**Title : Effect of artificial intelligence on employment in sub-Saharan Africa**

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Résumé :

Cet article analyse l'impact de l'intelligence artificielle (IA) sur l'emploi dans 08 pays de l'Afrique subsaharienne entre 2002 et 2022, en tenant compte des effets de plusieurs variables économiques. L'objectif est d'examiner la relation entre l'emploi, les investissements en IA, l'inflation et les investissements directs étrangers (IDE). L'étude s'appuie sur une approche GMM en système, une méthode économétrique qui permet de corriger l'endogénéité et d'améliorer la robustesse des estimations dans les modèles dynamiques. Les résultats montrent que les investissements en IA et l'inflation ont un effet négatif et significatif sur l'emploi, indiquant une possible réduction des opportunités professionnelles dues à l'automatisation et aux fluctuations économiques. En revanche, les IDE exercent un effet positif et significatif, ce qui souligne leur rôle potentiel dans la création d'emplois et le développement économique. Sur le plan des implications de politique, l'étude recommande aux décideurs de prioriser la formation et l'adaptation des compétences pour minimiser les effets négatifs de l'IA. Elle suggère également une régulation des technologies d'automatisation, ainsi que des investissements stratégiques en recherche et développement afin de maximiser les bénéfices technologiques tout en soutenant la croissance de l'emploi.

Mots-clés : intelligence artificielle, emploi, GMM, Afrique subsaharienne.

Code JEL : E24, J23, O33

**Abstract:**

This article analyzes the impact of artificial intelligence (AI) on employment in 08 sub-Saharan African countries between 2002 and 2022, considering the effects of several economic variables. The goal is to examine the relationship between employment, AI investments, inflation, and foreign direct investment (FDI). The study relies on a system GMM approach, an econometric method that allows for the correction of endogeneity and improves the robustness of estimates in dynamic models. The results show that AI investments and inflation have a negative and significant effect on employment, indicating a possible reduction in job opportunities due to automation and economic fluctuations. In contrast, FDI exerts a positive and significant effect, highlighting its potential role in job creation and economic development. In terms of policy implications, the study recommends that policymakers prioritize training and skills adaptation to minimize the negative effects of AI. It also suggests regulation of automation technologies, as well as strategic investments in research and development to maximize technological benefits while supporting job growth.

Keywords: artificial intelligence, employment, GMM, sub-Saharan Africa.

JEL Code: E24, J23, O33

1. **Introduction**

This paper focuses on the analysis of the effects of artificial intelligence on employment in Sub-Saharan Africa. Essentially, artificial intelligence (AI) refers to systems capable of processing information, deriving insights from it, and using those insights to generate results and achieve objectives (Kaplan and Haenlein, 2019).

In this regard, Africa suffers from a relative delay compared to other regions of the world concerning the adoption and preparation for AI (Azaroual, 2024). AI start-ups in Africa emerged nearly a decade after the beginning of the fourth industrial revolution, and no African nation is among the top 5 countries in terms of government readiness for AI (Arakpogun et al., 2021). This delay highlights the challenges that Africa faces in catching up and fully adopting AI technologies.

Regarding employment, the current era is a mix of contradictions and challenges where genuine progress intertwines with rigid economic obstacles (ILO, 2025). Thus, although the global unemployment rate has reached the historically low level of 5 percent (5%), which might suggest that the job market is thriving, behind the encouraging figures of 2024 lies an unshakeable reality (ILO, 2025). According to this report, millions of People, especially in the least developed countries, remain confined to informality, working poor conditions, and economic marginalization. As a result, the situation of employment and decent work in the world continues to be one of the major contemporary issues.

Moreover, Shen and Zhang (2024) argue that the rapid initiative-taking and cross-border integration of general information technologies in the era of the digital economy have made a significant contribution to stabilizing employment and promoting growth. However, AI in various industries is causing a notable shift in the job market where automation is replacing jobs, particularly in routine and manual sectors (Acemoglu and Restrepo, 2017). Following this, this work lays its foundations around the following question: What are the effects of artificial intelligence on employment in sub-Saharan Africa?

