Impact of Automation on Labor Market Polarization and Job Displacement in Developing Countries

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DECLARATION

I declare that this work has not been previously submitted and approved for the award of a degree by this or any other University. To the best of my knowledge and belief, the Research Project contains no material previously published or written by another person except where due reference is made in the Research Project itself.

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This Research Project has been submitted for examination with my approval as the Supervisor.

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ABSTRACT

African economies suffer from some of the highest unemployment rates in the world, and the use of automation and robots are crowding out labour jobs in the developing world. It is, therefore, necessary to assess the impact of (the fourth wave of the industrial revolution), automation, on unemployment in developing countries in Africa. This study used panel data obtained from the World Bank database of the World Development Indicators and from the Integrated Public Use Microdata Series (IPUMS) that harmonizes census micro-data from around the world to explore the impact of automation on labour market polarization and job displacement in developing countries. The study identified ways in which African developing countries can get ahead of the curve and mitigate the damaging effects of the adoption of robot technology on employment. The analysis reveals that automation (robot adoption) positively correlates with unemployment ($r = 0.302$, $p = 0.000$) but requires other factors for a significant impact on labor outcomes. In the panel regression model, adding GDP growth, education level, trade openness, and sectoral employment shares improves the model's explanatory power to 95.9% (R Square = 0.959, $p = 0.007$). These additional factors, particularly education ($B = -0.371$, $p = 0.000$) and trade openness ($B = -0.901$, $p = 0.000$), appear to mitigate some of the potential unemployment effects associated with automation. The study concludes that automation in Kenya is increasing labor market polarization and job displacement, with impacts particularly pronounced in middle-skilled roles. Automation contributes to a growing divide, benefiting high-skilled and certain low-skilled jobs while displacing workers in routine tasks, leading to limited middle-income job opportunities. The findings highlight the need for Kenya to prioritize educational investments in digital and technical skills, support inclusive economic growth, and implement retraining programs for those displaced by automation. The government should incentivize responsible automation practices among companies and strengthen social safety nets to support displaced workers. Additionally, a phased approach to technology adoption, international support, and enhanced data collection on labor market dynamics are recommended to help Kenya manage automation's impact while fostering economic resilience.

CHAPTER ONE: INTRODUCTION

1.1 Background of The Study

Automation is a technological change that allows capital to be used in tasks that were previously performed by labour or increase the productivity of capital in those tasks (Fierro, Caiani, & Russo, 2022). From the beginning of the Industrial Revolution, society has undergone four cycles of technological revolution; the first machine age, the second machine age, the computer and information age, and the smart revolution, and each change can be regarded as the deepening of automation technology (Sheng & Zhang, 2024) . In the process of replacing people with machines, the conflict and subsequent rebalancing of efficiency and employment are constantly being repeated (Morgan, 2019), and in appreciating the new wave of economic and social development we must also acknowledge the creative destruction brought by these new technologies. Creative destruction is the dismantling of long-standing practices in order to make way for innovation and is a driving force of capitalism. Jobs that cannot keep up with new technology impede employment, and therefore, make it more difficult to optimize talents and minimize shortcomings, leading to the destruction of jobs (Yeboah, 2023). It is thus necessary to evaluate whether the economies of developing countries in Africa have the capacity to dismantle their structures and practices to accommodate this new wave of the industrial revolution and still stand on their feet.

The adoption of automation and artificial intelligence technologies is still in its early stages in Africa, and there are many challenges to be addressed in order to leverage the opportunities it presents, such as; lessening poverty, reducing inequality, and increasing access to public services ultimately leading to growth and development (Yeboah, 2023). Artificial intelligence (AI) is one of the core areas of the fourth industrial revolution, along with, the transformation of mechanical technology, electric power technology, and information technology, and it serves to promote the transformation and upgrading of the digital economic industry (Sheng & Zhang, 2024). According to research conducted by Accenture and the Gordon Institute of Business Science (GIBS), artificial intelligence (AI) has the potential to double South Africa's economic growth rate and increase profitability rates by an average of 38 % by 2035 (Yeboah, 2023). This shows that an AI-dominated environment is good news for enterprises but it raises the issue of job displacement for a labour force whose skills may no longer be in demand.

In Africa, automation has significantly influenced labor market polarization and job displacement in developing countries, with particularly notable impacts in African nations. In recent years, automation has accelerated the polarization of labor markets, which refers to the growing divide between high-skill, high-income jobs and low-skill, low-income jobs. This polarization is driven by the increased adoption of technologies such as robotics and artificial intelligence (AI), which have enhanced productivity in sectors like manufacturing and services but have simultaneously reduced the demand for routine, manual tasks. For instance, in Kenya, the rise of automated agricultural technologies has led to the displacement of many low-skilled workers who previously relied on manual farming techniques (Omondi, 2022). This trend reflects a broader pattern across the continent, where automation is reshaping traditional job markets, often to the detriment of low-skilled laborers (Asongu, 2023). The disparity between the technological capabilities and the skills of the workforce exacerbates income inequality and labor market polarization in these economies.

In the context of job displacement, automation has led to a significant reconfiguration of employment opportunities in developing countries. In South Africa, for example, the mining industry has seen substantial automation with the introduction of advanced mining equipment and robotic systems. This shift has resulted in job losses for many workers who previously performed manual tasks (Mugisha, 2023). The displaced workers often struggle to find new employment due to a lack of relevant skills and education, contributing to high unemployment rates in affected regions. Furthermore, the pace of technological adoption often outstrips the ability of educational systems to provide the necessary retraining and upskilling programs for the displaced workforce (Nabigon, 2024). As a result, the benefits of automation, such as increased efficiency and productivity, are frequently accompanied by increased economic and social challenges for lower-skilled workers in these developing nations.

Automation's impact on labor market polarization also manifests in the form of job creation in high-skill sectors, which contrasts sharply with the decline in low-skill employment opportunities. In Nigeria, the rise of digital technologies and tech startups has created new job opportunities in fields such as software development and digital marketing (Abiola, 2023). However, these new roles require advanced skills that are often not possessed by the majority of the existing workforce, leading to a mismatch between available jobs and the skills of job seekers. This disparity contributes to labor market polarization, where high-skill jobs become more concentrated among those with relevant education and training, while low-skill jobs diminish due to automation and offshoring (Morris, 2023). The challenge of bridging this skills gap is critical for ensuring that the benefits of technological advancements are distributed more equitably across the population.

The polarization effect of automation on the labor market is also influenced by the sectoral distribution of employment in African countries. In many developing nations, agriculture remains a major source of employment, and advancements in agricultural technology, including automated machinery, have led to significant changes in this sector (Hassan, 2024). For instance, in Ethiopia, the introduction of automated irrigation systems and harvesting technologies has improved productivity but has also reduced the demand for manual labor (Tekle, 2023). This shift highlights a broader trend where automation in agriculture is contributing to job displacement and labor market polarization by making traditional farming roles obsolete, while creating new opportunities in tech-driven agricultural solutions that are accessible only to a limited segment of the workforce.

The policy responses to automation-induced job displacement and labor market polarization vary across African countries, but many face challenges in effectively addressing these issues. In Ghana, for example, the government has introduced various initiatives aimed at enhancing vocational training and promoting entrepreneurship as a means of mitigating the impact of automation on employment (Osei, 2024). However, the effectiveness of these measures is often limited by inadequate funding, insufficient infrastructure, and the rapid pace of technological change, which can outstrip the ability of policy interventions to keep up (Kwame, 2023). As automation continues to advance, there is an urgent need for more comprehensive and adaptive policy frameworks that can address the evolving labor market dynamics and support workers affected by technological disruptions. Automation in the retail sector has also led to job losses for informal sector workers who previously operated in small retail shops and markets (Kagoda, 2023). These workers often lack the formal education and training required for new types of employment opportunities, further exacerbating the challenges of job displacement and labor market polarization. The informal sector's vulnerability to automation highlights the need for this study (Chirwa, 2024).

