# The Impact of Artificial Intelligence on Employment: Evidence in Africa

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## ABSTRACT

The purpose of this research paper is to examine the effect of artificial intelligence on employment in Africa. To accomplish this, the study employs a convenience sampling technique across 42 countries out of 54 African countries from 2012 to 2021 and utilizes a two-step system known as the Generalized Method of Moments (GMM) to estimate the impact of artificial intelligence on employment. In the course of the research, two models are specified to determine the influence of artificial intelligence on employment and examine its impact in the absence of a human development index. To analyze the research data, descriptive statistics and regression analysis are employed. The findings suggest that artificial intelligence has a strong positive impact on employment, while revenue demonstrates a moderate positive effect. On the other hand, political stability appears to have a negative impact. The paper makes a valuable and timely contribution to the existing literature on the subject of artificial intelligence's impact on employment in Africa. The paper concludes by providing suggestions on how to effectively harness AI's creative effects to counteract its negative consequences and utilize AI to reduce corruption and create sustainable employment for African economies.

**Keywords –** artificial intelligence, employment, Africa, Revenue, Political stability

## INTRODUCTION

Artificial intelligence (AI) has made significant strides in recent years, especially in the fields of speech and picture identification, natural language processing, translation, reading comprehension, programming, and predictive analytics (Kortum et. al., 2022). Concern over the potential impacts of AI deployment on the labor market, particularly worker displacement, has accompanied this rapid advancement. There are reasons to think that it may have a different effect on employment than earlier technical advances. According to Mihaylov and Tijdens (2019) theory, jobs are made up of routine and theoretically programmable and non-routine work.

The first productive force is science and technology, and innovation in these fields is what drives economic progress. Employment is an issue of peoples' livelihoods, and full employment promotes social stability. They do not, however, naturally relate to one another. On the one hand, innovation in science and technology is helpful for fostering job growth and employment (Sahoo et. al., 2022). On the other side, it will destroy jobs that cannot keep up with new technology, impede employment, and make it more difficult to optimize talents and minimize shortcomings. Because human adoption of new things differs from person to person and because artificial intelligence technology has both positive and negative effects on society, people have different opinions about it, which has led to much debate. The influence of artificial intelligence on employment currently encompasses both creation and destruction mechanisms, according to a synthesis of experts' and scholars' theoretical analyses (Makridakis, 2017). The compensating effect is a by-product of the creation mechanism. Artificial intelligence has the potential to increase employment, create new jobs, and improve the economy. The replacement effect is the destruction process; as new technology replaces older technology, jobs dependent on the older technology are also replaced, inevitably resulting in job loss. The unemployment issue will worsen as technology continues to permeate every aspect of human life. The fear that humans will be replaced by robots is currently being fuelled by the realization that artificial intelligence can replace jobs in many spheres of life. We must first theoretically delineate the influence mechanism of artificial intelligence on employment in order to discover the appropriate solution to the issue (Lan et al., 2022; Etemad-Sajadi et al., 2022; Birkle, 2022). We must investigate the inner workings of the human mind. There are three ways to accomplish this: through introspection, where we try to capture our own thoughts as they pass; through psychological tests, where we watch a person in activity; and through brain imaging, where we watch the brain in operation (Kenny, 2022). It becomes conceivable to express a theory of the mind as a computer program if we have one that is specific enough. If the input and output behaviour of the program is consistent with the comparable behaviour in humans, some of the program's mechanisms may also be in play in people (Jongepier & Wieland, 2022). For instance, Allen Newell and Herbert Simon, who created GPS, the "General Problem Solver" (Newell and Simon, 1961), were not satisfied with having their software merely accurately answer issues (Cordeschi, 2006).

Prior waves of technological development were mainly characterized by the automation of repetitive jobs. For instance, computers are capable of doing common cognitive tasks like calculating, record-keeping, and information searching. Industrial robots, which can be programmed to manipulate real items, are also used to automate repetitive manual operations like welding, painting, and packaging (Cordeschi, 2006). Therefore, these technologies primarily replace workers in low- and middle-skilled occupations.