The contribution of this paper to the literature is found on two levels. Firstly, the theme of artificial intelligence remains, in our view, underutilized in the analysis of employment issues in developing countries in general and African countries in particular. There are authors such as Giwa and Ngepah (2024) who have documented the impact of AI on employment in the context of South Africa, as well as Fettouma (2023) who conducted the same analysis but in the context of Morocco. However, given the increasing adoption of Artificial Intelligence in Africa is a rapidly evolving phenomenon that necessitates a deep understanding of the social, economic, and technological dynamics at play (Azaroual, 2024). It becomes crucial to explore the effects of AI in one sub-region because by working together, African nations can transform current challenges into opportunities and pave the way for a future where AI significantly contributes to sustainable development and improves the quality of life for all Africans (Azaroual, 2024).

Then, the other contribution to the literature of this paper is related to the uniqueness of the field of investigation that is sub-Saharan Africa. It should be emphasized that in sub-Saharan Africa, where unskilled labor constitutes a significant part of the workforce, the integration of technologies the AI raises concerns about the future of job opportunities and economic stability. According to the ILO report published in 2025, in Sub-Saharan Africa, employment is increasing faster than unemployment, but most workers do not have productive and decent jobs. Moreover, deficits in decent work, including informality, continue to weigh on key indicators of employment and unemployment (ILO, 2025). Thus, Sub-Saharan Africa remains a particularly captivating area of investigation to analyze the relationship between AI and employment. This represents an enrichment of the literature on the tools highlighted to address the employment problem in developing countries in general and those in Sub-Saharan Africa in particular.

By focusing on methodology, the contribution of this research remains on two points. First, it expands the existing literature on the impact of artificial intelligence on employment in Africa by broadening the scope to a transnational level. Previous studies have largely concentrated on a single African country; these are among the few studies that have worked in a panel setting within sub-Saharan African countries. Secondly, it emphasizes an innovative approach to analyze the effect of artificial intelligence on employment. The two-step GMM estimator of the Blundell-Bond system allows for robust results. Furthermore, the proposed model offers substantial value for policy purposes, particularly for public decision-makers and stakeholders who wish to address the challenges and opportunities presented by the evolving economic landscape in Africa driven by technological progress.

The organization of this work is presented as follows: first, the first two sections deal respectively with the introduction, a presentation of the situation of intelligence and employment in Sub-Saharan Africa, and the literature review. Then follow the methodology, the interpretation of results, as well as the conclusion and the implications for economic policies.

1. **Presentation of the situation of artificial intelligence and employment in sub-Saharan Africa**

The integration of Artificial Intelligence (AI) in Africa presents promising prospects and poses substantial challenges (Azaroual, 2024). Indeed, a striking observation is noted; while some countries on the continent stand out for their commitment and progress in preparing for the adoption of AI, others face major obstacles, such as structural inequalities and digital divides. As the second largest continent by size and population, Africa has a diverse territory, rich in cultures, natural resources, and histories. With its increasing youth population, the continent benefits from a high penetration rate of new technologies, with more than 60% of its population under the age of 25. This demographic dynamic, combined with a growing openness to technological innovations, creates a fertile ground for the adoption and development of AI (Africa Data Protection, 2025). It is in this logic that the use of AI for Africa's social and economic development has aroused and continues to arouse growing interest in recent years. The impact of AI on Africa's social and economic development is enormous (AU, 2024). Price Waterhouse Coopers (PwC, 2017) estimates that AI could contribute $1.5 trillion to the African economy, or 6% of the continent's GDP. The marginal return on investment in AI is therefore high. The AI industry is also growing in Africa as data from the Center of Intellectual Property and Information Technology Law (CIPIT) shows that Africa has more than 2,400 organizations working on AI innovation, 41% of which are startups operating in various sectors, including health, agriculture, education, law and insurance (AU, 2024). In addition, research conducted on African contributions to GitHub shows an overall increase in the share of GitHub users, from 0.5% in 2010 to about 2.7% in 2020. The share of total real contributions from African authors also increased, from 0.3% in 2010 to about 2.3% in 2020. The EU's Joint Research Centre (JRC) comparison between AI economic actors in Africa, such as Research institutes (including universities), businesses, government institutions, and other regions in 2021 indicate that the region's contribution to AI remains low as the United States, China, the EU, the United Kingdom, and India still dominate global AI development (EU, 2021). Moreover, the Oxford Insight AI Global Index places African countries among the 'emerging' and 'nascent' nations in terms of investment, innovation, and implementation of AI. Mauritius leads in AI readiness with a score of 53.27, followed by South Africa, Rwanda, Senegal, and Benin according to the 2023 index.

