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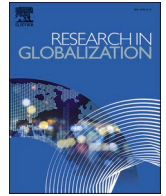
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Artificial intelligence and skilled employment in South Africa: Exploring key variables

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ABSTRACT

The discourse surrounding artificial intelligence (AI) and its repercussions on skilled employment merits careful consideration. While AI technologies have the potential to result in job displacement within specific sectors, they concurrently usher in new employment opportunities, especially for individuals possessing advanced skills. The primary objective of this paper is to thoroughly evaluate the impact of AI on skilled employment within the South African economy. To achieve this objective, the study employs the Autoregressive Distributed Lag (ARDL) model and Granger causality analysis, spanning from 2012Q1 to 2021Q4. The results derived from the ARDL estimation reveal a substantial and positive contribution of artificial intelligence to skilled employment in South Africa, a trend observed in both the long and short run. However, two structural breaks were identified in the data, hence a re-estimation of the ARDL model. The re-estimated ARDL model revealed a negative and significant relationship between AI and skilled employment. In light of these findings, this study advocates implementing regulations and labor market policies that promote the responsible deployment of AI technology while safeguarding workers' rights and job security. This could include establishing guidelines for AI deployment in the workplace, ensuring transparency and accountability in AI systems, and implementing social safety nets to support workers during job transitions.

1. Introduction

Artificial Intelligence (AI) emerges as a transformative force with immense potential for advancing African economies and reshaping the social and cultural landscape of the continent. These potential spans various sectors, offering opportunities to revolutionize business operations, boost productivity, and enhance critical services like healthcare, education, legal systems, and transportation in Africa. Furthermore, AI has the capacity to address pressing challenges and mitigate existing disparities, marking it as a catalyst for positive change (CIPIT, 2023).

Notable initiatives, such as the work of South African computer scientist Raesetje Sefala, exemplify how AI can be harnessed for positive societal impact. Sefala's pioneering efforts involve developing algorithms to identify poverty hotspots and creating datasets that inform targeted interventions such as aid distribution, housing construction, and healthcare clinic establishment. This underscores AI's potential as a powerful tool for data-driven decision-making, contributing significantly to uplifting and developing African societies and economies (CIPIT, 2023). Additionally, the mining industry is highly influenced by

artificial intelligence in South Africa. AI technology enables the deployment of autonomous vehicles, such as trucks, drills, and loaders, in mining operations. These vehicles use AI algorithms to navigate complex environments, optimize routes, and perform tasks without human intervention (Molopyane, 2021).

Furthermore, South Africa has shown keen interest in formulating policies and regulations concerning artificial intelligence (AI) to ensure its ethical and responsible application. The government is working to advance AI development while also addressing concerns surrounding privacy, bias, and job displacement. Although South Africa is still in the early stages of AI development compared to other countries, there is a growing momentum in research, education, and industry partnerships aimed at harnessing AI's potential for societal and economic benefits while ensuring adherence to ethical and regulatory standards (Gwagwa et al., 2021).

In the broader context, the historical impact of technological advancements on employment, particularly with the advent of AI, has been a subject of debate. While AI technologies may generate employment opportunities and enhance efficiency, they also introduce challenges

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and disruptions to existing employment frameworks (Klenert et al., 2023). Job displacement, particularly in industries like manufacturing, transportation, customer service, and data entry, poses significant challenges such as unemployment or underemployment for those unprepared for evolving job markets (Arntz et al., 2016; Frey & Osborne, 2017; Manyika 2017; Acemoglu & Restrepo, 2020).

Moreover, the uneven distribution of benefits and opportunities arising from AI introduces challenges, potentially widening existing socioeconomic gaps, including skill levels. This issue is exacerbated by the impact of technological progress on labor is contingent on the type of technological development, with low-skilled labor being more susceptible to substitutionary effects than high-skilled labor (Van Roy et al., 2018; Jung & Lim, 2020).

The JCSE-IITPSA (Johannesburg Centre for Software Engineering-The Institute of Information Technology Professionals South Africa) ICT Skills Surveys offer valuable insights into the challenges confronting South Africa's Information and Communication Technology (ICT) sector. A prominent recurring theme in these surveys is the persistent skills shortages across various domains within the sector, encompassing software development, cybersecurity, data science, and network engineering. Furthermore, the rapid pace of technological advancement exacerbates these shortages, particularly with emerging technologies like AI, blockchain, and cloud computing demanding specialized skills that are not yet widely accessible in the workforce (Masigo, 2021). Consequently, the surveys underscore the imperative for continual training and education initiatives to bridge skills gaps and stay abreast of evolving technological landscapes. Hence, it is anticipated that the adoption of AI will generate new employment prospects, particularly in domains requiring proficiency in AI-related skills. However, some jobs may suffer (Gombolay et al., 2018).

Despite these challenges, the adoption of AI, automation, and robotics can increase demand for high-skilled workers. Productivity gains from these technologies often result from the complementary work redesign of skilled professionals. The effective execution of process improvements and work reorganization requires the expertise of highly skilled individuals who can program, repair, customize, and work with artificial intelligence (Helper & Henderson, 2014; Felten et al., 2019; Dixon et al., 2023).

In South Africa, the acknowledgment of AI's potential by both public and private sectors has led to its increasing prominence. The Department of Telecommunication and Postal Services (DTPS) report reflects the government's dedication to promoting AI advancement, with initiatives like the Centre for Artificial Intelligence Research (CAIR) and the AI for Development (AI4D) program in place to improve learning (DTPS, 2016).