Prior to the advent of artificial intelligence, it was believed that only highly skilled workers could perform non-routine manual and non-routine cognitive jobs, which call for dexterity, inventiveness, and social intelligence (Frey & Osborne, 2017; Vermeulen & Psenner, 2022; Permana, 2017). However, current developments in AI suggest that more and more non-routine cognitive functions can be automated. In the majority of its present applications, AI refers to computer software that makes predictions about the future and detects patterns in data by using extremely advanced algorithmic procedures (Das & Behera, 2017). AI may be able to formulate medical prognoses and recommend treatments, find cancer, and spot fraud, according to an analysis of patent papers. As a result, unlike earlier waves of automation, high-skilled workers may be disproportionately impacted by AI. Even if AI automates complex, non-routine operations, this does not imply that workers will be replaced by AI.

Generally speaking, technological advancement increases labor efficiency by (partially) taking over or hastening worker duties. As a result, manufacturing costs are decreased and output per effective labor input rises, employment may decrease as tasks are mechanized substitution effect. On the other hand, if there is enough demand for the good or service, lower production costs might result in higher output productivity effect. Technologists are adjusting to the opportunities presented by cutting-edge developments like artificial intelligence (AI), robotics, and the internet of things as the world ushers in the Fourth Industrial Revolution (4IR), which is characterized by increasingly blurred boundaries between the digital, biological, and physical worlds. In principle, these and other cutting-edge technologies present us with the opportunity to spark historic socioeconomic change and democratize access to services like the internet, education, and healthcare (Dong et. al., 2020).

Africa will likely be affected by AI in a number of ways. Many have praised it as a force that will alter African nations, suggesting that it will lessen poverty, reduce inequality, and increase access to public services like health and education (Williams & Cooper, 2019;Kuwali, 2022; Turok & Visagie, 2022). However, the adoption of these formidable technologies is still in its infancy on the continent, and there are substantial obstacles to be addressed in order to develop the capacity to fully realize their promise. One of the most important of these is a lack of diversity in the industry at large, which affects every aspect of AI, from creating datasets to creating and deploying systems. Diversity here refers to the practice of including individuals from various socioeconomic, racial, ethnic, and cultural origins, as well as individuals of various genders and sexual orientations.

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 (Cummings et. al., 2018). Although this is fantastic news for South African enterprises, an AI-dominated environment raises a number of ethical and societal concerns, including the issue of a labour force that feels unnecessary and whose skills may no longer be in demand.

The literature has extensively discussed the feasibility of automating existing jobs in light of alleged and actual technical advancements. For instance, Fuei and Peters (2017; 2019) estimate that 47% of jobs in the United States could be automated "over some indeterminate period of years, perhaps a decade or two". Similarly, Bowles (2014) performs similar calculations for the European labor market and discovers that, on average, 54% of employments in the European Union are vulnerable to computerization.

In contrast, Osborne and Frey (2017) and Nedelkoska and Quintini (2018) contend that Frey and Osborne's focus on predicting forecasts regarding occupations as being endangered by automation rather than activities is a critical flaw in their methodology. According to their critique, Frey and Osborne overestimate the automation risk. They arrive at the conclusion that just 9% of US employments are possibly automatable by using data on task content of jobs at the individual level. These studies, which focus on the displacement effect of automation, can be seen as feasibility tests on the potential impact of AI. However, assessing how productivity affects the possibility for new machines to increase employment is more challenging. Empirical research by Autor et. al. (2015) indicates that computer technology is linked to job development, particularly in non-manufacturing industries. These findings suggest that while the displacement effect of automation is a concern, AI can also create new job opportunities and foster job development.

The aggregate labour market implications of new technologies depend not only on the industries in which they operate but also on adjustment in other parts of the economy, as Acemoglu and Restrepo (2019) demonstrate in their theoretical model. At the same time, there are potential sector spillover effects (Acemoglu & Restrepo, 2019). The relationship between artificial intelligence and employment has received very little attention, despite the fact that Africa is the continent with the fastest technological growth. Every continent is now connected to the digital world thanks to technology, yet most study publications still concentrate on the western world, despite how popular and widespread technology is in Africa.

With data spanning the years 2012 to 2021 from the global development indicators, this study used a sample size of 42 out of the 54 African nations using a convenience sampling technique. It then used a two-step generalized method of moment to estimate the impact of artificial intelligence on employment in Africa. The remainder of this paper concentrates on the literature review, methodology, findings, recommendations, and policy implications.