Furthermore, according to the ILO report published in 3, in Latin America and the Caribbean, as well as in sub-Saharan Africa, high rates of informality hinder access to social protection and fundamental rights at work. These situations are not limited to these regions or specific areas but affect all regions to varying degrees, and the global economic situation risks reversing progress and amplifying these problems. The increase in the cost of living and inflation particularly threaten to worsen working poverty and reduce the ability of workers and their households to earn enough to stay above the poverty line. The report also highlights that in sub-Saharan Africa and South Asia, 60.8% and 34.4% of the labor force, respectively, were considered working poor at $3.10 USD per day (PPP 2011 per capita) in 2021. Likewise, total employment in Africa is expected to reach 511 million by 2023, following an annual increase of 3.6% between 2021 and 2023, and 2.0% annually between 2019 and 2021. Strong job growth in Africa has mainly been driven by the growth of the working-age population in the sub-region of sub-Saharan Africa, but has tended to be associated with a decrease in the number of hours worked per person and higher rates of informality and other forms of lower-quality employment. The total informal employment rate in Africa rose from 84.3% in 19 to 85% in (ILO, 2023).

The strong demographic growth in the sub-region has kept employment and the average number of working hours at a low level, which has partly undermined progress in decent work. It appears that many people have jobs but work fewer hours than they would like, and underemployment related to working hours has increased in the region (ILO, 2023). Thus, the unemployment rate in the region has indeed risen, from 5.7 percent in 2019 to 6.4 percent in 2020, and has remained at 6.4 percent in 2021. A large portion of people in poor-quality jobs in sub-Saharan Africa are in the informal sector. New estimates indicate that 87.3 percent of the employed population in sub-Saharan Africa held informal jobs in 2022, equivalent to 373 million people, compared to 86.9 percent in 2019 (ILO, 2023).  
**3- Theoretical and empirical literature**

In economic literature, the link between artificial intelligence and employment is at the center of both theoretical and empirical debate (Acemoglu and Restrepo, 2021).

In theoretical terms, the effect of artificial intelligence on job opportunities presents two opposing sides. First, AI often complements human work, potentially increasing demand for low-skilled workers and creating job opportunities (Gmyrek et al., 2023). Second, the efficiency superiority of AI-enabled robots in performing tasks may lead to job displacement, as they can accomplish tasks quickly and at a lower cost, thus posing a risk of automation for low- and mid-skill occupations (Badiuzzaman and Rafiquzzaman, 2020). Following this, two major approaches oppose each other: on one side, the job substitution approach, and on the other side, the job complementarity approach. The job substitution approach specifies that the widespread adoption of AI across different industries leads to a significant change in the labor market where automation replaces jobs, particularly in routine and manual sectors (Acemoglu et Restrepo, 2017). AI has a significant impact on the dynamics of the manufacturing labor market, changing employment patterns, skill requirements, wage structures, and the overall economic environment (Lane & Saint-Martin, 2021). According to (Porter and Heppelmann, 2015; Pejić Bach et al., 3), AI is transforming this industry by automating routine and manual processes that were once vital to employment in the manufacturing sector, subsequently leading to job losses. This automation raises concerns about job displacement for tasks that are likely to be replaced by machines, but it also creates a demand for new skills that complement AI technologies.

