digital transformation increases, the manufacturing share of GDP slightly decreases by 0.209 units. The effect was also statistically significant, implying that digital transformation has a negative and significant effect on economic transformation (β = -.280, SE = 4.844, t = -2.337, $p < .05$). This could be due to factors like automation reducing the labour-intensive processes that traditionally contribute to GDP, or challenges in fully realizing the benefits of digital tools in the sector.

Table 6: Coefficients (Model 2)

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	54.230	4.844		11.195	.000
	Digital Transformation	-.209	.089	-.280	-2.337	.023

a. Dependent Variable: Economic Transformation

The model can be fitted as follows: Economic Transformation = 54.230 + a_3 Digital Transformation (-.280)

3.3 Digital Transformation, Economic Transformation and Employment Creation

The study finally sought to assess the mediating role of economic transformation on the relationship between digital transformation and employment creation within the country's manufacturing sector. Adopting Hayes' Model 4, four regression outputs were produced overall: Economic Transformation as the Outcome Variable, Employment Creation as the Outcome Variable, the Direct effect of X on Y; and the indirect effect of X on Y. In Table 7, the R-squared value is 0.0786, indicating that digital transformation (DT) explains 7.86% of the variance in economic transformation. The F-statistic (5.4626, p=0.0226) shows that the model is statistically significant, meaning digital transformation significantly impacts economic transformation. The coefficient for digital transformation is negative (-0.2092, p=0.0226), implying that increased digital transformation slightly reduces economic transformation, potentially due to challenges in adapting technologies or structural shifts within the sector.

Table 7: Model Summary (Model 3 - Outcome Variable: Economic Transformation)

R	R-sq	MSE	F	df1	df2	P
.2804	.0786	16.6700	5.4626	1.0000	64.0000	.0226

Model

	coeff	se	t	P	LLCI	ULCI
constant	54.2304	4.8441	11.1951	.0000	44.5531	63.9077
DT	-.2092	.0895	-2.3372	.0226	-.3880	-.0304

For Table 8, the R-squared value of 0.9440 suggests that 94.4% of the variance in employment creation is explained by digital transformation (DT) and economic transformation (ET). The F-statistic of 530.6471 (p=0.0000) confirms the model's overall significance. While digital transformation has an insignificant effect on employment creation (p=0.7871), economic transformation significantly drives employment creation, with a coefficient of 0.8229 (p=0.0000). This emphasizes that economic transformation is a strong predictor of job creation in the manufacturing sector.

Table 8: Model Summary (Model 3 - Outcome Variable: Employment Creation)

R	R-sq	MSE	F	df1	df2	P
.9716	.9440	.7352	530.6471	2.0000	63.0000	.0000

Model

	coeff	se	t	P	LLCI	ULCI
constant	-1.3866	1.7498	-.7924	.4311	-4.8832	2.1101
DX	.0053	.0196	.2712	.7871	-.0338	.0444
ET	.8229	.0263	31.3453	.0000	.7704	.8753

Table 9 evaluates the direct effect of digital transformation on employment creation. The coefficient (0.0053) is positive but very small, and the p-value (0.7871) indicates that the effect is statistically insignificant. This implies that digital transformation does not have a meaningful direct influence on employment creation in the manufacturing sector. The confidence interval (-0.0338, 0.0444) also crosses zero, reinforcing the lack of significance in the direct effect.

Table 9: Direct effect of X on Y

Effect	se	t	P	LLCI	ULCI
.0053	.0196	.2712	.7871	-.0338	.0444

Table 10 examines the indirect effect of digital transformation on employment creation, mediated by economic transformation. The indirect effect (-0.1721) is significant, as shown by the confidence interval (-0.3159, -0.0072) not crossing zero. This suggests that economic transformation (β = -.1721, BootSE = .0785, BootLLCI = -.3159, BootULCI = -.0072) mediates the relationship, meaning digital transformation indirectly impacts employment creation through changes in the economic structure. The negative value indicates that digital transformation may reduce employment through its influence on economic transformation.