Understanding the effects of AI on skilled employment is crucial for individuals, policymakers, and researchers to navigate the evolving job market effectively. Research in artificial intelligence (AI) and skilled employment is pivotal for identifying specific in-demand skills, addressing skill deficiencies, reducing inequalities, formulating effective policies, and positioning economies for success in the digital age (Klenert et al., 2023). This study seeks to contribute to the ongoing debate and limited scholarly literature on AI's impact on employment, specifically in South Africa. Despite challenges and concerns about workforce displacement, the adoption of AI is recognized for its potential to create new employment opportunities, particularly in fields requiring proficiency in AI-related skills. The study aims to provide insights into the implementation of AI in the workforce and address associated concerns. The paper consists of six sections. We begin with the introduction, the literature review, theoretical review, methodology, empirical results, and discussion, and conclude with policy implications.

2. Literature review

Despite the potential for artificial intelligence (AI) to stimulate advancements in human welfare and economic development, doubts

persist about the prospect of a digitalized work environment. According to various scholarly sources (Autor, 2015; Acemoglu & Restrepo, 2018; Neves et al., 2019). AI and robotics have been found to generate new employment categories, creating career opportunities focused on developing, educating, and producing these technologies (Vermeulen et al., 2018). However, concerns exist over the potential displacement of human labor in various processes (Caruso, 2018; Pinheiro et al., 2019) and the social security implications that may arise. It is worth highlighting that some literature review in the paper discusses robots and employment. This is because many robots use artificial intelligence (Tasioulas, 2019).

Graetz and Michaels (2018) analyzed the correlation between industrial robots and economic outcomes in various developed nations. Their study utilized a cross-sectional dataset of industries across seventeen countries from 1993 to 2007. The Ordinary Least Squares (OLS) and Two-Stage Least Squares (2SLS) approaches were employed in the analysis. According to the research, the implementation of robots can reduce job opportunities for workers with limited skill sets while simultaneously enhancing opportunities for employment for those with higher-level skill sets.

Subsequent studies by Dixon et al. (2021) investigated the adoption and employment of robots using evidence at the firm level. The analysis was conducted using the Ordinary Least Squares (OLS) and the Fixed Effect (FE) methods. According to the findings, employees whose skills are more complementary to robot investments may have a higher chance of experiencing overall employment benefits, depending on their skills' complementarity level. The study observed a decline in middle-skilled employment and a rise in low- and high-skilled employment. Similarly, Dahlin (2019) conducted a study on the impact of robotics on employment displacement in the United State in 2010 and 2015. The findings indicate a positive correlation between the presence of robots and the prevalence of high-skill occupations. Individuals with high-skill jobs are the most probable candidates to generate, innovate, and code automated machines.

Furthermore, the presence of technology in an economy substantially influences the demand for workers with high levels of skill and those with lower levels of skill within the labor market. Technology creates a heightened need for proficient workers who can operate complex machinery and serves as a supplementary component for individuals with advanced skills. However, technology may also replace insufficiently skilled human workers with machinery in certain vital regions of an economy, resulting in a decline in employment opportunities (Saba et al., 2022).

Studies by Xie et al. (2023), Babina et al. (2023), Plumwongnot and Pholphirul (2022), and Buera et al. (2022) corroborate these findings, indicating that AI diminishes the relative need for low-skilled labor while amplifying the relative demand for high-skilled labor. The allocation of resources towards AI implementation, as seen in the United States and Chinese manufacturing companies, leads to a shift towards a more educated labor force, resulting in a corresponding rise in skilled employment.

In conclusion, the discourse on the impact of artificial intelligence (AI) on employment is nuanced and multifaceted. While the potential for these technologies to stimulate advancements in human welfare and economic development is acknowledged, concerns persist about the potential displacement of human labor and the associated social security implications. The literature reviewed in this paper underscores the dual nature of AI's influence on employment dynamics. On the one hand, AI and robotics generate new employment categories, creating opportunities in the development, education, and production of these technologies. On the other hand, studies, such as those by Graetz and Michaels (2018), Dixon et al. (2021), Dahlin (2019), and others, suggest that the implementation of robots may lead to a decline in job opportunities for workers with limited skill sets while enhancing opportunities for those with higher-level skill sets. The evolving landscape of technology in economies reinforces the heightened demand for proficient workers

capable of operating complex machinery. The observed shift towards a more educated labor force, particularly in AI implementation in countries like the United States and China, further emphasizes the importance of advanced skills in the modern workforce (Xie et al. 2023; Babina et al. 2023; Plumwongrot and Pholphirul, 2022; Buera et al. 2022). As we navigate this dynamic intersection of technology and employment, policymakers, businesses, and educational institutions must remain vigilant in addressing the challenges and opportunities presented by the ongoing integration of AI into various sectors of the economy.

3. Theoretical review

This study is grounded in the theoretical framework of Skilled Based Technical Change (SBTC), renowned for effectively elucidating the intricacies of the labor market's skill level dynamics. Skilled Based Technical Change (SBTC) is a form of technical change that results in a rise in the demand for skilled labor and a decline in the demand for unskilled labor. The SBTC perspective argues that advancements in technological innovation will lead to a greater demand for highly educated individuals in high-skill occupations that typically require a college degree or higher. On the other hand, there is a decline in the demand for middle-skill occupations, which necessitate a high-school diploma but not a college degree, as well as low-skill occupations, which only require a high-school diploma or less (Wang, Hu et al., 2021).