However, according to the approach on job complementarity, while some jobs may be substituted, others will experience growth due to the implementation of AI, especially in areas such as AI modeling and Business Intelligence (data analytics) (WEF, 2023). There is strong potential for the creation of new jobs, as seen in recent years. Generative AI models can enhance the value of jobs requiring social interactions, while the potential for AI augmentation is deemed greater than its automation potential, affecting a wide range of tasks in various types of jobs (Gmyrek et al., 2023). Overall, most business leaders (69%) acknowledge the necessity for their workforce to acquire new skills to effectively leverage generative AI (PwC, 2024). AI can also improve jobs by reducing strain, enhancing engagement, and improving safety, as evidenced by its use in predicting workplace accidents (Luo et al., 2023) and personalizing training through AI-based virtual tools (Chen, 2023).

In examining the empirical review, numerous studies are observed but also with controversial results, particularly the studies that highlight the positive effect of AI on employment and those that reveal the negative effect of AI on employment. In the first group of studies, Saba and Ngepah (2024) examines the impact of AI investments on employment and economic growth in the BRICS countries from 2012 to 2022, taking into account the moderating role of global governance as well as specific governance indicators such as political governance, institutional governance, economic governance, etc. The augmented distributed lag autoregressive technique with cross-sections (CS-ARDL) is used to analyze the data. The results of the study suggest a long-term equilibrium relationship between the analyzed variables in the employment and growth models. The causal results for our main variables of interest differ in the employment-growth models. Based on the CS-ARDL results, the study recommends that BRICS governments and policymakers prioritize and strengthen the integration of AI into their governance systems to promote employment and stimulate growth in the short and long term. However, the study warns against the ignorance of the interaction between AI and general governance as it has not demonstrated support for growth; it is crucial to implement robust measures to mitigate potential negative effects arising from the interaction of AI with political and institutional governance. Therefore, the study proposes the formulation of AI-friendly governance policies among BRICS nations to boost employment and growth, recognizing the embryonic status of AI as a key technology of the Fourth Industrial Revolution.

Krstić (4) analyzes the relationship between labor market changes and artificial intelligence, using Romer's endogenous growth theory, Schumpeter's creative destruction, the Solow growth model, and Becker's human capital theory as theoretical frameworks. The aim of this research is to clarify the multifaceted impacts of artificial intelligence on economic growth, labor adjustment, and the emergence of new employment trends, specifically focusing on job losses and gains, wage inequalities, and the evolution of skills requirements. The results suggest that while artificial intelligence significantly enhances productivity and innovation, it has a complex effect on the labor market, leading to job gains in technically sophisticated industries and losses in sectors likely to be automated. The study emphasizes the need for strategic interventions in policies and educational reforms that maximize the economic benefits of AI while minimizing its disruptive effects on employment.

On the other hand, in the second group, Giwa and Ngepah (4) examine the impact of AI on employment in the context of South Africa. Based on key economic indicators such as inflation, interest rates, and foreign direct investments (FDI), the authors apply the Vector Error Correction Model (VECM) approach from Q1 2012 to Q4 2021. The results of the study reveal a significant negative correlation between artificial intelligence and low-skilled employment in the long term. Granger causality tests reveal directional relationships, with investment in AI unidirectionally causing low-skilled employment. As a policy implication, this study recommends the implementation of training programs to equip workers with the necessary skills to adapt to the evolving job market influenced by technological advancements. Furthermore, it suggests monitoring the implementation of AI technologies and establishing policies to mitigate disruptions in the labor market. Focusing on the case of Morocco, Fettouma (3) conducts a study on the impact of artificial intelligence on employment in the manufacturing sector. This study relies on an econometric approach using a multiple regression model, and it focuses on quantitative data collected from 41 companies in the sector. The results of this work show that artificial intelligence has had a differentiated impact on the labor market, with job losses in some traditional sectors and the creation of new opportunities in burgeoning technological fields.