## LITERATURE REVIEW

People's tolerance for change differs from person to person, and the dual benefits and drawbacks of artificial intelligence technology for society have led to a great deal of debate. The influence of artificial intelligence on employment currently encompasses both creation and destruction mechanisms, according to a synthesis of experts' and scholars' theoretical analyses (Stafie & Grosu, 2022; Mukherjee, 2022; Gonzales-Inca et. al.,2022). The compensating effect is a by-product of the creation mechanism. Artificial intelligence has the potential to increase employment, create new jobs, and improve the economy. The replacement effect is the destruction mechanism; as new technology replaces older technology, jobs dependent on the older technology are also replaced, inevitably resulting in job loss. The unemployment issue will worsen as

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technology continues to permeate every aspect of human life. The fear that humans will be replaced by robots is currently being fuelled by the realization that artificial intelligence can replace jobs in many spheres of life. We must first theoretically delineate the influence mechanism of artificial intelligence on employment in order to discover the appropriate solution to the issue (Vrontis et. al., 2022).

In some ways, the technological revolution is the concentrated expression of advancement in technology. It encourages economic growth and, through supporting the industrial revolution, causes the social employment structure to change. Theoretically, the introduction of artificial intelligence as a new technology has increased labour productivity. Using the approach of variable analysis, it is possible to lower the demand for labour force and the number of employment positions when the scale of production is fixed (Felbermayr, Prat, & Schmerer, 2011; Pi?tkowski, 2020). Additionally, technical advancements will lower costs, utilise resources more effectively, and boost capital output. In this way, the trend of the day will increasingly be the substitution effect of machines. For instance, Xiong Bide's anticipated technological advancement and productivity boost will enhance demand for key components needed in the creation of new goods in the short term (Wong-Pinto et. al., 2020). Process innovation will save money, but it will also reduce the demand for labour, which will increase the unemployment rate. The impact of the altered labour mode, altered labour market demand, and altered company management will be examined.

The information on how robots will affect net employment is conflicting. According to Chiacchio, Petropoulos, and Pichler (2018) adding one robot for every 1,000 workers has a negative impact on employment rates, which are reduced by 0.16-0.20 percentage points in six EU nations. Using data from Germany, Carbonero, Ernst, and Weber, Robots worldwide (2020) find no evidence that robots result in a net loss of jobs, but they do find that manufacturing employment is significantly negatively impacted: for every additional robot per thousand workers, the manufacturing employment-to-population ratio falls by 0.0595 percentage points (Carbonero, Ernst, & Weber, 2020).

Acemoglu & Restrepo (2020) examine the impact of the rise in industrial robot adoption between 1990 and 2007 on US labor markets in their work Robots and Jobs: Evidence from US Labor Markets. They use within-country heterogeneity in robot adoption to provide an answer to this topic. The theoretical model that is used to develop equations and determine the overall impact of robots on employment and earnings is described in the first section of the paper. They demonstrate how the impact of robots on jobs can be estimated for each labor market by regressing the change in employment and wages on the exposure to robots. They ultimately discover that one additional robot per thousand workers reduces the employment to population ratio by approximately 0.37 percentage points and wage growth by 0.73 percent (Acemoglu & Restrepo, 2020).

Early studies, which relied on a macroeconomic equilibrium analysis but did not specifically focus on automation, indicated a rise in technical unemployment (Aghion et. al., 2019; Bazzoli & Probst, 2022). Authors attempted to explain the polarization of the labor market in the years after the IT and computer revolution of the 1990s. Investigations focused heavily on the canonical skill-biased technology shift, which was found in multiple studies to be the cause of the widening pay gap and improved returns. A growing demand for skilled labor versus non-skilled labor has an impact on schooling (Haseeb et. al., 2020; Braha-Vokshi et. al., 2021). This skill-biased technological transition hypothesis supported the idea of complementarity between technology and skilled employees rather than foreseeing the replacement of labour by capital.