1.2 Problem Statement

It is unclear how developing countries in Africa will be impacted by this new wave of technology or whether they have the necessary complementary skills to attract the parts of the employment chain that still require workers. Previous work gives a mixed picture, where work broadly following (Goos, Manning, & Salomons, 2014) finds evidence that middle-skilled occupations, intensive in routine cognitive and manual skills have decreased across the developing world, while (Maloney & Molina, 2019) offers less evidence for polarization in absolute levels of employment of share of the workforce. The vagueness of the future of African developing countries in relation to this new wave of automation may hinder growth opportunities that can be obtained from this new wave and even slow down the development that African countries are currently, and it may lead to stagnation or even detriment of African countries in their journeys to become self-sufficient (sustainable) and economic powers.

1.3 Research Objectives

The study aimed to assess the unemployment levels in developing countries in Africa such as Kenya, to assess the impact of automation on unemployment in these countries, and to identify ways in which we can leverage from this new wave of technological revolution.

1.4 Significance of the Study

This study's significance extends across policy, practice, and theory, offering valuable insights into the complex interplay between automation and unemployment in developing countries. From a policy perspective, the research aims to provide empirical evidence on how automation affects unemployment rates, which is crucial for developing targeted and effective policy interventions. By highlighting the specific challenges and opportunities posed by automation, policymakers can design strategies that not only mitigate the negative impacts on the labor market but also capitalize on the potential benefits. For instance, the study's findings could inform policies related to education and training, ensuring that workforce development initiatives are aligned with the technological advancements shaping the job market. Such evidence-based policies could support sustainable economic growth and reduce the adverse effects of automation on vulnerable populations.

In terms of practice, the study offers practical recommendations for businesses and organizations navigating the new wave of technological advancements. Understanding how automation influences employment trends can help companies make informed decisions about technology adoption and workforce management. By identifying the sectors most affected by automation, businesses can better plan for workforce transitions and invest in upskilling programs to prepare employees for new roles created by technological innovations. Additionally, the study's insights could aid in the development of strategic partnerships between businesses, educational institutions, and government bodies to foster a more adaptable and resilient workforce. This practical guidance is crucial for leveraging automation to enhance productivity while minimizing job displacement.

Theoretical contributions of this study include advancing the understanding of labor market dynamics in the context of rapid technological change. By examining the relationship between automation and unemployment in developing countries, the research can refine existing theories related to labor market polarization and technological impact. It offers an opportunity to explore how automation influences different economic sectors and contributes to shifts in employment patterns. The study's findings could lead to the development of new theoretical frameworks that integrate technological advancements with labor market theory, providing a more nuanced understanding of how automation affects developing economies. This theoretical advancement can inform future research and contribute to a more comprehensive understanding of labor market changes driven by technological progress.

CHAPTER TWO: LITERATURE REVIEW

2.1 Theoretical Literature Review

2.1.1 Skill-Biased Technological Change (SBTC) Theory

The Skill-Biased Technological Change (SBTC) Theory was prominently introduced by economists such as Goldin and Katz in the early 2000s and further developed by Acemoglu and Restrepo (2021). This theory posits that technological advancements, including automation, favor high-skilled workers by increasing their productivity and wages, while low-skilled workers face displacement and stagnant wages. The core assumption of the SBTC Theory is that technological progress disproportionately benefits those who can complement and leverage new technologies, leading to greater income inequality. The theory highlights how automation drives demand for high-skilled labor while reducing demand for low-skilled, routine tasks.

A major strength of the SBTC Theory is its ability to explain the widening wage gap between high-skilled and low-skilled workers. By focusing on the differential impact of technological change on various skill levels, the theory provides a clear framework for understanding labor market polarization. For instance, Aslam and Kingdon (2022) demonstrate that in South Asia, automation has led to increased wage disparities, reinforcing the relevance of this theory. However, a limitation of the SBTC Theory is its focus on wage disparities without fully addressing the complexities of job displacement and the broader socio-economic impacts on low-skilled workers. This limitation suggests that while the theory explains wage differentials, it may not fully capture the extent of job losses or shifts in employment patterns.

For a study on automation's impacts on labor market polarization in developing countries, the SBTC Theory offers valuable insights into how automation exacerbates skill-based inequalities. It proposes that as automation advances, high-skilled workers will continue to see increased opportunities and wages, while low-skilled workers may face greater job insecurity and wage stagnation. This theoretical perspective is crucial for understanding the differential impacts of automation across various skill levels and informs strategies for addressing the growing disparities in labor markets.

2.1.2 Task-Based Approach

The Task-Based Approach, developed by Autor and Dorn (2023), provides a nuanced perspective on how automation affects labor markets by focusing on the nature of tasks rather than entire occupations. This approach assumes that automation tends to replace routine and repetitive tasks while complementing non-routine and cognitive tasks. Autor and Dorn's research suggests that while some tasks are automated, creating displacement in roles involving routine work, other tasks that require problem-solving and complex decision-making are less affected and can even see increased demand.

One strength of the Task-Based Approach is its ability to differentiate the impact of automation on various job tasks, rather than treating occupations as homogeneous entities. This approach highlights how automation's effects are more complex than a simple replacement of jobs, as demonstrated by Gollin and Rogerson (2023) in their study of sub-Saharan Africa. They found that automation led to the displacement of workers in routine tasks, while those in non-routine roles experienced fewer disruptions. However, a limitation of this approach is that it may not fully capture the broader economic and structural changes resulting from automation, focusing instead on the task-level impacts. This limitation underscores the need to integrate this approach with broader economic theories to understand the full scope of automation's effects.

In studying the impacts of automation in developing countries, the Task-Based Approach is valuable for understanding which specific tasks are more vulnerable to automation. It suggests that while automation may displace workers engaged in routine tasks, those involved in more complex tasks might benefit from increased demand. This perspective can guide research on how to adapt workforce development strategies to align with the changing nature of work and mitigate job displacement caused by automation.

2.1.3 Structural Transformation Theory

The Structural Transformation Theory, as articulated by Rodrik (2022), examines how automation drives shifts in economic structure and employment patterns, transitioning economies from agriculture to industry and services. This theory assumes that technological advancements induce structural changes in the economy, leading to job losses in traditional sectors while creating new opportunities in emerging industries. Rodrik's work emphasizes that automation can have profound effects on labor markets by altering the distribution of employment across different sectors.

A key strength of the Structural Transformation Theory is its broad perspective on economic shifts, highlighting how automation can drive long-term changes in employment and economic structure. Mendez and Piñeiro (2024) illustrate this in their study of Latin American agriculture, where automation has led to significant job displacement in traditional sectors but also spurred growth in other areas. However, a limitation of this theory is that it may oversimplify the transition process, not fully accounting for the short-term hardships and inequalities faced by displaced workers. This limitation points to the need for a more nuanced understanding of how these structural changes affect different segments of the workforce.

For research on automation’s impact on labor market polarization in developing countries, the Structural Transformation Theory offers insights into how automation can reshape employment patterns and economic structures. It proposes that while automation may initially lead to job losses in traditional sectors, it also has the potential to create new opportunities in emerging industries. This theoretical framework is essential for understanding the broader economic implications of automation and for developing policies to support workers through periods of transition and economic restructuring.