1. **Methodology**

**Theoretical model**

To study the link between artificial intelligence and employment, the model of this study is based on the work of Fiyinfoluwa et al (4) who used the production function equation and modified it within the framework of the RBTC theory to incorporate the effect of technological progress on the labor market. We examine a simplified production function establishing a relationship between production (Y) and the factors of production, namely labor (L) and capital (K):

Y = F(L,K) (1)

The equation presented here illustrates the production function, denoted as F, which shows how labor and capital inputs combine to generate output. Furthermore, it is interesting to examine a basic production function that establishes a relationship between output (Y), labor (L), and technology (A). This can be written as follows:

Y= F(L,A) (2)

The RBTC theory posits that technological advancements may have a disproportionate effect on jobs, thereby altering the demand for labor and its composition within the labor market. To account for this bias, the production function equation can be expanded to include the influence of biased technological progress in favor of employment. A commonly used strategy is to include an additional variable called task content (T), which denotes the degree of regularity or irregularity associated with the work activities performed:

Y=F(L,A,T) (3)

The parameter T is used to quantify the effect of technological advancements on the nature and characteristics of jobs. The phenomenon studied has a noticeable effect on work efficiency and exhibits variability across job categories. The demand for employment is likely to decrease due to automation or substitution, which means their prevalence.

On the contrary, some jobs can acquire great value or complement technology, leading to an increase in demand. Moreover, the equation of the production function can be reformulated to establish a direct relationship with the labor market, placing labor at the heart of the formula. In order to integrate RBTC theory and its implications for the labor market, it is possible to reformulate the production function, as described by equation (1), by relating it to labor productivity (P) rather than output (Y). Thus, the first equation can be represented as follows:

P=Y/L (4)

Subsequently, productivity can be represented as a mathematical function incorporating technology change biased by employment (T), labor (L), and technology (A). This is presented as follows:

P=F(T,L,A) (5)

In this modified equation, P denotes labor productivity, T represents the effect of employment-focused technological changes on labor productivity, L designates labor, and A represents technology. These data illustrate the effect of technological advancements on the relative demand for certain jobs, noted by the parameter P.

In order to achieve the objective of this work, this study adopts and modifies the study by Xiaowen et al. (4) who analyzed how artificial intelligence affects the employment structure from the perspective of optimizing the industrial structure in China.

Ln = + + + + (6)

The regression analysis of this study takes the following linear form:

Ln = + + + + + (7)

Where Ln refer respectively to the employment to population ratio of country i during year t; AI is the development of artificial intelligence in the region i during year t and INF, and IDE are a set of control variables.. Furthermore, designates a fixed effect of a country, a temporal effect and is an error term.

**Sources and descriptions provided**

This study examines artificial intelligence on employment in eight sub-Saharan African countries. The data comes from the World Bank database (WDI, 2024) and the International Labour Organization (ILO, 2024) over a period from 2002 to 2022. The choice of the period and countries was based on data availability.

Ra\_emp\_Pop: The employment/population ratio is the share of people with a job as a percentage of the total working-age population. Employed persons include all individuals of working age who, during a specified short period, belonged to one of the following categories: paid employment or self-employment. Human capital, which encompasses individuals' knowledge, skills, and health, plays a crucial role in economic growth (Asteriou et al, 2001). Investments in education, training, and health improve the quality of the workforce, foster innovation, and optimize labor market performance (Barro et al, 2013). A skilled workforce enhances productivity and competitiveness, facilitating adaptation to economic changes (World Bank, 2018). Furthermore, the development of human capital stimulates employment by attracting job opportunities and supporting economic transformation (Khan et al, 2019).

AI: Artificial intelligence (AI) is a computer science that aims to create machines with intelligence similar to that of humans. It involves the design of algorithms capable of analyzing data, learning, making decisions, solving problems, and simulating human cognitive abilities. Artificial intelligence promotes economic growth through automation, improving the productivity and efficiency of processes (Bessen, 18; Acemoglu et al.). It also stimulates innovation by facilitating the creation of new products and business models (Brynjolfsson et al., 2017) Furthermore, AI optimizes decision-making through advanced data analysis, allowing for better resource allocation (Manyika et al., 2017; Balliester et al., 2018). Its development opens new job opportunities, particularly in sectors requiring skills in creativity and problem-solving (Franken et al., 2019; Strack et al., 2021).

INF : Inflation measured by the consumer price index reflects the annual percentage change in the cost for the average consumer to acquire a basket of goods and services that may be fixed or changed at specified intervals, such as each year.