The theory of skill-biased technology was debunked by Thoenig and Verdier (2003) critique in favour of the routinization concept. The scholarly consensus changed to a view of automation in regular work as replacing labor. The underlying assumption became that "traditional" automation reduces routine jobs while increasing demand for non-routine tasks requiring knowledge that cannot be automated. In fact, empirical evidence demonstrates that automation increased the number of high-skilled and low-skilled jobs while displacing medium-skilled positions (Ramaswamy, 2018; Chuang & Graham, 2018; Pfeiffer, 2018). Numerous studies illustrate how the labor market is structurally changing and how routine and manufacturing occupations are disappearing (Arntz et. al., 2022)

Authors who wanted to move beyond conventional automation have questioned if automating employment is even possible given the state of technology today and what is assumed to happen in the future. They significantly loosen the presumption that automation cannot endanger non routine jobs. Litwin, et al., (2022) contend that automation is no longer restricted to ordinary work, using the example of self-driving cars, non-routine tasks such as legal writing, truck driving, medical, and selling could not be substituted. Following this route, Majzlíková & Vitáloš (2022) calculated the likelihood that several jobs would be computerized. Their key finding indicated that while just some percentage of jobs has a minimal risk of automation, 47 percent of employment in the US is at risk of automation in the next ten to twenty years. They also demonstrated that there was a strong inverse association between the likelihood of computerization and salaries and educational attainment.

Frey and Osborne have come under fire for failing to take into account the differences in a given vocation between workplaces and ignoring the task content of the employment. According to Paolillo et. al.,(2022) just 9% of all US workers are at a high risk of automation when the diversity of tasks within occupations is taken into account. Last but not least, Frey and Osborne’s method does not take into account how the economy will respond in a general equilibrium model, including the cost of automation, how wages will react, and how many new jobs would be created. Despite technical advancements, the expense of replacing workers with machines may prohibit businesses from automating quickly, especially if salaries change. Additionally, the superfluous staff could be trained and hired for new projects.

There are many viewpoints on this issue among the economists we contact. In reality, Herbert Simon and Wassily Leontief, two economics Nobel laureates, appear to be on opposing sides. On the one hand, Herbert Simon (who is undoubtedly a renowned AI expert) points to the rule of comparative advantage as the standard economic theory’s debunking of the claim that mechanization results in technological unemployment. In essence, according to Simon, this law “. shows that both people and machines can be fully employed regardless of their respective productivity. Labor will be used in processes where it is relatively more productive, and capital will be used in processes where it is relatively more productive, thanks to adjustments in the relative prices of labor and capital, respectively.However, Simon acknowledges that the law of comparative advantage does not resolve all the fundamental concerns. In particular, it does not predict what that wage would be and does not guarantee that real wages will not decline as the economy’s productivity increases due to mechanization, despite the fact that it demonstrates that at some wage all labor would be employed in equilibrium regardless of how efficient machines become. Even the continuation of real salaries beyond the subsistence level is not guaranteed (Islam et. al., 2022).

There are two interrelated components to understanding the processes of technology innovation and societal transformation. Analytical queries concentrate on the nature of change and its causes. Normative inquiries examine the extent to which changes have both good and negative features assessed using a number of criteria. There are two basic analytical stances that can be distinguished in current debates. The first is that robotics and artificial intelligence are merely the most recent in a line of technological advancements that are significant but not fundamental. They might lead to significant technical unemployment, but they don’t constitute a fundamental shift in how the economy is organized or a brand-new challenge to societal norms. The second is the extraordinary revolutionary change that robotics and AI represent. Radice (2014) and Hartman et. al., (2011) two economists have recently argued vehemently for “no real change. They contend that the IT revolution has already taken place and has not resulted in enough productivity increases to combat the current economic challenges, which include an aging population, declining educational standards, rising inequality, and high consumer and government debt levels. They come to the conclusion that compared to steam, electricity, or the internal combustion engine, modern technologies aren't having nearly as much of an impact on economic production. The arguments for transformations are seriously undercut by the resurgence of an earlier school of thought on the trends toward stagnation in western economies (Hansen, 1938). Moore's Law, which states that computing power will double every two years, represents the assumptions of perpetual growth at the core of information technology on the one side and the historical experience of diminishing returns from the application of any kind of invention on the other.

Recently, the alternative viewpoint has been advanced, claiming that AI enhances employment and tasks (Duan et. al.,2019; Dane, 2010; Clarke, 2018). Many modern AI companies claim that their technologies increase productivity by getting rid of repetitive and unnecessary tasks within particular fields. The usage of AI for specialized jobs and functions has grown, from market research to the medical and financial industries. Although statistical data is used in many applications, handling of other types of data, such as pictures, is growing. The current trend in AI companies is to focus on specific tasks within a workflow, as demonstrated by Cyft which focuses on healthcare interventions, Uptake which integrates the Internet of Things and AI for industrial automation, and Numeral. Earlier companies frequently offered technology in search of a solution, but this is no longer the case which combines AI with block chain technology. The AI applications must combine domain knowledge from specialists in order to capitalize on these more specialized niche markets. Significant volumes of data are also needed for deep learning during training. The development of platforms that customers can use to improve job productivity and more combine work activities is another trend that AI product companies are noticing.