2.2 Empirical Literature Review

The rapid advancement of automation technologies raises concerns about their potential impact on employment markets, particularly in developing countries. According to (Yeboah, 2023), the influence of artificial intelligence on employment encompasses both creation and destruction mechanisms. Such that AI has the potential to increase employment, create new jobs, and improve the economy through the compensating effect which is a by-product of the creation mechanism. The replacement effect, which is the destruction mechanism, occurs when as new technology replaces older technology, jobs dependent on the older technology are also replaced. (Yeboah, 2023) states that the aggregate labour market implications of new technologies depend on, the industries in which they operate, with the manufacturing industry having the highest impact, the adjustment in other parts of the economy, and potential spillover effects. While AI and technological advancements drive economic progress, they also pose challenges by displacing jobs that cannot adapt to new technologies, highlighting the paradoxical relationship between technological innovation and employment. The research concludes that while AI may lead to job displacement in some industries, it has the potential to create new roles in areas such as data analysis, software development, and digital marketing while enhancing productivity and efficiency in industries such as healthcare and education.

The study (Maloney & Molina, 2019) provides evidence that automation, specifically robot adoption, has had little to no impact on labour displacement in developing countries, including those in Africa. It suggests that automation may not lead to job loss in developing countries due to factors such as off-shoring and the different initial occupational structures in these countries. The study highlights the differing roles of routine tasks in advanced and developing economies. In advanced countries, automation tends to displace routine middle-skill jobs, leading to polarization. In contrast, developing countries may experience a complementary effect, where automation does not displace but rather supports manufacturing jobs due to factors like off-shoring and the structure of their labour markets. In addition, this study examines how off-shoring and foreign direct investment (FDI) influence labour markets in developing countries. It suggests that these countries can benefit from automation through increased employment in certain sectors such as manufacturing, and data science due to off-shored jobs from advanced economies. (Maloney & Molina, 2019) also introduce the concept of technological absorptive capacity, which affects the feasibility and impact of automation in developing countries. This concept helps explain the slower adoption of automation technologies in these regions and its implications for labour markets.

The research paper, (Sheng & Zhang, 2024) gives insights into the impact of modern digital technologies, specifically artificial intelligence, on employment in developing countries. It discusses the role of artificial intelligence in promoting employment by improving labour productivity, deepening capital, and refining the division of labour. The study introduces the concept of virtual agglomeration, which has evolved from traditional industrial agglomeration, and highlights its significance in increasing employment in the digital economy by creating new forms of employment clusters. This study also delves into the concept of creative destruction, where old jobs are destroyed, but new ones are created through technological advancements. This aligns with Schumpeterian theories of economic development and innovation.

The study on unemployment in Africa (Caporale & Gil-Alana, 2018) focuses on analyzing the long-term dynamics of unemployment in African countries and provides a foundation for understanding how structural changes such as automation, impact unemployment rates over time, and it suggests that hysteresis models are the most relevant for the African countries behaviour of unemployment as it considers the low degree of economic and financial development as well as the existence of various type of rigidities in their labour markets.

The study on macroeconomic determinants of unemployment in Africa (Tsaurai, 2020), provides insights into the various factors influencing unemployment rates in Africa , such as economic growth, foreign direct investment, education, and trade openness and this understanding allows for a comprehensive view of the broader economic context in which automation is introduced. The study also emphasizes the significant negative influence of the interaction between information and communication technology (ICT) and human capital development on unemployment. This finding underscores the importance of enhancing human capital development and financial inclusion in adapting to the changing labour market and therefore, economically benefit from new technologies.

The results of the study (Pavez & Martínez-Zarzoso, 2023) provide insights for policymakers in emerging economies by suggesting the need to invest in human capital, educational policies, and flexible tax policies to mitigate job losses due to automation and enhance productivity. Policymakers can use information on automation trends in developed countries to evaluate labour, distributive, and macro policies in emerging economies. Additionally, the study highlights the importance of complementary measures to achieve Sustainable Development Goals related to decent work, economic growth, and reduced inequality. The study also highlights the potential negative impact of automation on employment in routine-intensive occupations, which could be relevant for understanding potential unemployment dynamics in African countries heavily reliant on such jobs

The study on Unemployment in Africa (Caporale & Gil-Alana, 2018) applies fractional integration techniques to analyze unemployment dynamics, providing a sophisticated empirical method that can be adapted to offer insights into the long-term effects of automation on unemployment trends. The study’s analysis of unemployment data from eleven African countries using long-memory models to examine the stochastic behaviour of unemployment over time provides a foundation for understanding how automation may influence employment patterns empirically. The study’s findings regarding the lack of mean reversion in unemployment rates allows for the consideration of the persistent effects of shocks on unemployment and therefore exploration of how automation impacts job displacement and long-term unemployment trends.

The study on macroeconomic determinants of unemployment in Africa (Tsaurai, 2020) utilizes various econometric approaches, including fixed effects, random effects, pooled ordinary least squares, and dynamic generalized methods of moments, to analyze the determinants of unemployment in Africa. The study identified variables that were found not to be significant determinants of unemployment in Africa, such as information and communication technology, human capital development, and infrastructural development. This insight guides focus toward other relevant factors that may have a more significant impact on employment outcomes in the context of technological advancements. The study provides policy recommendations for African authorities such as enhancing financial inclusion, promoting trade openness, and investing in human capital development to reduce unemployment. This study also addresses the methodological weaknesses in previous empirical research on unemployment determinants in Africa, particularly the neglect of dynamic features in unemployment data and the failure to consider the endogeneity problem. By filling these methodological gaps, the study has set a precedent for rigorous empirical analysis that considers the interplay between automation, unemployment, and other economic variables in developing countries in Africa.

The study on the impact of artificial intelligence on unemployment in Africa, (Yeboah, 2023), offers a data-driven analysis. Employing data from 42 out of 54 African countries, using a robust Generalized Method of Moments (GMM) approach. It offers quantitative findings that provide empirical support for the theoretical discussions on AI's impact on employment such as, that AI has a strong positive impact on employment, with revenue showing a moderate positive effect and political stability having a negative impact. By comparing the impacts of AI in different African countries, the study highlights the varying degrees of AI adoption and this shows how different contexts within Africa influence the outcomes of AI integration.

The study (Novella, Rosas, & Alvarado, 2019) done in Peru offers a comparative basis for researchers studying similar trends in African countries that can help researchers draw parallels and distinctions between different regions. Additionally, (Pavez & Martínez-Zarzoso, 2023) conducted a study on developing countries outside Africa that analyzed the impact of automation on employment, wages, and the labour share. The results showed that local automation does not affect employment, while foreign robots have a negative and significant impact and in contrast, neither local nor foreign automation affects the nominal annual wage and labour share in developing countries.

The study (Maloney & Molina, 2019), which questions whether automation is labour displacing uses extensive global census data to empirically test the presence of labour market polarization and the impact of automation in developing countries. It provides empirical evidence that unlike in advanced economies, labour market polarization is not evident in many developing countries. Instead, the study finds that employment in middle-skill manufacturing jobs has increased in absolute terms. By controlling for Chinese import penetration, the study isolates the impact of automation from that of trade competition. It finds that trade competition is less significant compared to the influence of robots, offering a clearer picture of automation's direct impact on employment in developing countries. The study also identifies early signs of labour market polarization in certain developing countries such as Mexico and Brazil, providing a nuanced view of how automation effects might evolve over time in these regions.