FDI: Foreign direct investment is a category of cross-border investment associated with a resident of one economy having control or a significant degree of influence over the management of a business located in another economy. FDIs contribute to economic growth by providing capital to finance businesses and infrastructure, thus promoting industrial expansion and job creation (Mwakabungu et al, 2023). Furthermore, multinationals transfer technologies and cutting-edge skills, enhancing the productivity and competitiveness of the host country. This dynamic stimulates employment by diversifying opportunities and strengthening local capacities (Megbowon et al. 2016; Osabohien et al. 2020).

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| ***Variables*** | ***Moyenne*** | ***Ecart-type*** | ***Minimum*** | ***Maximum*** | ***Obs.*** |  |
| ***Ra\_emp*** | ***58,51*** | ***14,27*** | ***32,72*** | ***85,84*** | ***189*** |  |
| ***AI*** | ***0,25*** | ***0,27*** | ***0*** | ***2,28*** | ***189*** |  |
| ***INF*** | ***20,99*** | ***34,32*** | ***-16,86*** | ***235,52*** | ***189*** |  |
| ***IDE*** | ***3,11*** | ***3,58*** | ***-10,04*** | ***20,08*** | ***189*** |  |

*Source: Authors based on World Bank data*

We first conduct statistical tests for each set of variables in the model to verify the central tendency. The analysis of Table 1 reveals several disparities. Employment shows moderate dispersion, indicating heterogeneity of the observed levels. Artificial intelligence shows a very low average, with a strong concentration around zero and a few Atypical values Inflation experiences strong fluctuations, and a maximum value of 35.5 could indicate a period of hyperinflation. Foreign direct investment remains low on average, with significant dispersion and negative values suggesting divestments. These trends highlight marked differences, and consequently, the unit root test is necessary for the panel data model.

Tableau 2 : unit root test

|  |  |  |
| --- | --- | --- |
| ***Variables HT test*** |  | ***IPS test*** |
| ***Statistique P-value*** | ***Statistique P-value*** |
| ***Ra\_emp 0.7510 0.0084 2.0189 0.9783***  ***AI 0.4904 0.0000 -0.2685 0.3942***  ***INF 0.7051 0.0004 -3.7608 0.0001***  ***IDE 0.4998 0.0000 -3.1270 0.0009*** | | |

Source: authors based on data from the WDI (2024) and ILO (2024)

Table 2 presents the results indicating that all the tested variables have a p-value lower than 0.5, which means that we can reject the null hypothesis (H0) and conclude that all our variables are stationary. However, the results of the IPS test reveal that employment and artificial intelligence have p-values greater than 0.5, which means they are non-stationary, whereas inflation and foreign direct investments are stationary.

***Estimation Procedure***

Our econometric analysis begins with identifying the nature of the panel studied, composed of 17 sub-Saharan African countries over the period from 2002 to 2022. Given that (N < 20), this is a microeconomic panel, often subject to problems of heteroscedasticity and autocorrelation, thus requiring the use of a robust estimation model. Panel data have a dual dimension: individual and temporal. Static models, although useful for analyzing relationships between variables at a given moment, may overlook the evolution of the phenomena studied and lead to biased estimates. In contrast, dynamic models incorporate lagged effects, allowing for a better understanding of the temporal dynamics. In our case, current employment depends on employment in previous periods, justifying the use of a dynamic model.

The introduction of artificial intelligence into our model aims to assess its effect on employment. Artificial intelligence offers potential solutions to streamline processes, improve efficiency, and increase productivity. By integrating artificial intelligence, we seek to capture its role in the dynamics of the labor market. However, the addition of this variable may lead to endogeneity issues, especially if artificial intelligence is itself influenced by employment and other economic factors. Consequently, classical estimators are not suitable. Alternative methods, such as instrumental variable estimators and GMM (Generalized Method of Moments), are necessary. In response to criticisms of differenced GMM, we favor system GMM, which allows for more robust estimates and better accounting for dynamic effects.