The SBTC method posits that individuals with advanced skills are presumed to have the requisite capabilities and engage in cognitive tasks complementary to digital technology. For instance, according to [Violante, \(2008\)](#) the introduction of computers holds the capacity to supplant human labor, leading to the redundancy of specific workers, particularly those with lower levels of expertise.

In addition, the perspective of the SBTC suggests that job expansion has taken place among occupational categories that are highly educated and possess the ability to acquire and adjust to new technological developments ([Cooley et al., 1997](#)). Analogous to debates surrounding the substitution of human employment by technology advancement, the underlying assumption is that professions that involve repetitive duties and possess restricted physical agility, as observed in intermediate-level vocations, are vulnerable to being replaced by automated processes, particularly those involving computerization. Middle-skill jobs such as manufacturing, record-keeping, and office work are easily automated due to their routine and well-defined tasks that can be executed by new technologies. Reducing middle-skill job opportunities prompts workers previously employed in such roles to transition to low-skill service sector jobs requiring minimal training but greater physical coordination ([Benzell et al., 2019](#)).

SBTC is a phenomenon that may be represented as an effect that affects the relative productivity of various skill groups at almost the same pace across all industries. To further understand how this model works, let us assume that a steady elasticity of substitution between skilled and unskilled employees creates the aggregate labor demand ([Hutter and Weber, 2021](#)). The model begins with the aggregate level of Y (final output) denoted by:

$$Y = \left[\frac{\sigma - 1}{Y_J^\sigma} + \frac{\sigma - 1}{Y_H^\sigma} \right]^{\frac{\sigma}{\sigma - 1}} \quad (1)$$

Y_J and Y_H denote goods produced with unskilled labor, J , and skilled labor, H , respectively. σ denotes the elasticity of substitution between Y_J and Y_H .

The production of goods requires the use of technology by workers. Therefore, to incorporate technology, equation 1 can be expressed as:

$$Y = \left[\frac{\sigma - 1}{Y_J^\sigma} + \frac{\sigma - 1}{Y_H^\sigma} \right]^{\frac{\sigma}{\sigma - 1}} + \left(\frac{A_H}{J} \right)^{\frac{\sigma}{\sigma - 1}} \quad (2)$$

A_H and A_J represents the (endogenous) technological state of the production of skill-intensive or labor-intensive goods by skilled and unskilled workers. Hence, the skill bias of technological progress can be written as:

$$\frac{A_H}{A_J} = \left(\frac{H}{J} \right)^{\sigma - 1} \quad (3)$$

According to Equation (3), the workforce is crucial in driving technological progress, favoring skill premium. Acemoglu (2002) defines a skill premium as the wage differential between skilled and unskilled workers. Hence, the utilization of technology as a component of the workforce can be presented as follows:

$$L \left(\frac{H}{J} \right) = \frac{\sigma}{\sigma - 1} \left[T \left(\frac{A_H}{A_J} \right) + \frac{W_H}{W_J} \right] \quad (4)$$

where $L \left(\frac{H}{J} \right)$ denotes labor of skilled and unskilled, $\frac{\sigma}{\sigma - 1}$ represents a substitution elasticity effect, $\frac{A_H}{A_J}$ denotes technological use by skilled and unskilled workers, and $\frac{W_H}{W_J}$ denotes relative wages of skilled and unskilled workers.

The Skilled Based Technical Change (SBTC) perspective suggests that advanced technology will benefit jobs requiring advanced skills. Moreover, the perspective of SBTC anticipates negative impacts on jobs that demand low-level skills, which aligns with the displacement viewpoint.

The incorporation of Artificial Intelligence (AI) into South Africa's economic framework is consistent with the principles of Skilled-Based Technical Change (SBTC) philosophy. As AI technologies advance, the demand for skilled labor intensifies, particularly in roles involving the design, implementation, and maintenance of these systems. Nevertheless, while there is a favorable change in the employment of highly trained individuals, it is also accompanied by the automation of repetitive work, which has the potential to displace positions that need lower levels of skill and worsen the existing wage disparity. South Africa faces the challenge of addressing a skills gap, necessitating strategic investments in education and training to equip the workforce with the requisite expertise for the AI-driven economy.

4. Methodology

Building upon the earlier discussion, we can streamline the theoretical framework presented in Equation 4 to explore the influence of artificial intelligence (AI) on skilled employment in South Africa. Formula 4 initially outlined the impact of technology and wages on the skilled-to-unskilled labor ratio. To simplify, we integrate the components of this ratio directly into the equation. In essence, labor, technology, and wages are the key variables in the modified equation, denoted as Equation 5.

$$L = T + W \quad (5)$$

Therefore, to simplify equation 5 to fit the analysis of this study, equation 5 can be expressed as equation 6 below.

$$SEMP = f(AI, WG) \quad (6)$$

where SEMP, AI, and WG denote skilled employment (labor), venture capital artificial intelligence investment (technology), and wages, respectively. [Adendorff and Collier \(2015\)](#) posit that artificial intelligence is a vital element for 4IR technology. In addition, the model will incorporate the inflation rate and GDP, as suggested by [Yildirim et al. \(2020\)](#) and [Ayhan and Elal \(2023\)](#). The incorporation of inflation and GDP into the estimated model is crucial due to their significant impact on employment as a driving force. Failure to include these variables may lead to the omitted variable bias, as noted by [Dogan and Inglesi-Lotz \(2020\)](#) and [Adeyemi \(2023\)](#). Thus, equation 6 can be expressed as:

Table 1
Dataset and measurement.