The study (Sheng & Zhang, 2024) contributes to the understanding of the impact of modern digital technologies on employment in developing countries, specifically mentioning the importance of improving the social security system, developing high-end domestic robots, and reforming the education system to enhance the positive role of artificial intelligence technology in employment. It presents empirical findings from panel data in China, showcasing how AI and automation have influenced employment over time, this can be contrasted with findings from African countries to draw broader conclusions. The study employs methodologies such as the two-way fixed-effect model and the two-stage least squares method to analyze the data. These robust empirical techniques enhance the credibility and reliability of the findings. The study also examines the heterogeneity of AI's impact on employment across different regions and industries, offering insights into how context-specific factors influence the outcomes of automation such as employee gender and industry attributes. The findings of this study suggest that AI and automation serve to relatively improve the job share of women and workers in labour-intensive industries.

2.3 Summary of Literature Review and Research Gaps

Research on the impacts of automation on labor markets, particularly in developing countries, reveals several critical gaps. Yeboah (2023) highlights a paradox in how artificial intelligence influences employment by creating and destroying jobs, suggesting that while AI can boost economic growth and job creation in certain sectors, it also displaces jobs reliant on older technologies. This research underscores a need to better understand how the aggregate impacts of

AI vary across industries and regions, and how automation affects labor markets in nuanced ways. In contrast, Maloney and Molina (2019) argue that automation, particularly through robot adoption, has had a minimal effect on job displacement in developing countries, attributing this to off-shoring and differing initial occupational structures. This suggests a research gap in exploring how factors like technological absorptive capacity and the initial economic structure of developing countries influence automation's impact on employment.

Sheng and Zhang (2024) introduce concepts such as virtual agglomeration and creative destruction, providing a framework for how AI and automation can foster new employment opportunities while phasing out older jobs. Their focus on digital technologies and employment clusters highlights a gap in understanding how these technological advancements intersect with regional labor market dynamics. Furthermore, Caporale and Gil-Alana (2018) emphasize the need for analyzing long-term unemployment dynamics using sophisticated empirical techniques to understand how automation influences unemployment trends. Tsaurai (2020) adds to this by examining various macroeconomic determinants of unemployment and highlights methodological gaps in previous studies, such as neglecting the dynamic features of unemployment data. These studies collectively indicate a need for more comprehensive research that integrates these diverse aspects to better understand automation's multifaceted impacts on labor markets in developing countries.

CHAPTER THREE: RESEARCH METHODOLOGY

3.1 Introduction

This chapter discusses all information on the research methodology used to carry out the study. It also discusses the research design that is applied, the population targeted for the study, the sample design and techniques used, and the procedures used to obtain the samples. This chapter also discussed the data collection organization methods. It also presents how data was analyzed and how it was presented after analysis.

3.2 Research Design

Research design encompasses the overall outline and approach undertaken in conducting the study (Saunders, Lewis & Thornhill, 2009). The research design provides a framework which the research is based on in data collection and analysis. A good research design ought to be comprehensive, flexible, economical and efficient (Saunders., 2015). The study was carried out using descriptive research design. A descriptive research design is a design that is used to answer the questions what, how and why, and used to determine the relationship between variables.

3.3 Target Population

The population for this study was Kenya. The focus on Kenya is motivated by the country's unique economic and social context, which may experience the effects of automation differently compared to more developed countries. The sample included data from different regions and industries within Kenya to capture a comprehensive picture of the labor market. The sampling technique was purposive, ensuring that the sectors and regions with substantial data on automation, employment, and economic indicators are included in the analysis. This approach helped in identifying sector-specific and regional disparities in the impact of automation.

3.4 Data collection

Data collection involved the extraction of relevant variables from the WDI and IPUMS databases, supplemented by national statistics from Kenya’s National Bureau of Statistics. Key variables of interest included measures of automation such as the adoption of robot technology, labor market polarization indicators like changes in employment shares across different skill levels, and job displacement metrics such as unemployment rates and changes in sectoral employment. Additional control variables were collected to account for other factors that may influence labor market outcomes, including GDP growth, education levels, trade openness, and demographic characteristics. The data collection process was systematic and rigorous, ensuring that the extracted data is accurate and relevant to the research objectives.

3.5 Data analysis

Data analysis is defined as the process of analyzing, cleaning, transforming and modelling data collected in a research. The collected data was checked for completeness prior to data entry and data analysis aided by Statistical Package for Social Sciences. Panel data regression models were used to exploit the longitudinal nature of the data, allowing for the analysis of temporal changes and the identification of causal relationships. Fixed-effects and random-effects models were considered to account for unobserved heterogeneity across different sectors and regions within Kenya. The choice between these models was guided by appropriate statistical tests such as the Hausman test.

3.5.1 Panel Regression Model

$$Y_{it} = \alpha + \beta X_{it} + \gamma Z_{it} + \mu_i + \lambda_t + \epsilon_{it}$$

- Y_{it}: Labor market outcomes (e.g., labor market polarization, job displacement) for sector i at time t
- X_{it}: Automation variables (e.g., adoption of robot technology)
- Z_{it}: Control variables (e.g., GDP growth, education levels)
- μ_i: Sector-specific effects
- λ_t: Time-specific effects
- ϵ_{it}: Error term

This model helped to isolate the impact of automation on labor market outcomes while controlling for other influencing factors.

3.6 Diagnostic Tests

Several diagnostic tests were undertaken to validate the robustness and accuracy of the panel regression. These included assessing multicollinearity using the Variance Inflation Factor (VIF), testing for heteroscedasticity with the Breusch-Pagan and White tests, and examining autocorrelation via the Wooldridge test. Endogeneity concerns were addressed using instrumental variable techniques, and robustness checks ensured consistency across various model specifications.

3.7 Results Interpretation

The results of this analysis provided an understanding of the relationship between automation and unemployment in Kenya. Using panel data regression models, the study specifically evaluated how the adoption of robot technology impacted unemployment rates and labor market polarization. By analyzing changes in employment shares across various skill levels, the study aimed to identify significant shifts in labor demand, with a particular focus on low-skilled versus high-skilled jobs. In addition to statistical significance, the results revealed how factors such as GDP growth, education levels, and trade openness interacted with automation effects. When the Hausman test indicated that fixed-effects models were more appropriate, the study interpreted variations within sectors and regions to understand localized impacts of automation. Conversely, when random-effects models were deemed suitable, the study focused on broader trends across different regions and sectors. This detailed analysis offered insights into which sectors were most vulnerable to job losses and which were likely to benefit, guiding policy recommendations for education and training programs tailored to the evolving job market.

CHAPTER FOUR: FINDINGS

4.1 Introduction

This section discusses findings obtained on the impact of automation on labor market polarization and job displacement in Kenya. Secondary data was collected for the past ten years (2014-2023). It entails the descriptive statistics, correlation analysis and regression analysis.

4.2 Descriptive Statistics

The descriptive statistics were used to summarize key metrics for the variables under study including measures of automation such as the adoption of robot technology, labor market polarization indicators like changes in employment shares across different skill levels, and job displacement metrics such as unemployment rates and changes in sectoral employment. Additional control variables will be collected to account for other factors that may influence labor market outcomes, including GDP growth, education levels, trade openness, and demographic characteristics. Table 4.1 shows the results obtained.