Table 10: Indirect effect(s) of X on Y

	Effect	BootSE	BootLLCI	BootULCI
ET	-.1721	.0785	-.3159	-.0072

The model can be fitted as follows: Employment creation = -1.3866 + c'Digital Transformation (.0053) + b_2Economic Transformation (.8229)

IV. Discussion

The findings demonstrate that the integration of AI in Kenya's manufacturing sector has both disruptive and transformative effects on economic transformation and employment creation. Statistically, AI and related digital technologies exhibit a significant negative effect on employment creation ($\beta = -.265$, SE = 4.112, $t = -2.196$, $p < .05$), underscoring that automation, robotics, and predictive analytics displace routine and manual tasks. This mirrors global evidence where labour-intensive industries have experienced reductions in low-skilled employment as machines and smart systems substitute human input (Frey & Osborne, 2017; Acemoglu & Restrepo, 2020). In Kenya, where the sector remains heavily reliant on such labor, the immediate impact of AI adoption is contraction in traditional job categories.

Despite this displacement, AI unlocks substantial opportunities for sustainable industrial transformation. It enhances operational efficiency, reduces energy and material wastage, strengthens product quality, and enables predictive maintenance, cumulatively positioning manufacturing for long-term competitiveness and environmental sustainability. These benefits reflect Bessen's (2019) argument that the productivity gains from AI often manifest over time through innovation, new products, and the creation of entirely new industries. In embedding AI into Kenya's BETA, the sector can transition from labour-intensive operations to a knowledge- and technology-driven contributor to GDP growth and sustainable development.

The results also show that AI exerts a negative and significant effect on economic transformation ($\beta = -.280$, SE = 4.844, $t = -2.337$, $p < .05$). This suggests that in the short term, digital tools may not yield immediate positive results in GDP growth. Instead, adjustment costs, job displacement, and skill mismatches temper economic gains. Sub-Saharan African economies, including Kenya, face particular challenges, such as inadequate infrastructure, limited digital readiness, and persistent skills gaps, that delay the realization of AI's full benefits. Similar to global patterns, automation in developing economies often reduces the contribution of labour-intensive processes to GDP, even as it enhances efficiency (Frey & Osborne, 2017).

Importantly, the mediation analysis reveals that economic transformation ($\beta = -.1721$, BootSE = .0785, BootLLCI = –.3159, BootULCI = –.0072) negatively mediates the relationship between AI adoption and employment creation. This indicates that while AI boosts productivity and reshapes economic structures, these shifts reduce employment opportunities in labour-intensive manufacturing. However, the long-term net effect depends on how effectively industries and governments manage the transition. If AI adoption is accompanied by deliberate workforce upskilling, innovation ecosystems, and inclusive policies, job displacement can be offset by the creation of new high-skilled opportunities in robotics, AI systems management, and data-driven innovation (Brynjolfsson & McAfee, 2014).

These findings illustrate the paradox of AI-driven development: short-term disruption, characterized by reduced low-skilled employment and GDP contribution, alongside long-term potential for sustainable growth and high-quality job creation. This indicates the need for proactive policies that facilitate adaptation, workforce readiness, and equitable access to AI-enabled opportunities. With such measures, AI can become a transformative technology that accelerates Kenya's industrialization and aligns with the Sustainable Development Goals (SDGs), particularly SDG 8 (Decent Work and Economic Growth), SDG 9 (Industry, Innovation and Infrastructure), and SDG 12 (Responsible Consumption and Production).

V. Conclusions

The findings highlight the complex and paradoxical relationship between AI adoption, economic transformation, and employment creation in Kenya's manufacturing sector. The statistically significant negative effect on employment reflects the disruptive nature of AI-driven automation, which replaces many routine and manual roles in labour-intensive industries. This outcome is consistent with global literature showing that low-skilled jobs are most susceptible to technological substitution. However, the study also confirms that AI does not simply eliminate work; it simultaneously creates new opportunities in high-value areas such as robotics engineering, AI systems management, data analytics, and innovation-driven services. This duality indicates AI's role as both a disruptor and a catalyst for economic modernization.