Variables	Definition of variables	Description	Expected Signs	Source
Skilled Employment (SEMP)	Skilled employment refers to work or occupations that require a certain level of specialized knowledge, expertise, and proficiency in specific skills. Skilled employment typically involves roles that demand higher education, training, or experience.	Skilled employment formal sector (millions)	Positive	Quantec database
Venture Capital AI investment (AI)	Refers to financial backing for businesses or startups engaged in developing, researching, or applying artificial intelligence (AI) technologies. The investment aims to support the growth and innovation of companies working on AI-related projects.	USD millions	Positive	OECD
Wages (WGS)	Employee wages refer to the compensation and remuneration paid by an employer to an employee in exchange for their labor, services, or work performed within an organization.	Compensation of Skilled Employees in the formal sector (Millions)	Positive	Quantec database
Inflation (INF)	Inflation is the sustained increase in the general price level of goods and services over time, which results in a decrease in the purchasing power of currency.	Annual percentage	Negative	Quantec database
GDP per capita growth (GDPPC)	Gross Domestic Product (GDP) per capita is a measure that represents the average economic output or income per person in a specific country or region.	Annual percentage	Positive	Quantec database

$$SEMP = \alpha_0 + \beta_1 AI_t + \beta_2 WGS_t + \beta_3 INF_t + \beta_4 GDP_t + \varepsilon_t \quad (7)$$

where INF and GDP denote inflation and GDP. In logarithm equation 7 can be expressed as follows:

$$\ln SEMP = \alpha_0 + \beta_1 \ln AI_t + \beta_2 \ln WGS_t + \beta_3 \ln INF_t + \beta_4 \ln GDP_t + \varepsilon_t \quad (8)$$

According to the SBTC economic theory, artificial intelligence (AI) is predicted to have a favorable effect on skilled employment. The same holds for wages and GDP. On the other hand, inflation limits producers' ability to hire more workers by reducing their real income and purchasing power (Aminu & Ogunjimi, 2019; Adeyemi, 2023). Thus, it is anticipated that inflation will have a negative impact on skilled employment.

4.1. Variables and data Source

This study utilizes data from the OECD <https://oecd.ai/en/data>, and the Quantec database from 2012Q1 to 2021Q4. The analysis will specifically employ quarterly data, even though certain variables such as Venture Capital AI investment and GDP per capita originally existed as yearly data. It is important to note that these variables were converted to quarterly data using EViews 13 software.

Furthermore, the COVID-19 pandemic has exerted significant and multifaceted impacts on global economies, and these effects are anticipated to manifest in the dataset under analysis. The pandemic triggered widespread economic contractions spanning various sectors and regions, potentially leaving discernible marks in the dataset. Notably, GDP-related variables might indicate declines in economic output, consumption, and investment. Simultaneously, disruptions in the labor market caused by the pandemic have resulted in unemployment and shifts in workforce dynamics. Consequently, employment-related variables within the dataset may display fluctuations, particularly during the periods directly influenced by the pandemic. For a comprehensive understanding of the dataset, measurement, and definition of variables used in the study, refer to Table 1.

Table 2
Descriptive Statistics.

Variable	Mean	Median	Maximum	Minimum	Std. Dev	Skewness	Kurtosis	J-B Stat	Prob	Ob
SEMP	14.991	15.002	15.056	14.893	0.051	-0.436	1.853	3.202	0.201	40
AI	15.999	16.727	18.871	12.345	1.519	-1.182	3.668	10.069	0.006	40
WGS	13.838	13.852	13.867	13.787	0.026	-0.359	2.353	1.556	0.081	40
INF	5.157	5.150	6.700	3.200	0.935	-0.359	2.353	1.556	0.459	40
GDP	-0.484	-0.240	3.870	-7.481	2.021	-1.630	6.538	38.590	0.000	40

Source: Calculation by the authors through EViews 13 software.

4.2. Estimation technique

The model estimation in this study relies on the Autoregressive Distributed Lag (ARDL) methodology, as introduced by Pesaran, Shin, and Smith in 2001. Three primary reasons underpin the selection of this approach. Firstly, the inherent capacity of ARDL, notably its bounds test, enables the evaluation of the presence or absence of a long-term relationship between the variables. Additionally, this methodology proves flexible in accommodating both stationary and non-stationary series, particularly when they lack an integration order of two (I(2)). According to Pesaran et al. (2001), the third advantage lies in ARDL's ability to generate short-term and long-term estimates simultaneously. The representation of Equation 7 can be expressed in the ARDL form as follows:

$$\begin{aligned} \Delta \ln SEMP = & \alpha_0 + \sum_{i=1}^{n_1} \alpha_{1i} \Delta \ln SEMP_{t-i} + \sum_{i=1}^{n_2} \alpha_{2i} \Delta \ln AI_{t-i} \\ & + \sum_{i=1}^{n_3} \alpha_{3i} \Delta \ln WGS_{t-i} + \sum_{i=1}^{n_4} \alpha_{4i} \Delta \ln INF_{t-i} + \sum_{i=1}^{n_5} \alpha_{5i} \Delta \ln GDP_{t-i} \\ & + \beta_1 \ln SEMP_{t-1} + \beta_2 \ln AI_{t-1} + \beta_3 \ln WGS_{t-1} + \beta_4 \ln INF_{t-1} + \beta_5 \ln GDP_{t-1} + \mu_t \end{aligned} \quad (8)$$