Table 4.1 Descriptive Statistics

Variable	Minimum	Maximum	Mean	Std. Deviation	Variance
GDP Growth (%)	-.2728	7.5905	4.639159	1.9949571	3.980
Education Level (% with secondary education)	35	44	39.50	3.028	9.167
Trade Openness (% of GDP)	26.7	32.0	29.210	1.8735	3.510
Robot Adoption (Units per 10,000 workers)	.5	5.3	2.600	1.6700	2.789
Low-Skilled Employment Share (%)	40	47	43.70	2.214	4.900
Medium-Skilled Employment Share (%)	30	32	31.10	.876	.767
High-Skilled Employment Share (%)	23	30	25.20	2.348	5.511
Unemployment Rate (%)	8.2000	10.4000	9.120000	.6160808	.380
Manufacturing Employment (%)	11.4	13.1	12.610	.4954	.245
Services Employment (%)	41	50	44.40	3.026	9.156
Agricultural Employment (%)	38	46	43.00	2.582	6.667
Valid N (listwise)					

The findings show for GDP growth, the minimum recorded growth was -0.27% (likely due to the 2020 pandemic), while the maximum growth was 7.59%, with a mean of 4.64% and a standard deviation of 1.99. This variability indicates that Kenya's economic growth has been moderately fluctuating, with occasional declines that may affect labor market dynamics. The mean education level, representing the percentage of the population with secondary education, was 39.5% with a standard deviation of 3.03, showing Kenya's steady but gradual improvement in education levels over the past decade. Such growth in education is likely to influence the labor market, potentially enabling the workforce to adapt to technological advancements, albeit with some variability (variance = 9.17). Similarly, trade openness fluctuated between 26.7% and 32.0%, with a mean of 29.21% and a variance of 3.51, indicating moderate exposure to international markets, which could affect employment in automation-sensitive industries.

The descriptive analysis of automation, measured by robot adoption rates, shows a significant increase over the decade, with values ranging from 0.5 to 5.3 units per 10,000 workers and a mean of 2.6 (SD = 1.67). Although the mean value is relatively low, indicating limited automation penetration in Kenya compared to developed nations, the observed increase suggests a gradual adaptation to robotic technology. This trend, even with moderate automation levels, could have notable implications for low- and medium-skilled labor in sectors where tasks are routine and prone to automation. The variability in automation adoption (variance = 2.79) points to uneven adoption rates across industries, which might lead to differential impacts on employment by skill level. Given this gradual rise in automation, understanding its effect on employment distribution by skill level and job displacement remains crucial to this analysis. As robot adoption continues, it is essential to monitor how it affects different labor segments and potentially contributes to labor market polarization.

Employment distribution by skill level reveals insights into labor market polarization trends over the past decade. The low-skilled employment share ranged from 40% to 47%, with a mean of 43.7% (SD = 2.21), suggesting that a substantial portion of the workforce remains in lower-skilled jobs despite gradual increases in automation. In contrast, medium-skilled employment had a narrower range (30%–32%) and a lower variance (0.77), indicating a relatively stable demand for this skill group. Meanwhile, the high-skilled employment share ranged from 23% to 30% (mean = 25.2%, SD = 2.35), reflecting a slowly growing but smaller portion of the workforce engaged in high-skilled jobs. These figures highlight that while low-skilled jobs still dominate, there is a gradual shift toward high-skilled employment, potentially as automation reduces the demand for low- and medium-skilled tasks. This polarization effect may signal emerging inequality in the labor market, with low-skilled workers facing a higher risk of displacement due to automation.

Unemployment rates reveal another critical aspect of job displacement. The unemployment rate over the period fluctuated from 8.2% to 10.4%, with a mean of 9.12% (SD = 0.62), showing relative stability but with slight increases in periods of economic downturns. Notably, the peak unemployment rate of 10.4% in 2020 corresponds with the COVID-19 pandemic, which significantly impacted labor markets globally. This consistency in unemployment rates, despite increasing automation, could imply that automation has not yet significantly disrupted employment levels, although specific sectors may still experience shifts in employment types. However, the lower variance (0.38) in unemployment rates suggests that other economic factors, like GDP growth and education, may be stabilizing labor market dynamics amid the gradual rise in automation. As automation adoption grows, ongoing monitoring of unemployment rates will be crucial to discern if automation alone might exert a more significant impact on overall job displacement.

Further, sectoral employment shares further illustrate the structural shifts in Kenya’s labor market. Agricultural employment saw the largest share, ranging from 38% to 46%, with a mean of 43% (SD = 2.58), indicating agriculture remains a vital sector despite some shifts toward services. Services employment rose notably, ranging from 41% to 50% (mean = 44.4%, SD = 3.03), pointing to a sectoral shift toward services. Manufacturing employment, meanwhile, remained relatively stable between 11.4% and 13.1% (mean = 12.61%), showing minimal growth likely due to Kenya's limited industrial automation. These sectoral trends reflect Kenya’s structural economic transformation, with a gradual move from agriculture to services. The relatively low variance in manufacturing employment (0.25) suggests limited automation effects on this sector, while the rise in services employment could indicate more job opportunities in roles less susceptible to automation.

4.3 Diagnostic Tests

Diagnostic tests on the assumptions of regression analysis were done to ensure that the quality of quantitative assessment was valid. The study used normal Q-Q plots in accessing the fit of the regression model to ensure the dependent variable was normally distributed as per figure 4.1 and figure 4.2.