The negative and significant short-term effect of AI on economic transformation suggests that the benefits of technological adoption are not immediate. Adjustment costs, skill mismatches, and infrastructural deficits hinder rapid realization of AI's economic promise, particularly in developing contexts like Kenya. Yet, over time, AI fosters productivity gains, efficiency improvements, and the emergence of new industries that can drive sustained GDP growth and global competitiveness. This aligns with the SDGs, where AI's potential lies in accelerating industrial innovation, enhancing resource efficiency, and promoting more sustainable production patterns.

The study finds that economic transformation negatively mediates the link between AI adoption and employment creation. This implies that while AI-driven economic shifts may initially reduce labour-intensive jobs, they also set the foundation for structural transformation and long-term employment realignment. The eventual impact on job creation will depend on how effectively Kenya invests in workforce reskilling, fosters inclusive innovation ecosystems, and supports small and medium-sized enterprises (SMEs) in adopting AI responsibly.

AI represents a transformative technology that can unlock opportunities for sustainable development in Kenya's manufacturing sector. Its disruptive short-term effects on jobs and GDP contribution can be mitigated through targeted policies on upskilling, infrastructure development, and social protection. If managed strategically, AI adoption will not only enhance industrial efficiency and competitiveness but also create pathways for inclusive employment growth, positioning Kenya's manufacturing industry as a driver of sustainable economic transformation.

Recommendations

The study's findings indicate the urgency of deliberate interventions to maximize the benefits of AI in Kenya's manufacturing sector while minimizing its disruptive effects on employment and economic transformation. To this end, several interlinked recommendations emerge:

Policymakers should prioritize comprehensive training programs that prepare the workforce for emerging roles in AI-driven manufacturing. Embedding AI literacy, robotics, machine learning, and data analytics into Technical and Vocational Education and Training (TVET) institutions, universities, and industry-based training schemes is essential. Partnerships between government, industry, and academia can facilitate the design of curricula that match evolving labor market demands. Special emphasis should be placed on youth and women, ensuring inclusivity and equitable participation in the digital economy. Such proactive measures will mitigate job displacement while building a future-ready workforce.

The government should develop robust AI governance frameworks that set ethical standards, protect data, and safeguard intellectual property. Clear regulations will give confidence to investors and industry players while ensuring responsible AI adoption. Fiscal incentives, such as AI-specific tax credits, grants, and concessional financing, should be introduced to support small and medium-sized enterprises (SMEs), which constitute the backbone of Kenya's manufacturing base. Streamlined regulatory processes and reduced bureaucratic hurdles will further accelerate innovation and private sector investment.

AI adoption should be strategically aligned with Kenya's sustainability and climate resilience agenda. Manufacturers should leverage AI for green industrialization by deploying energy-efficient systems, carbon-tracking platforms, and waste-minimization tools. Predictive maintenance powered by AI can reduce downtime, extend equipment life, and lower energy consumption, thereby cutting costs while supporting the transition to a low-carbon economy. These measures not only enhance competitiveness but also contribute directly to the Sustainable Development Goals (SDGs), particularly SDG 9 and SDG 12.

To foster broad-based transformation, the establishment of AI innovation hubs and incubators is essential. Collaborative ecosystems involving government, academia, industry, and development partners can support start-ups and SMEs to design AI-driven solutions for manufacturing. Such ecosystems would provide platforms for research, experimentation, and knowledge exchange, ensuring that AI adoption contributes to job creation, entrepreneurship, and inclusive economic transformation across regions.

Given the likelihood of job displacement in routine and manual roles, social safety nets must complement technological reforms. Expanding unemployment insurance, introducing reskilling vouchers, and developing transition programs can provide temporary relief to affected workers while supporting their entry into emerging AI-enabled job categories. This holistic approach balances technological advancement with social welfare, ensuring no segment of society is left behind in the shift toward an AI-driven economy.

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