To address the occurrence of structural breaks within the variables under examination, we have modified our model by including a dummy variable denoting the structural breakpoints, specifically those occurring in 2015Q4 and 2020Q1. Equation 9, which introduces the ARDL equation and the dummy variables, reflects this adjustment.

$$\begin{aligned} \Delta \ln SEMP = & \alpha_0 + \sum_{i=1}^{n_1} \alpha_{1i} \Delta \ln SEMP_{t-i} + \sum_{i=1}^{n_2} \alpha_{2i} \Delta \ln AI_{t-i} \\ & + \sum_{i=1}^{n_3} \alpha_{3i} \Delta \ln WGS_{t-i} + \sum_{i=1}^{n_4} \alpha_{4i} \Delta \ln INF_{t-i} + \sum_{i=1}^{n_5} \alpha_{5i} \Delta \ln GDP_{t-i} \\ & + \beta_1 \ln SEMP_{t-1} + \beta_2 \ln AI_{t-1} + \beta_3 \ln WGS_{t-1} + \beta_4 \ln INF_{t-1} + \beta_5 \ln GDP_{t-1} \\ & + \beta_6 DUMMY_{2015q4} + \beta_7 DUMMY_{2020Q1} + \mu_t \end{aligned} \quad (9)$$

5. Empirical result and discussion

This section presents the findings and discussion of the results, beginning with the descriptive test, unit root test, optimum lag and ARDL bound test, followed by the autoregressive distributed lag (ARDL)

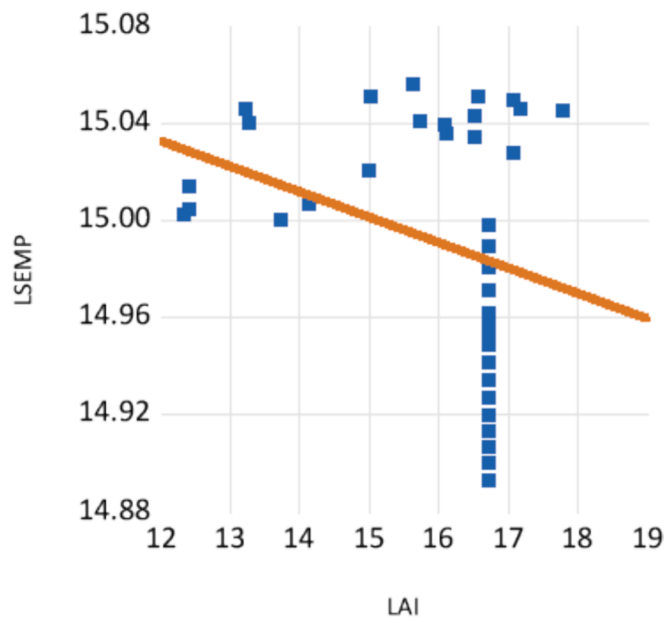


Fig. 1. Scatter plot.

result, Granger causality test, and diagnostic tests. The empirical objectives addressed in this section are twofold:

- *To analyse the long and short-run relationship between artificial intelligence and skilled employment in South Africa.

- *To examine the causal association behaviour between artificial intelligence and skilled employment.

The null hypothesis of the study.

- *Ho: There is no long and short run relationship between artificial intelligence and skilled employment in South Africa.

- *Ho: There is no causal relationship between artificial intelligence and skilled employment in South Africa.

5.1. Descriptive Statistics

Table 2 presents the descriptive statistics for the complete sample of the study, encompassing quarterly data from 2012 to 2021. The mean values for skilled employment, artificial intelligence, wages (skilled compensation), inflation, and GDPPC were recorded as 14.991, 15.999, 13.838, 5.157, and -0.484 , respectively, over the entire sample period. The range of values for these variables spanned from a minimum of -7.481 to a maximum of 18.871.

Notably, all variables exhibit a negatively skewed distribution, indicated by their negative skewness values. This skewness suggests that the degree and direction of skew in the data lean toward the left, providing insights into the shape of the distribution and its impact on increasing and decreasing values. Furthermore, the Jarque-Bera test results affirm the normal distribution of the dataset, underscoring its

suitability for empirical analysis. This validation contributes to the reliability of the statistical analyses performed in the study.

5.2. Scatter plot

In Fig. 1, the scatter plot reveals a minimal correlation between artificial intelligence and skilled employment. This seemingly weak correlation contrasts with the findings from other analyses, such as the Granger causality test, which indicates a significant level of causation and association between the two variables. Overall, the study reflects correlation, hence it can be concluded that there is correlation between skilled employment and artificial intelligence.

5.3. Unit root test

The application of the ARDL model is versatile, allowing for its use regardless of the variable integration order. However, it is crucial to highlight that bounds testing for cointegration exclusively applies to variables lacking $I(2)$ integration. As outlined in Table 3, both the Dickey-Fuller GLS and Phillips-Perron tests indicate either zero-order or first-order integration. The outcomes of the stationarity tests affirm the absence of $I(2)$ characteristics, providing robust support for the appropriateness of employing the ARDL model in this research.