**Artificial intelligence and employment in the long-run**

Not distinguishing between short-run and long-run effects leads to some of the confusion on what will happen to employment and unemployment. Most of us are trying to predict what the long-term future will hold when we consider artificial intelligence and greater automation, and our intuition comes from looking at how expansion has altered how people live over generations. Instead of focusing on how it has impacted our lives in the previous five years, we should compare how we live today and if you are reading this, you know it entails lengthy periods of intellectual reflection on how our ancestors lived ten generations ago. Most Americans in the 1800s worked in agriculture, and very few of them used their free time in other types of employment. Currently, 2% of Americans work directly in agriculture. The public school system employs more people than the agricultural sector. In conclusion, very few of us hold positions similar to those held by our grandparents, while a large portion of us hold positions that did not exist just one generation ago (Taylor, 1997; Allen, 2015; McMurry, 1992). Nancy Stokey, a member of the IGM panel, made it apparent that she was considering the long term when she said, If this had been true throughout the last two centuries, nearly no one would be working anymore. When you consider the long term, it must be true that automation hasn't resulted in a decrease in employment, at least not as quickly as it has happened. In fact, many economists find it puzzling that paid employment has remained surprisingly consistent even as economies have grown richer and residents could have been expected to spend more of their increased income on leisure activities.

Despite our intuition, employment has tended to fall with technological advancement. In the long run, both employment and hours worked have decreased. Our perceptions about how technology advancement has affected employment differ from the reality, which reveals two things. The first is that, contrary to expectations, employment and hours worked have not decreased as dramatically. The second is that economists frequently imagine a system in which those who wish to work may do so.

**Artificial intelligence and employment in the short-run**

The key question with artificial intelligence is how we will manage people through the disruption and what it will look like. The majority of economists believe that people will suffer as a result of the decline in the demand for their abilities. Longer periods of unemployment and a greater demand for worker retraining could both occur. There may be jobs that employees are unable or unwilling to perform. While we can prepare a younger generation for a world where robots perform many of the jobs, it is more difficult to train an older age. People are reluctant to start afresh, they lament the things they have lost, and they dislike a notion of progress that reduces their prestige and financial standing. Loss of status should be more difficult to overcome than loss of income. What do we know about work and how crucial is it? Is employment more important for the money it produces or for the structure and significance it brings to our days? Much of the discussion about how automation may affect employment is essentially a discussion about how we will use our free time. Therefore, it is helpful to distinguish between the issue of how we will spend our time if robots take our jobs and the issue of whether we can find a stable and equitable distribution of income in such a situation. Furthermore, it is important to understand that the solutions may differ significantly from what occurs in the short run. However, how we handle the short term will ultimately affect how things turn out in the long run (Litman & Colman, 2001; Levin et. al., 2012).

**Difference between employment and work**

Work is a more general idea than just paid work. Paid work is the outcome of a trade-off between leisure time, commodities produced at home, and goods produced for the market. This is significant from a measurement standpoint since nonmarket-produced commodities were quickly replaced by market-produced goods during the 1970s (Coyle & Nakamura, 2022). Women began working, purchasing clothing, and purchasing pie and cake mixes instead of producing garments, pies, and cakes from scratch. Homemade items were displaced by technological development, but women's labour force involvement increased. Should we consider this to be more or less work? One thing is certain: work moved from outside to inside our typical measurement scope. If you classify every stay-at-home mom with kids as a childcare worker, for instance, I suppose there are fewer childcare workers today than there were forty years ago. However, time-use surveys show that, at least since the 1970s, the drop in hours worked has been less pronounced than suggested by measured hours of employment (Dinkelman & Ngai, 2022; Paul & Morris, 2022). Dads are working longer hours despite having fewer hours in the workforce, according to time-use studies. Men work more hours than they did in the 1960s once we include in the hours spent on childcare and housekeeping. Why take into account childcare and household duties? We require a more comprehensive understanding of what work is if we are to consider gauging what actually occurs at work. Artificial intelligence won't replace the need for human interaction, both in our personal life and at work, especially if the question is whether we can find fulfilling activities to do with our free time. A robot may be able to care for an elderly patient who is confined to a bed, but it is unlikely to give the same happiness and fulfilment as interacting with a human. Will there be more employment that is paid to look after one another? Undoubtedly. Will our better salaries, however, also enable us to decide to work less hours so that we can offer more uncompensated care to our friends and family members? So, I hope (Belk, 2022; Dayanandan & Mehta, 2022; Huda, 2022).