Figure 4. 1 Normal Q-Q Plot

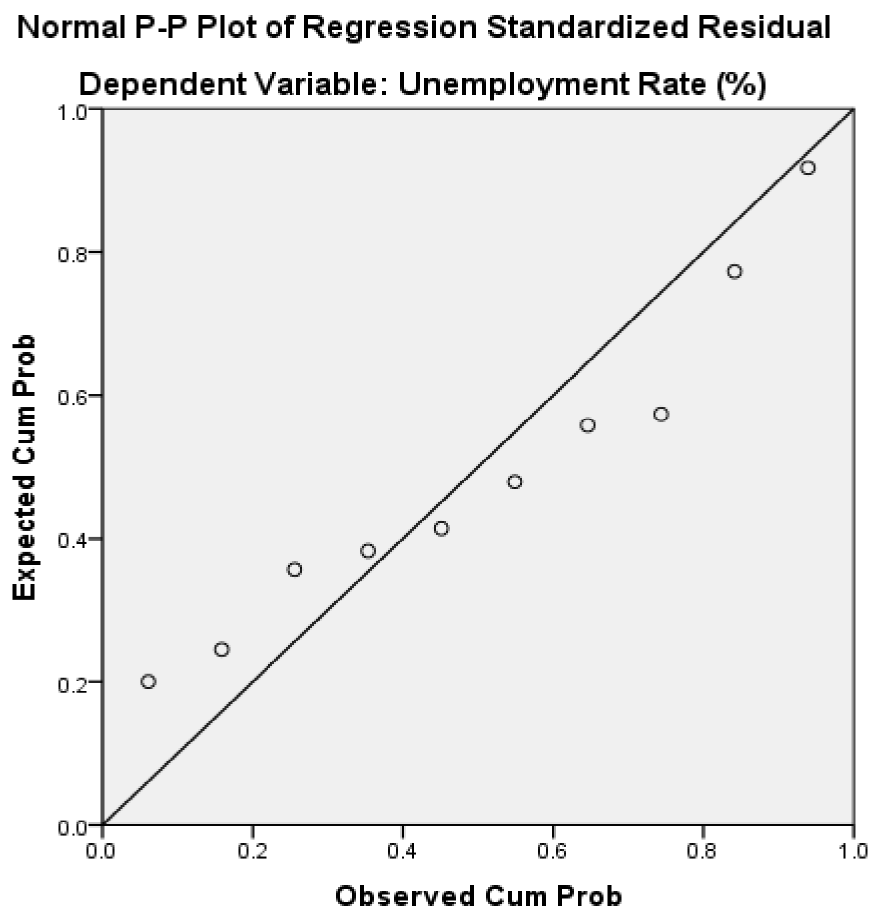
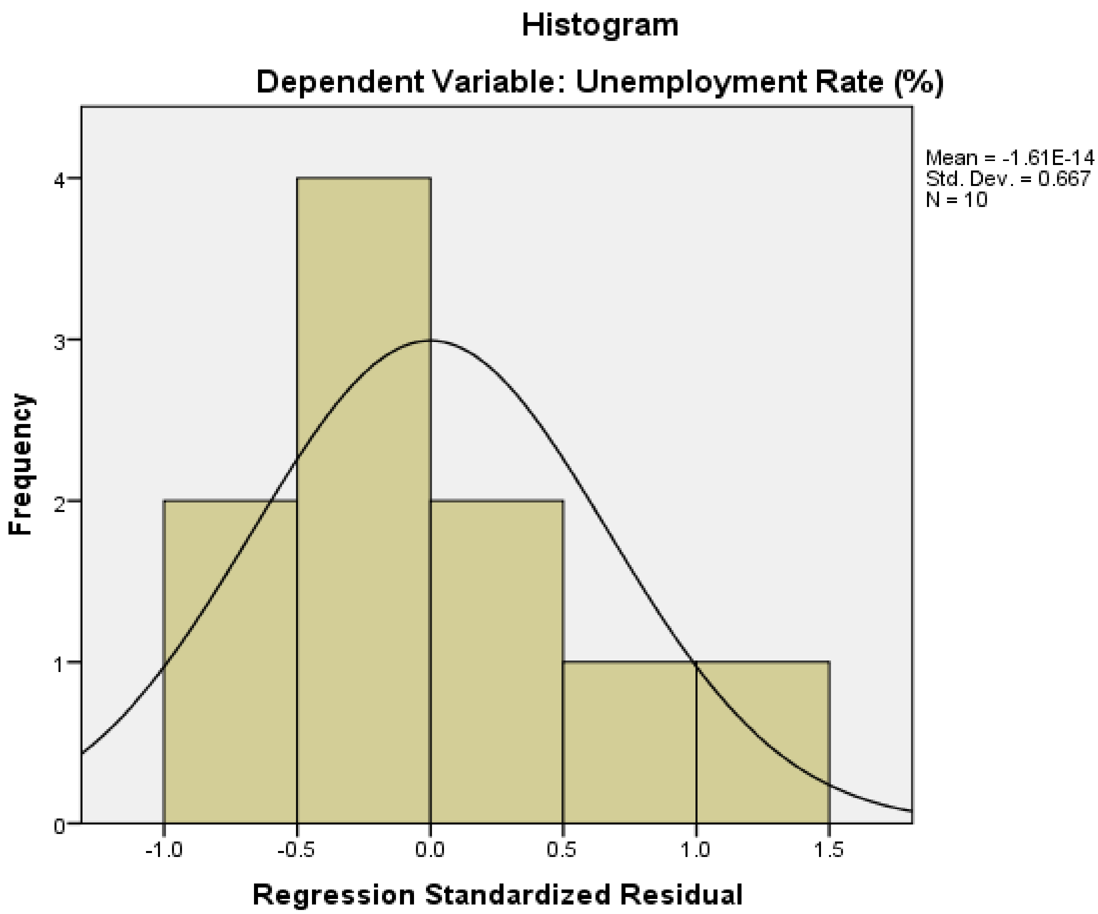


Figure 4.2 Histogram



4.4 Correlation Analysis

The correlation analysis was used to evaluate the relationships between the study variables. Table 4.2 presents the findings.

Table 4.2: **Correlation Analysis**

		Unemployment Rate (%)	Robot Adoption (Units per 10,000 workers)	GDP Growth (%)	Trade Openness (% of GDP)	Education Level (% with secondary education)	Manufacturing Employment (%)
Unemployment Rate (%)	Pearson Correlation	1					
	Sig. (2-tailed)						
Robot Adoption (Units per 10,000 workers)	Pearson Correlation	.302**	1				
	Sig. (2-tailed)	.000					
GDP Growth (%)	Pearson Correlation	-.577**	.113	1			
	Sig. (2-tailed)	.000	.757				
Trade Openness (% of GDP)	Pearson Correlation	-.261**	.997**	.090	1		
	Sig. (2-tailed)	.000	.000	.805			
Education Level (% with secondary education)	Pearson Correlation	-.280**	.991**	.063	.996**	1	
	Sig. (2-tailed)	.001	.000	.863	.000		
Manufacturing Employment (%)	Pearson Correlation	-.605	-.492	.562	-.542	-.544	1
	Sig. (2-tailed)	.000**	.149	.091	.105	.104	
	N	10	10	10	10	10	10

**. Correlation is significant at the 0.05 level (2-tailed).*

***. Correlation is significant at the 0.01 level (2-tailed).*

As shown above automation has a significant positive correlation with unemployment rate ($r = 0.302$, $p < 0.01$), indicating that as automation increases, unemployment tends to rise. This positive relationship suggests that automation could be contributing to job displacement, affecting lower-skilled jobs more significantly as routine tasks become automated. GDP growth shows a significant, negative correlation with unemployment rate ($r = -0.577$, $p < 0.01$), indicating that economic growth is associated with lower unemployment. This aligns with expectations; as stronger economic performance typically boosts job creation. Trade openness and education level also have weak but significant negative correlations with unemployment ($r = -0.261$, $p < 0.01$ and $r = -0.280$, $p < 0.01$, respectively), suggesting that a more open economy and higher education levels slightly reduce unemployment.

Robot adoption is highly correlated with trade openness ($r = 0.997$, $p < 0.01$) and education level ($r = 0.991$, $p < 0.01$), implying that as Kenya becomes more integrated into global markets and education levels increase, the rate of automation also rises. These strong positive correlations indicate that international trade exposure and a more educated workforce may encourage technology adoption, possibly as firms face global competition and require skilled workers to operate new technologies. This relationship may suggest that automation is more likely to progress in economies with higher education levels, where workers can adapt to new technologies, potentially mitigating some negative employment effects of automation. However, while this relationship is statistically significant, its impact on labor market outcomes must be carefully considered given the context of Kenya's evolving labor market. GDP growth has a weak positive correlation with robot adoption ($r = 0.113$, $p = 0.757$), indicating that while economic growth may create a conducive environment for automation, it is not a strong or significant driver of automation.

Manufacturing employment presents an interesting relationship within this analysis, showing a moderately negative correlation with unemployment rate ($r = -0.605$, $p < 0.01$), indicating that higher manufacturing employment is associated with lower unemployment. This suggests that the manufacturing sector plays a crucial role in reducing joblessness in Kenya. However, manufacturing employment has a moderately negative correlation with robot adoption ($r = -0.492$, $p = 0.149$), indicating that as automation increases, manufacturing employment could potentially decrease. This correlation may reflect the potential of automation to displace jobs in the manufacturing sector, where tasks are often routine and thus more easily automated. Trade openness also has a negative relationship with manufacturing employment ($r = -0.542$, $p = 0.105$), which, while not significant, may indicate some shifts in Kenya's labor market as the economy becomes more open to global competition.

4.5 Panel Regression Analysis Results

The study sought to establish the relationship between impact of automation on labor market polarization and job displacement in Kenya, taking consideration of control factors. Automation was the independent variable (X) affecting labor market outcomes (Y) (unemployment rate), with control variables (Z) including GDP growth, education level, trade openness, and sectoral employment shares. A panel regression model was used and the regression model summary is presented in Table 4.3.