The findings from the unit root test, as presented in Table 3, lead to the conclusion that skilled employment (LSEMP), artificial intelligence (LAI), wages (LWGS), and inflation (INF) exhibit stationarity at the first difference ($I(1)$). In contrast, GDP per capita (GDPPC) demonstrates stationarity at the level ($I(0)$). These results highlight the differing order of integration for each variable, a crucial consideration in the subsequent analyses and model applications.

The study further employs the Lee and Strazicich (2003) LM unit root

Table 4
Lee and Strazicich (2003) (LM) unit root test.

Skilled Employment	
Null Hypothesis: SEMP has a unit root with break	
Minimum test Statistics	-5.867
Breakpoint	2020Q1
Test Critical Values 1 % level	-4.741
5 % level	-4.172
10 % level	-3.819
Artificial Intelligence	
Null Hypothesis: AI has a unit root with break	
Minimum test Statistics	-6.360
Breakpoint	2015Q4
Test Critical Values 1 % level	-4.760
5 % level	-4.190
10 % level	-3.897

Source: Calculation by the authors through EViews 13 software.

Note: Significance levels are 1 %, 5 %, and 10 %, denoted by ***, **, and *, respectively.

Table 3
Stationarity Tests.

Dickey-Fuller GLS					Phillips-Perron				
Variables	Stationarity of Variables at level		Stationarity of Variables at first difference		Stationarity of Variables at level		Stationarity of Variables at first difference		
	No Trend	Trend	No Trend	Trend	No Trend	Trend	No Trend	Trend	
LSEMP	0.8341	0.0552*	0.0292**	0.0094***	0.1338	0.9696	0.0262**	0.0118**	I(1)
LAI	0.0461	0.1912	0.0000***	0.0000***	0.0547	0.2242	0.0000***	0.0000***	I(1)
LWGS	0.1086	0.0664*	0.0987*	0.0215**	0.4388	0.8364	0.0461**	0.0312**	I(1)
INF	0.1434	0.0123***	0.0000***	0.0000***	0.3528	0.2371	0.0000***	0.0000***	I(1)
GDPPC	0.0000**	0.0000***			0.0427**	0.0411**			I(0)

Source: Calculation by the authors through EViews 13 software.

Note: Significance levels are 1 %, 5 %, and 10 %, denoted by ***, **, and *, respectively.

Table 5

Chow Breakpoint test.

Chow Breakpoint Test: 2020Q1			
Null Hypothesis: No breaks at specified breakpoints			
F-statistic	5.284132	Prob. F(2,33)	0.0102**
Log likelihood ratio	10.27939	Prob. Chi-Square(2)	0.0059
Wald Statistic	10.56826	Prob. Chi-Square(2)	0.0051
Chow Breakpoint Test: 2015Q4			
Null Hypothesis: No breaks at specified breakpoints			
F-statistic	5.643210	Prob. F(2,33)	0.0078***
Log likelihood ratio	10.88431	Prob. Chi-Square(2)	0.0043
Wald Statistic	11.28642	Prob. Chi-Square(2)	0.0035

Source: Calculation by the authors through EViews 13 software

Note: Significance levels are 1%, 5%, and 10%, denoted by ***, **, and *, respectively

test to evaluate breakpoints in the data. This Lagrange Multiplier (LM) unit root test is specifically designed to detect multiple structural breaks in time series data. It serves as an extension of the Augmented Dickey-Fuller (ADF) test, enabling the identification of structural breaks at unknown points within the data. The outcomes of this analysis specifically concentrate on skilled employment and its relationship with artificial intelligence, as highlighted in Table 4.

Based on the results in Table 4, skilled employment (LSEMP) and artificial intelligence (AI) reject the null hypothesis, as the t-statistics exceed the critical value of 2. Additionally, the findings indicate structural breaks in 2020Q1 for skilled employment and 2015Q4 for artificial intelligence.

The structural break identified in skilled employment in 2020Q1 may be attributed to the global impact of the COVID-19 pandemic. The widespread implementation of lockdowns, travel restrictions, and economic disruptions could have significantly affected skilled employment across various industries. Moreover, the pandemic prompted organizations to rapidly adopt remote work and digital technologies, potentially influencing the demand for specific skills and leading to shifts in skilled employment patterns, as discussed by Amankwah-Amoah et al. (2021).

Furthermore, the structural break observed in artificial intelligence in 2015Q4 might be linked to changes in government policies or regulatory environments related to AI. Policies supporting innovation in AI or creating a regulatory landscape conducive to AI startups may have attracted increased investments, aligning with the observations made by Scherer (2015). These regulatory and policy changes could have fueled a surge in venture capital investments in artificial intelligence during this period.

Considering the breakpoints of the study, the Chow Breakpoint test is carried out to decide between the two structural breaks- 2020Q1 and 2015Q4. The result is reflected in Table 5.

The associated probabilities (p-values) for all test statistics are below the typical significance level of 0.05, indicating strong evidence to reject the null hypothesis. Therefore, based on these results, it can be concluded that there is a significant structural break at the specified breakpoints of 2020Q1 and 2015Q4. Both Chow breakpoint tests indicate significant structural changes in the relationships between the variables, but the second result suggests that the change in the

relationship with artificial intelligence in 2015 may be slightly more pronounced.