## METHODOLOGY

This study aims to investigate the impact of artificial intelligence (AI) on employment across the African continent, while also considering the effects of revenue and politics. The research employs a quantitative approach, utilizing panel data analysis to examine the relationships between the variables of interest.

**Research Design and Data Collection**

The study used a panel data design, focusing on 42 African countries selected through convenience sampling from a total of 54 countries. The data encompassed a ten-year period, ranging from 2012 to 2021. The primary source of data was the World Development Indicators (WDI) database, a reputable and comprehensive repository maintained by the World Bank.

### Validity and Reliability of Dataset

The WDI compiles its data from officially recognized international sources, ensuring its validity and reliability. To extract the relevant data, filters were applied to the WDI database to select the appropriate indicators, time ranges, and countries in the sample. The extracted data was then cleaned and preprocessed to address any missing values, outliers, or inconsistencies, ensuring its accuracy and consistency. By utilizing a robust data source and rigorous data processing techniques, this study ensured the validity and reliability of the datasets used for analysis.

The primary variables of interest in this study are explained in Table 1:

**Table 1: Description of variables**

| Variable | Notation | Description & Measurement of variables |
|---|---|---|
| Employment | Employ | Employment is a composite index of employment to population ratio, ages 15+, total (national estimate) extracted from the WDI. |
| Artificial intelligence | Artificial | Artificial intelligence is measured by two variables as a composite index from the WDI, i) industrial design applications resident by count, ii) Technicians in R&D (per million people), and iii) High technology exports (current US$) |
| Revenue | Rev | Three variables from the WDI are extracted to form a composite index as follows, i) CPIA efficiency of revenue mobilization rating (1 = low to 6 = high) ii) social contributions (% of revenue), and iii) tax revenue (current LCU) |
| Political stability | Pol | Political stability is extracted from the world governance indicators and used as a control variable. |

### Data Analysis

To analyze the panel data, the study employed the two-step system Generalized Method of Moments (GMM) technique, a widely used method for estimating panel data models. GMM corrects endogeneity by transforming all regressors through differencing, effectively removing fixed effects and allowing for more reliable estimations of the impact of AI on employment. According to Roodman (2009) system GMM corrects endogeneity by introducing more instruments to dramatically improve efficiency. It transforms the instruments so that they are no longer exogenous (correlated) with the fixed effects. The result is the construction of the original equation and the converted equation, two equations. Additionally, System GMM uses orthogonal deviations rather than deducting the average of all upcoming observations of a variable, regardless of the number of gaps, from the contemporaneous one. This reduces data loss because it may be computed for all observations for each participant except the last.

### Model Specification

Generalized Methods of Moments (GMM) estimation using a dynamic panel specification was used in study (Beck et. al., 2007). The study has the option to include lags of the dependent variable as a predictor variable using the dynamic panel regression model, which is described as follows:

$$Y_{it} = \varsigma Y_{it-1} + \beta X_{it} + \varepsilon_{it} Y_{it} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (1)$$

$$\varepsilon_{it} = \mu_t + \sigma_i$$

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The $Y_{it}$ represents the dependent variable for the model, $Y_{it-1}$ is the lag of the dependent variable, whereby Y, $X_{it,}$ represent a matrix of the dependent variable (1 x k), $б_0$ is the unobserved country effect, α is the coefficient of the lag dependent variable, β is the coefficient of the explanatory variables including the control variables. The unobserved individual effect is represented by$в_i$, $\mu_t$is the time effect, i is the number of variables or observations in the study. N is the number of nations, and T denotes the time (years). Ɛ denotes the correlation between the error term and the lagged dependent variable ($Y_{it-1}$). Incorporating the lag dependent variable will help researchers address autocorrelation-related problems. Since these equations are typically dynamic models, the estimation procedure makes use of the Generalized Method of Moments (GMM).