The generalized method of moments (GMM) in systems, developed by Hansen (198), extends the classical GMM to estimate complex simultaneous equation systems. It is widely used in econometrics, particularly for dynamic models and instrumental variable models, where distribution assumptions are difficult to satisfy. The essential objective is to achieve an accurate estimation of parameters by minimizing the gap between theoretical and empirical moments. To address endogeneity issues, the model relies on instruments that are strongly correlated with the explanatory variables while being independent of the errors.

Tableau 3 : résultats des estimations

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
|  | ***(1)*** | ***(2)*** | ***(3)*** | ***(3)*** | ***(4)*** | ***(5)*** | ***(6)*** |
| **Variables** | ***POLS*** | ***FE*** | ***RE*** | ***DGMM1*** | ***DGMM2*** | ***SGMM1*** | ***SGMM2*** |
| *AI* | *-13.070\*\** | *-1.195* | *-1.274* | *-4.037\*\** | *0.121\*\** | *0.493\*\*\** | *0.374\*\*\** |
| *INF* | *0.028* | *-0.049\*\** | *-0.049\*\** | *-0.005* | *-9.347\** | *-3.157\** | *-8.121\*\** |
| *IDE* | *0.653\*\** | *0.393\*\** | *0.394* | *-0.013* | *0.418* | *-0.0490* | *-0.144\*\*\** |
| *Constante* | *60.370* | *58.626* | *58.636* | *14.720* | *0.649* | *0.0855* | *-0.160* |
| *Hausman* |  | *Oui* | *Non* |  |  |  |  |
| *Nombre d’instruments* |  |  |  | *139* | *168* | *167* | *139* |
| *Observations* | *189* | *189* | *189* | *171* | *171* | *189* | *171* |
| *R-carré* | *0.110* | *0.140* | *0.140* | *0.152* | *0.140* |  |  |
| *Hansen\_test* |  |  |  | *16.19* | *14.53* | *12.67* | *11.52* |
| *Hansen Prob* |  |  |  | *1* | *1* | *1* | *1* |
| *Sargan\_test* |  |  |  | *123* | *77.64* | *165.4* | *158.4* |
| *Sargan Prob* |  |  |  | *0.111* | *0.176* | *0.185* | *0.0517* |
| *AR(1)\_test* |  |  |  | *0.6549* | *-0.9186* | *-0.0130* | *0.0038* |
| *AR(1)\_P-value* |  |  |  | *0.001* | *0.000* | *0.249* | *0.956* |
| *AR(2)\_test* |  |  |  | *0.6549* | *0.241* | *1.403* | *0.830* |
| *AR(2)\_P-value* |  |  |  | *0.288* | *0.288* | *0.809* | *0.161* |

*Source: Authors based on the aforementioned data and the STATA software.*

1. **Interpretation of the results**

The different estimates in Table 3 reveal significant variations depending on the model used. On one hand, the effect of artificial intelligence (AI) on employment is negative in POLS and DGMM, indicating a reduction in employment of 13.7% and 4.3% respectively. On the other hand, the results obtained in SGMM1 (49.3%) and SGMM2 (37.4%) suggest a positive effect, highlighting that the effect of AI heavily depends on the chosen estimation model. This disparity is largely explained by the role of AI in automating tasks previously carried out by human workers. Indeed, as shown by Spring et al. (2022) and Filippi et al. (2023), the rise of AI is profoundly transforming the labor market, reducing the demand for labor in certain sectors while increasing the need for advanced technical skills. Thus, this transition could widen the gap between the required qualifications and the current capabilities of workers, increasing the risk of technological unemployment.

Artificial intelligence is transforming the labor market, leading to a reallocation of skills and influencing employment trends. Its adoption can cause wage fluctuations and alter career prospects (Anakpo, 2022). Some industries are experiencing increased productivity due to automation, while others are struggling to adapt, which impacts job opportunities. This evolution could lead to significant changes in labor demand and the structure of work in the long term (Millington, 2017).