5.4. Optimum lag and ARDL bound test

Table 6 displays the outcomes of the bounds cointegration test. The conducted cointegration test yields an F-statistic value of 19.573. Significantly, this F-statistic surpasses the critical value thresholds at the 1 %, 5 %, and 10 % significance levels, leading to the rejection of the null hypothesis that posits no cointegration. This outcome strongly indicates the presence of a cointegrating relationship among the examined variables, and this relationship is sustained over the long term.

Additionally, the optimal lag criteria chosen by the model for both the dependent (skilled employment) and independent variables (artificial intelligence, wages, inflation and GDP per capita) is lag two. This optimal lag selection enhances the model's accuracy in capturing the dynamics of the relationships among the variables, contributing to the robustness of the analysis.

5.5. Granger causality test

In this study, the causality test developed by Clive Granger (1974) was employed to analyze the causal relationship between the variables of interest: skilled employment, artificial intelligence, wages, inflation, and GDP per capita. The results in Table 7 provide compelling evidence of a unidirectional causal relationship among the variables under investigation.

The causality relationship of artificial intelligence (AI), wages (WGS), inflation (INF), and GDP per capita (GDPPC) with skilled employment (SEMP) is statistically significant at the ten percent significance level. Consequently, the null hypothesis of no causality is rejected, concluding that artificial intelligence investment, wages, inflation, and GDP per capita Granger cause variations in skilled employment. This Granger causality finding implies that changes in artificial intelligence investment, wages, inflation, and GDP per capita have the potential to cause fluctuations in skilled employment in South Africa.

Some of the economic implication could be that changes in skilled employment can have implications for income inequality within the economy. Skilled workers typically command higher wages than

Table 7

Granger Causality Test.

Null hypothesis	Chi-Square	P-value	Nature of Direction
AI → SEMP	7.925	0.0190**	AI → SEMP
SEMP → AI	0.156	0.9247	None
WGS → SEMP	3.655	0.0908*	WGS → SEMP
SEMP → WGS	2.704	0.2586	None
INF → SEMP	7.949	0.0188**	INF → SEMP
SEMP → INF	3.652	0.1610	None
GDPPC → SEMP	4.996	0.0822*	GDPPC → SEMP
SEMP → GDPPC	0.879	0.6442	None

Source: Calculation by the authors through EViews 13 software.

Null hypothesis: There is no cointegration

Table 6

Lag Criteria and Bound Test.

Lags		Critical Value Bounds							
Dependent Variable	Independent Variable	F-Stat	Sample Size	10 %		5 %		1 %	
2	2	19.573	30	I (0)	I (1)	I (0)	I (1)	I (0)	I (1)
			35	2.525	3.560	3.058	4.223	4.280	5.840
			Asymptotic	2.460	3.460	2.47	4.088	4.093	5.532
				2.200	3.090	2.560	3.490	3.290	4.370

Source: Calculation by the authors through EViews 13 software.

Note: Significance levels are 1 %, 5 %, and 10 %, denoted by ***, **, and *, respectively.

Table 8
ARDL Short-run Estimate.

Dependent Variable: Skilled Employment D(InSEMP)				
Variables	Coefficients	Std. Error	t-Statistics	Probability*
D(InAI)	0.010715	0.020240	-4.416272	0.0002***
D(InWGS)	0.100381	0.014209	7.064808	0.0000***
D(INF)	-0.019770	0.002536	-7.795197	0.0000***
GDPPC	0.000790	0.000373	-2.115424	0.0460**
C	0.616119	0.175269	-3.515284	0.0020***

Source: Calculation by the authors through EViews 13 software.

Note: Significance levels are 1 %, 5 %, and 10 %, denoted by ***, **, and *, respectively.

Null hypothesis: There is no causality.

Table 9
ARDL Long-Run Estimate.

Dependent Variable: Skilled Employment D(InSEMP)				
Variables	Coefficients	Std. Error	t-Statistics	Probability*
D(InAI)	0.074738	0.004522	-3.259036	0.0028***
D(InWGS)	0.813457	0.056183	14.47857	0.0000***
D(INF)	-0.407773	0.076711	-5.315717	0.0000***
GDPPC	0.010230	0.000720	-4.438951	0.0001***
COINTEQ	-0.048482	0.004296	-11.28471	0.0000***

Source: Calculation by the authors through EViews 13 software.

Note: Significance levels are 1 %, 5 %, and 10 %, denoted by ***, **, and *, respectively.

Source: Calculation by the authors through EViews 13 software.

Note: Significance levels are 1 %, 5 %, and 10 %, denoted by ***, **, and *, respectively.

unskilled workers, so fluctuations in skilled employment driven by AI investment and GDP growth can affect income distribution.

5.6. Estimated ARDL results without structural breaks

Tables 8 and 9 showcase the empirical results of the ARDL model, both in the short and long run. Artificial intelligence investment (AI) significantly positively impacts skilled employment (SEMP) in South Africa. In the short term, a 1 % increase in artificial intelligence investment corresponds to a 0.011 % increase in skilled employment. This relationship is even more pronounced in the long term, with a 1 % increase in AI investment leading to a substantial 0.075 % increase in skilled employment. This relationship indicates a positive contribution of South African artificial intelligence investment to the demand for high-skilled labor.