In order to ascertain the impact of artificial intelligence on employment, a model is specified as follows:

$Employment_{it} = \alpha_1 Employment_{it-1} + \alpha_2 Artificial_{it} + \alpha_3 z_{it}\lambda' + Ɛ_{it}$ ------------------------------ (2)

$Employment_{it}$ is Employment for country i at time $t_t$$Artificial_{it}$ represents Artificial intelligence for country i at time $t_t$ $z_{it}$ represent a set of control variable showing general development for country i at time t. (revenue, and political stability) parameter estimates measuring the effect of explanatory variables on the dependent variables.

The $\alpha_3 z_{it}\lambda'$ is the variable that determines employment, $Ɛ_{it}$ is the error term.

## RESULTS AND DISCUSSION

**Table 2: Descriptive Statistics**

| Variable | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| artificial | 420 | 75.378 | 27.303 | 5.302 | 140.68 |
| employ | 420 | 91.233 | 27.089 | 12.207 | 187.21 |
| rev | 420 | 79.577 | 30.789 | 8.173 | 160.19 |
| pol | 420 | 25.192 | 30.321 | -19.837 | 170.689 |

This provides a concise overview of the coefficients that summarize the research data. According to table 2, artificial intelligence, employment, revenue, and political stability have sample size of 420. The mean score of artificial intelligence is 75.378% with a standard deviation of 27.303%, this shows how the standard deviation departs from the mean. This indicates that the standard deviation and the mean value differ significantly. Employment also has a mean of 91.233% standard deviation of 27.089%, revenue has a mean score of 79.577% and a standard deviation of 30.321. The mean score of political stability is 25.192% and standard deviation of 30.321%. The minimum and maximum values for artificial intelligence, employment, revenue, and political stability are 5.302, 12.207, 8.173, -19.837 for the minimum values and 140.68, 187.21, 160.19, and 170.689 respectively for the maximum values.

**Table 3 Matrix of correlations**

| Variables | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| (1) artificial | 1 | | | |
| (2) employ | 0.851 | 1 | | |
| (3) rev | 0.512 | 0.656 | 1 | |
| (4) pol | -0.212 | -0.172 | -0.062 | 1 |

Table 3 presents the heat map generated from the correlation matrix among the variables included in the analysis, which are (1) artificial intelligence, (2) employment, (3) revenue, and (4) politics. The correlation coefficient for each pair of variables is displayed in the corresponding cell of the table, with the diagonal elements representing the correlation of each variable with itself (always equal to 1, shown in green color cells). The results reveal that artificial intelligence has a strong positive correlation with employment (r = 0.851) as indicated by a light green cell, and a moderate positive correlation with revenue (r = 0.512) represented by an orange cell. In contrast, a weak negative correlation exists between artificial intelligence and politics (r = -0.212), displayed in a red cell, suggesting an inverse relationship between these variables. Additionally, the correlation between employment and revenue is moderately positive (r = 0.656), highlighted by a light orange cell, while the correlation between employment and politics is weakly negative (r = -0.172) and shown in a red cell. Lastly, there is a weak positive correlation between revenue and politics (r = -0.062), also represented by a red cell. These findings offer insights into the relationships between the variables and serve as a foundation for further analysis.

According to the findings, there is no evidence of multi collinearity among the explanatory variables. Thus,no perfect or near-perfect collinearity was detected. Consequently, no variable may be omitted from the model since the presence of multicollinearity concerns has been ruled out.

### Diagnostic Test

Homoscedasticity is a fundamental assumption of linear regression, which posits that the residuals are distributed with equal variance across all levels of the predictor variable. Deviations from this assumption, also known as heteroskedasticity, can result in unreliable regression results. To test for heter oskedasticity, the Breusch-Pagan test examines whether the null hypothesis of constant variance can be rejected, with p- values greater than 0.05 indicating an inability to reject the null hypothesis and, hence, no heteroskedasticity. Conversely, a p-value less than or equal to 0.05 suggests the presence of heteroskedasticity, as the variance is not constant. In this regard, the results of the heteroskedasticity, Hausman, and Lagrangian Multiplier tests demonstrate that the model exhibits random effect and constant variance.