The negative correlation between investment in artificial intelligence (AI) and employment is consistent with the findings of Ma et al. (2022), who studied the evolution of AI development and the skill structure in China from 2003 to 2017. Their analysis highlights a reduction in employment due to the impact of technological changes on wage levels. Furthermore, these conclusions align with the theory of routine-biased technological change (RBTC), which posits that automation tends to decrease the demand for labor for routine tasks, often performed by unskilled workers.

Inflation (INF), for its part, has a negative effect in the FE and RE models, amplified in SGMM2. In particular, a 1% increase in inflation leads to a decrease in employment of 4.9% to 8.1%. This trend aligns with the findings of Salazar (2022), which highlights the role of inflation in hindering job creation. Furthermore, high inflation induces economic uncertainty, prompting companies to slow down their investments and limit hiring. This instability hinders the creation of new positions and jeopardizes job prospects in several sectors (Vermeulen, 2015).

Inflation affects different economic sectors in Sub-Saharan Africa. Industries that are heavily dependent on unskilled labor, such as agriculture and certain manufacturing branches, may struggle to absorb the cost increases associated with inflation. In response to these economic pressures, businesses adjust their strategies, which can lead to a reduction in hiring or job cuts, thereby impacting the stability of the labor market.

The effect of FDI is also contrasted. While POLS and FE show a positive effect on employment (increases of 65.3% and 39.3%), SGMM2 reveals a negative influence (-14.4%). As a result, the dynamics of FDI appear to depend on the sector of capital allocation and the economic climate of the host country. As emphasized by Bozsik et al. (2023) and Le et al. (2022), FDI can stimulate employment, provided that they are directed towards productive sectors.

The economic and technological dynamics specific to sub-Saharan Africa influence the effects of artificial intelligence (AI) and foreign direct investment (FDI). The integration of AI in the region faces major obstacles, including structural inequalities and a digital divide that hinder its adoption (Policy Center for the New South, 2024). The lack of suitable infrastructure and specialized training limits the benefits of AI, which explains its negative observed effect in some models. However, SGMM estimates, where endogeneity is better controlled, suggest that better structuring of investments and an appropriate training policy could transform AI into a lever for growth and job creation.

The IDE also play a crucial role in the industrial and economic development of the region. Their impact is generally positive on industrialization, but depends on the exchange rate and the business climate (Zongo et al. 2022). While the POLS and FE models confirm their beneficial effect, GMM estimates show non-significance or a negative influence, possibly due to issues of inefficient capital allocation. According to NKOA (2018), the concentration of FDI in the extractive industries limits their multiplier effect on the economy. A better distribution towards innovative and productive sectors would amplify their contribution to growth and employment.

The model validity tests show an over-identification of instruments, with a Hansen probability equal to 1.000, which may require a revision of the instrumentation. Furthermore, the AR(1) tests reveal first-order autocorrelation (p-values < 0.05), while AR() confirms the absence of second-order autocorrelation (p-values > 0.05), validating the robustness of the GMM model. Thus, reducing the number of instruments would improve the accuracy of the estimates and strengthen the credibility of the conclusions.

1. **Conclusion**

This article analyzes the relationship between artificial intelligence (AI) and employment in eight sub-Saharan African countries from 2002 to 2022, incorporating various economic variables. The study is based on a system GMM approach, examining the interactions between employment, investment in AI, inflation, and foreign direct investment (FDI). The results show a significant negative effect of AI investments and inflation on employment, while FDI has a positive impact. These findings highlight the challenges that policymakers and economic actors must anticipate, especially regarding technological transition. The study underscores the limitations of research and development (R&D) spending as an indicator of AI integration. Technological disparities, infrastructure constraints, and limited funding for innovation make it difficult to generalize the results. Furthermore, the predominance of the informal sector and low industrialization influence the impact of AI on employment. To overcome these limitations, future research should adopt: a comparative approach across several African and international countries, better integration of key economic factors (public policies, digital infrastructure, technological skills training, economic crises), and a longitudinal approach, allowing for an analysis of the effects of AI on employment in the agricultural, industrial, and service sectors in the long term. Additionally, an inclusive technological transition, combining innovation and social protection, could foster positive outcomes for employment and mitigate the negative effects of automation.

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