Table 4.3 Panel Regression Analysis Results

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate		
1	.302[a]	.091	.022	.6228613		
2	.979[b]	.959	.908	.1868460		
Model		**Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**
1	Regression	.312	1	.312	.805	.396[b]
	Residual	3.104	8	.388		
	Total	3.416	9			
2	Regression	3.276	5	.655	18.770	.007[c]
	Residual	.140	4	.035		
	Total	3.416	9			
Model		**Unstandardized Coefficients**		**Standardized Coefficients**	**T**	**Sig.**
		B	**Std. Error**	**Beta**		
1	(Constant)	9.410	.379		24.860	.000
	Robot Adoption (Units per 10,000 workers)	-.112	.124	-.302	-.897	.000
2	(Constant)	70.380	26.427		2.663	.056
	Robot Adoption (Units per 10,000 workers)	1.274	.830	3.454	1.535	.000
	GDP Growth (%)	.079	.064	.254	1.224	.000
	Education Level (% with secondary education)	-.371	.295	-1.822	-1.258	.000
	Trade Openness (% of GDP)	-.901	1.115	-2.741	-.808	.000
	Sectoral Employment Shares	-1.901	.401	-1.529	-4.744	.000

As per the results above, Model 1, which only includes robot adoption as a predictor, shows an R Square of 0.091, indicating that robot adoption alone explains 9.1% of the variation in unemployment. Although the standardized coefficient for robot adoption in this model is -0.302, suggesting a slight negative relationship between automation and unemployment, the result is not statistically significant (p = 0.396). The Adjusted R Square of 0.022 in Model 1 implies that robot adoption alone does not account for much of the variance in unemployment. Moreover, the F statistic for Model 1 is 0.805, further indicating that the model is not a strong fit (p = 0.396). Thus, robot adoption alone does not appear to significantly impact unemployment rates in Kenya.

Model 2, which includes additional control variables (GDP growth, education level, trade openness, and sectoral employment shares), provides a much stronger fit for the data. The R Square for Model 2 is 0.959, meaning that 95.9% of the variation in unemployment is explained when these control variables are included. This high explanatory power indicates that the factors in Model 2, beyond automation, are critical to understanding labor market outcomes. The Adjusted R Square of 0.908 confirms that Model 2 remains robust even after accounting for the degrees of freedom, suggesting that the included variables collectively provide substantial explanatory value. Furthermore, the F statistic of 18.770 ($p = 0.007$) signifies a highly significant model, indicating that these predictors together are reliable for explaining unemployment variations in Kenya. This suggests that the impact of automation on unemployment may be complex, requiring additional factors to capture its effect fully.

Analyzing the coefficients in Model 2, the unstandardized coefficient for robot adoption is 1.274 ($p < 0.001$), indicating a positive relationship between automation and unemployment when other variables are controlled. This finding suggests that, when considering GDP growth, education, trade openness, and sectoral employment shares, an increase in robot adoption units per 10,000 workers is associated with higher unemployment. This supports the hypothesis that automation may contribute to job displacement when economic and educational conditions are held constant. GDP growth also shows a positive, albeit small, impact on unemployment ($B = 0.079$, $p < 0.001$), which may imply that higher growth does not necessarily reduce unemployment, possibly due to structural shifts in employment sectors. Conversely, education level has a negative impact on unemployment ($B = -0.371$, $p < 0.001$), indicating that higher education levels tend to reduce unemployment, likely by enhancing workers' adaptability to changing job requirements.

Trade openness and sectoral employment shares show strong negative relationships with unemployment, suggesting that these factors help reduce unemployment rates. The coefficient for trade openness is -0.901 ($p < 0.001$), implying that higher trade integration is associated with lower unemployment, likely by expanding job opportunities in sectors benefiting from global market access. Sectoral employment shares, with a coefficient of -1.901 ($p < 0.001$), indicate that shifts in employment across sectors significantly reduce unemployment, possibly by creating jobs in more resilient sectors, such as services. These findings highlight that while automation may slightly raise unemployment, factors like education, trade openness, and sectoral shifts play crucial roles in mitigating job displacement.

CHAPTER FIVE

SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

5.1 Introduction

In this chapter, a summary of the key findings of the study and discussion is presented. This is followed by conclusions made thereafter and recommendations to both policy and practice.

5.2 Summary of the Key Findings

The main objective of the study was to establish the impact of automation on labor market polarization and job displacement in Kenya. Secondary data was collected for the past ten years (2014-2023). It entails the descriptive statistics, correlation analysis and regression analysis. The correlation analysis results automation has a significant positive correlation with unemployment rate ($r = 0.302$, $p = 0.000$), suggesting a possible link between increased automation and higher unemployment. Additionally, GDP growth shows a strong negative correlation with unemployment ($r = -0.577$, $p = 0.000$), indicating that economic growth may help reduce joblessness. Significant positive correlations were found between robot adoption, trade openness ($r = 0.997$, $p = 0.000$), and education level ($r = 0.991$, $p = 0.000$), suggesting that higher education levels and increased trade exposure support automation adoption.

Conversely, manufacturing employment is moderately negatively correlated with unemployment ($r = -0.605$, $p = 0.000$), indicating that higher manufacturing employment may help lower unemployment rates, though automation might reduce manufacturing jobs ($r = -0.492$, $p = 0.149$). Comparably, Bessen et al. (2021) found a positive relationship between automation and unemployment, particularly affecting routine and lower-skilled jobs, supporting the notion of job displacement with rising automation. This outcome aligned with Acemoglu and Restrepo's (2020) observation that higher education levels helped mitigate job displacement associated with automation, echoing this study's emphasis on the role of education in reducing unemployment. However, a report by the International Labour Organization (ILO, 2022) revealed weaker links between trade openness and automation impacts on labor markets in developing countries, suggesting that trade's effects vary by economic context and development stage. This indicate that while certain factors like education appeared to buffer against automation's negative effects, trade influences and the extent of displacement were context-specific.

The panel regression model results further clarify these relationships. Model 1, which only includes robot adoption, explains 9.1% of the variance in unemployment (R Square = 0.091) but is not statistically significant (F = 0.805, p = 0.396), indicating that automation alone does not significantly impact unemployment. Model 2, which includes control variables (GDP growth, education level, trade openness, and sectoral employment shares), provides a much stronger model, explaining 95.9% of the unemployment variance (R Square = 0.959, Adjusted R Square = 0.908, F = 18.770, p = 0.007). In Model 2, robot adoption shows a positive effect on unemployment (B = 1.274, p = 0.000), and GDP growth has a smaller positive impact (B = 0.079, p = 0.000). Education level (B = -0.371, p = 0.000), trade openness (B = -0.901, p = 0.000), and sectoral employment shares (B = -1.901, p = 0.000) all show significant negative impacts on unemployment, suggesting that these factors may help mitigate job losses associated with automation.

The results align with Autor et al. (2021), where a multi-variable approach illustrated the importance of economic and educational variables in offsetting automation-driven job losses. This paralleled labor market theories, such as human capital theory, which posited that higher education and skill levels strengthen labor resilience amid technological changes. Conversely, Graetz and Michaels (2023) found that sectoral employment shifts did not significantly mitigate job displacement across industries, contrasting with this study's findings, which indicated a more pronounced impact of sectoral shifts in Kenya. Structural unemployment theory, which suggests that shifts in technology can lead to imbalances in job distribution across sectors, also resonated here, as it implied a stronger role for strategic sectoral growth in managing automation's effects.