### Main Results

**Table 4: Dynamic two-step systems GMM estimation for Artificial Intelligence and Employment, Revenue and Political stability**

| | (1) | (2) |
|---|---|---|
| | employ | artificial |
| L.employ | 1.052*** | |
| | (4.15) | |
| Employ | | 0.508*** |
| | | (0.73) |
| Artificial | 0.0537*** | |
| | (0.36) | |
| Rev | 0.0937*** | 0.145*** |
| | (-0.31) | (-0.40) |
| Pol | 0.00774*** | -0.191*** |
| | (0.04) | (-0.44) |
| L.artificial | | 0.711 |
| | | (1.54) |

| | | |
|---|---|---|
| _cons | -0.975 | -19.34 |
| | (-0.10) | (-0.70) |
| N | 378 | 378 |

**t statistics in parentheses**

**$^{*}p< 0.05$, $^{**}p< 0.01$, $^{***}p< 0.001$**

The coefficient for lagged employment is positive and statistically significant at the 1% level, indicating a strong positive relationship between past and current employment as shown in Table 4. The coefficient for current employment is also positive and statistically significant at the 1% level, suggesting that employment growth is positively associated with employment levels. The coefficient for artificial intelligence is positive and statistically significant at the 1% level, suggesting that AI is positively related to employment growth. For employment to decrease or increase, it will depend on how the past values of employment performed as well as the future values or its future performance. Robots will eventually replace manual and procedural labour in the near future. Additionally, there is little possibility that they will quickly grasp advanced abilities because the professional talents they already possess are undoubtedly not suitable for the requirements of new occupations produced by new artificial intelligence technology. As a result, as time goes on and technology is applied more widely, the number of unemployed people will rise. In order to maintain social stability for these unemployed individuals, the government should enhance the security system and support policies for the unemployed, establish unemployment insurance or unemployment assistance, and take other steps to address the unemployment problem. From the findings, artificial intelligence may not necessarily bring about unemployment in the job market even in the presence of a highly technological world. In addition to these findings, reports from the United Nations Conference on Trade and Development (UNCTAD) and the World Economic Forum (WEF) highlight the potential of AI to create new job opportunities and foster the emergence of new industries and business models. For example, the WEF's "The Future of Jobs 2018" report suggests that while AI may lead to job displacement in some industries and occupations, it also has the potential to create new roles in areas such as data analysis, software development, and digital marketing. Similarly, UNCTAD's "The Digital Economy Report 2019" notes that AI can enhance productivity and efficiency in industries such as healthcare and education, and create new roles in areas such as personalized medicine and online education. While these reports provide evidence that AI can create new job opportunities and lead to the emergence of new industries and business models, they also emphasize the need for policies and strategies that address the potential impact of AI on employment and the workforce. Education and training programs are critical to preparing the workforce for the new skills and roles required in the era of AI. Policies and regulations should also be developed to address the potential job displacement and ensure that workers are protected. Political stability has a positive significant relationship with employment instability, employment reduces significantly, also, effective political systems bring about an increase in employment, all other things being equal. However, there is a negative significant relationship between artificial intelligence and political stability, when there is political instability, artificial intelligence will reduce since there will not be a congenial atmosphere for scientist to research and come out with new ideas leading to the development of new computerized systems.

## CONCLUSION, RECOMMENDATION AND POLICY IMPLICATIONS

This study thoroughly examines the impact of artificial intelligence on employment by fusing theory and practice, starting with the question of whether it will lead to widespread unemployment, which is the current reality terror of humans. Artificial intelligence is more detrimental to employment in the short term, but technology has the potential to both preserve existing jobs and create new ones in the long term. This study concludes by offering some ideas and recommendations on how to actively utilize artificial intelligence's creative effect to mitigate the negative effects. Like previously, technology development has the capacity to alter but also comes with risks and constraints. However, in public discourse, the technical determinants are trailing in terms of rhetorical momentum in business and policy decisions. In this study, it is contended that sociological and social scientific viewpoints provide means of guaranteeing a less deterministic analytical approach that is sensitive to both artificial intelligence and employment. It is clear that, is not all jobs that the artificial intelligence can do, for instance, driving, piloting, operation of industrial equipment, restaurants and other works that require direct human sense application will still be available in the presence of high artificial intelligence. Future research on the relationship between artificial intelligence and poverty can be investigated to ascertain how artificial intelligence contributes to human development in Africa. African leaders should also leverage on artificial intelligence to reduce the menace of corruption and other leadership bottle necks that currently hinder the growth of African economy. African leaders can also leverage on same to create industries that will produce goods and services to sustain their economies.

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