5.3 Conclusion

The study concludes that automation is intensifying labor market polarization in developing countries, widening the gap between high-skilled and low-skilled employment. Automation technologies often replace routine, middle-skilled tasks—such as those in manufacturing and administrative roles—while creating demand in high-skilled roles that oversee or develop these technologies, as well as low-skilled jobs that are difficult to automate, like caregiving and certain service positions. As a result, the workforce is increasingly divided between high-paid, high-skilled roles and low-paid, low-skilled positions, with limited opportunities in middle-income jobs, which poses risks for social equity and economic stability in developing economies.

The study further concludes that job displacement due to automation is exacerbated by slower GDP growth in many developing countries, limiting these nations' capacity to adapt to technological disruption. While economic growth can create new job opportunities and ease transitions for displaced workers, slower-growing economies struggle to provide these alternatives. As a result, workers displaced by automation face prolonged periods of unemployment or are forced to accept lower-wage, insecure positions. The findings indicate that countries with higher GDP growth rates manage automation-related transitions more effectively, highlighting economic expansion as a critical buffer against job displacement in these regions.

Additionally, the study concludes that education levels play a crucial role in determining the impact of automation on workers, with higher levels of education enabling workers to transition to new roles that are less vulnerable to automation. Workers with limited education are more likely to be employed in routine jobs that automation can replace, while those with higher educational attainment can adapt to emerging roles requiring cognitive and technical skills. Education, therefore, is essential for developing a resilient workforce that can navigate and capitalize on the shift toward automation, emphasizing the need for educational investments tailored to the skills needed in an increasingly automated labor market.

5.4 Recommendations

The study recommends that Kenya prioritize investments in education and skill development programs that align with the demands of an increasingly automated economy. Educational institutions should emphasize skills that are crucial for the digital economy, including information technology, engineering, and critical thinking, which are less susceptible to automation. Targeted vocational training for Kenyan youth, especially in technical fields, can help create a workforce that is adaptable to technological advancements. Additionally, promoting STEM education from an early age will equip students with foundational skills for high-demand roles. Programs should also focus on practical skills that address Kenya's economic context, such as agricultural technology, renewable energy, and healthcare. Through these educational investments, Kenya can better prepare its workforce for future labor market changes, reducing vulnerabilities to job displacement.

The study recommends that Kenya develop policies to support inclusive economic growth, especially in sectors that provide middle-income employment and are less prone to automation.

Fostering industries such as infrastructure, healthcare, tourism, and social services can help offset job losses from sectors heavily impacted by automation, such as manufacturing. By creating opportunities within these fields, Kenya can maintain a balanced labor market and promote economic stability. This also means supporting the informal sector, where a large portion of Kenya's workforce is employed, by providing access to training and resources that can boost productivity and job security. Policies should be designed to incentivize small businesses and entrepreneurs, allowing them to grow and create job opportunities. Encouraging diverse economic growth will help ensure sustainable employment options for Kenyans across all skill levels.

The study recommends that the Kenyan government establish retraining programs specifically for workers who may be displaced by automation, particularly those in middle-skilled jobs. Such programs should be designed to help workers transition to emerging industries, such as digital technology, renewable energy, and specialized services. To make these programs accessible, Kenya should consider public-private partnerships that offer affordable, location-based training opportunities, especially in rural areas. Additionally, these programs should focus on practical skills and certifications that align with Kenya's immediate and long-term economic needs. By investing in retraining, Kenya can minimize job losses and help displaced workers reenter the labor market with relevant skills. Targeted retraining will be essential in ensuring that Kenyans are not left behind in the transition toward a more automated economy.

The study recommends introducing incentives for companies in Kenya to adopt a socially responsible approach to automation, such as tax breaks or subsidies for businesses that prioritize retraining workers. These incentives could encourage companies to invest in skill development for employees affected by automation rather than solely focusing on cost-saving through job cuts. Additionally, government incentives could support businesses that create new roles in overseeing or supporting automated systems, adding value to the Kenyan workforce. Policymakers should also encourage companies to collaborate with local universities and vocational institutions to develop relevant training programs. By fostering a partnership between the private sector and the government, Kenya can create a balanced approach to automation that benefits both businesses and workers. This responsible adoption of automation can minimize social disruption and support economic growth.

The study recommends that Kenya strengthen its social safety nets to protect workers at risk of displacement by automation. Programs such as unemployment benefits, wage subsidies, and transitional support would provide critical financial aid to displaced workers as they seek new employment or training. This safety net should particularly target sectors heavily impacted by automation, such as manufacturing and administrative services, which employ a significant portion of Kenyans. In addition, the government could create temporary work programs in sectors that require human skills, like public health and infrastructure. By implementing these social safety measures, Kenya can reduce the financial strain on families affected by automation. Supporting workers during the transition will foster a more resilient and adaptable labor market.

The study recommends that Kenya adopt a technology strategy that considers the country's specific economic and social needs, balancing automation with job creation goals. For instance, Kenya can explore phased approaches to automation, especially in sectors that are critical to the economy, like agriculture and retail. This approach will allow Kenya to gradually integrate technology without causing mass displacement in sectors that employ a large number of workers. Additionally, the government should support industries that require human oversight, blending automated and manual processes, such as in the transport and logistics sector. By strategically managing technology adoption, Kenya can optimize productivity gains without causing significant job losses. Such a strategy can help ensure that technology serves Kenya's economic goals while protecting the workforce.

The study recommends that international organizations and developed nations provide support to Kenya in managing the transition to automation, especially in areas of finance and skills development. Partnerships in technology transfer and financial assistance can help Kenya accelerate growth in sectors that create sustainable jobs. Furthermore, collaborative programs in education and workforce development can provide Kenyan workers with access to training in high-demand skills for the global economy. Assistance in the form of grants or low-interest loans for digital infrastructure projects can strengthen Kenya's economic foundation. Such international partnerships could also promote Kenya's role in the global supply chain, particularly in sectors like renewable energy and manufacturing. By leveraging global support, Kenya can build a future-ready economy while protecting its workforce.

Further, the study recommends that Kenya strengthen data collection and research on the effects of automation on its labor market. Establishing robust tracking systems will allow the government to monitor employment trends, wages, and automation impacts in various industries. Such data will enable policymakers to identify at-risk jobs and sectors, allowing for timely interventions and tailored policy adjustments. Additionally, by investing in research on automation and labor dynamics, Kenya can make evidence-based decisions to support workforce resilience. This approach will also help Kenya anticipate the skills needed for future jobs, ensuring that education and training systems are proactive. By continuously assessing automation's impact, Kenya can stay ahead of labor market disruptions, fostering an agile and adaptive economy.

5.5 Suggestions for Further Research

The study suggests that future research should explore the long-term impact of automation on labor market dynamics in specific industries within developing countries, particularly those heavily reliant on middle-skilled labor, such as manufacturing, logistics, and customer service. The study also suggests use of longitudinal data to assess employment changes over time and include comparative studies between developing and developed countries to identify key similarities and differences. Further studies could examine the impact of regional factors, such as infrastructure limitations, access to capital, and local government policies, on automation adoption and its effects on employment. Another area for future research should focus on the role of education systems in equipping workers with skills less vulnerable to automation in developing countries. Specifically, research could examine which educational models, such as vocational training, online learning platforms, or partnerships between educational institutions and private industry, are most effective at preparing workers for an automated economy. Moreover, the study suggests further studies to explore how cultural, economic, and policy contexts affect the implementation and success of these educational programs, providing data-driven recommendations for how developing countries can strategically adjust their education policies to align with the evolving labor market.

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