This finding aligns with previous studies by Xie et al. (2021) and Babina et al. (2023), supporting that AI investment reduces the relative demand for low-skilled labor while increasing the demand for high-skilled labor. Babina et al. (2023) specifically demonstrated that firms investing in AI tend to transition to a more educated workforce. The growth of AI in South Africa is anticipated to generate new job opportunities in specialized fields like data science, machine learning, and AI programming, thereby expanding skilled employment opportunities (Rapanyane and Sethole, 2020).

Moreover, the recognition of the importance of developing a skilled workforce in AI-related fields is evident in South Africa. Carrim (2022) highlights the country's commitment to promoting STEAM (Science, Technology, Engineering, Art and Mathematics) education, encouraging research and development in AI, and fostering collaboration between academia, industry, and government. The South African government's initiatives, such as the Digital Skills Initiative and the Fourth Industrial Revolution (4IR) Strategy, further underscore the commitment to the development of digital skills, innovation, and entrepreneurship. These endeavors aim to equip the South African workforce with the essential skills to thrive in an AI-driven economy (Manda and Ben Dhaou, 2019).

Wages emerge as a key factor influencing skilled employment, exhibiting a positive and significant impact. In the short term, a 1 % increase in wages corresponds to a 0.10 % increase in skilled employment, while in the long term, this relationship becomes more pronounced, with a 0.813 % increase in skilled employment for every 1 % rise in wages. This implies that offering competitive wages serves as a potent tool for attracting skilled workers to industries or regions. Higher wages act as an incentive for individuals possessing specialized skills, particularly in fields like science and technology, thereby increasing the pool of skilled workers in the labor market (Slatten et al., 2021).

South Africa has grappled with a substantial brain drain, where skilled professionals leave the country in pursuit of better employment opportunities and higher wages elsewhere. Offering higher wages for skilled employment can mitigate this outflow, encouraging skilled workers to either stay or return to the country. This strategic approach contributes to talent retention, preserving valuable skills and expertise within the local workforce (Sehoolle et al., 2019; Iruo, 2021; Zakus & Anteh, 2021). This finding aligns with Angelopoulos et al. (2017), who demonstrated that while there may be a short-term decline in the wages of skilled employees, the long-term trend is characterized by an increase in wages for skilled workers.

Conversely, inflation exerts a significant negative impact on skilled employment. A 1 % increase in inflation results in a 0.019 % decrease in skilled employment in the short term and a more substantial 0.40 % decrease in the long term. This finding resonates with the conclusions drawn by Vermeulen (2015) and Salazar (2022), both of whom highlighted the adverse effects of higher inflation on employment creation, whether skilled or unskilled. Additionally, as posited by Reiche and Meyler (2022), high inflation rates can introduce uncertainty and diminish business confidence. Businesses, faced with rising costs in areas such as raw materials, energy, or borrowing, may hesitate to invest in expanding operations or hiring skilled workers. This hesitation has the potential to limit job opportunities for skilled individuals.

Furthermore, persistently high inflation can precipitate an overall economic slowdown. When inflation is poorly managed, it erodes consumer purchasing power, diminishes demand, and introduces instability. In such circumstances, businesses may be reluctant to invest and expand, leading to a decrease in skilled employment opportunities (Ha et al., 2022).

GDP per capita has a positive and significant impact on skilled employment. For every 1 % increase in GDP per capita, skilled employment increases with little or no incredible increase of 0.0007 % in the short run and 0.010 % in the long run. The overall positive impact of GDP per capita on skilled employment is consistent with Hami and Orhan (2022), who demonstrated that GDP per capita is among the factor that increases high-skilled employment. Furthermore, higher GDP per capita often corresponds to a growing economy with increased economic activity. This growth can stimulate various sectors of the economy, including those that require skilled labor. As the economy expands, there is a greater demand for skilled workers in industries such as finance, manufacturing, technology, engineering, and professional services (Martinez, 2022).

Additionally, higher GDP per capita also fosters technological advancement and innovation. A robust GDP per capita can support the adoption of new technologies and encourage research and development activities. This progress not only creates new industries but also generates job opportunities that demand specialized skills. South Africa stands to benefit from this by attracting investments in technology-driven sectors and simultaneously developing a skilled workforce to support these emerging industries (Jahanger et al., 2022).

Furthermore, the negative error correction term coefficient in Table 6 suggests that the dependent variable (skilled employment) adjusts downward toward its equilibrium level in response to positive deviations. The magnitude of the coefficient, with the ECM being -0.048, indicates a relatively slower adjustment, providing insights into the speed at which the system returns to equilibrium following a

Table 10
ARDL Structural Breaks Estimate.

ARDL Structural Breaks Short-run Estimate				
Dependent Variable: Skilled Employment D(InSEMP)				
Variables	Coefficients	Std. Error	t-Statistics	Probability*
D(InAI)	-0.012037	0.000109	-2.179195	0.0394**
D(InWGS)	0.946966	0.098480	-2.179195	0.0000***
D(INF)	-0.018454	0.002485	-7.426257	0.0278**
GDP	0.003329	0.001506	0.158031	0.0447**
DUMMY2015Q4	-0.000343	0.000877	-0.391580	0.6988
DUMMY 2020Q1	0.015674	0.004007	3.911531	0.0007***
C	-0.775619	0.229904	-3.373668	0.0034***

ARDL Structural Breaks Long-run Estimate				
Dependent Variable: Skilled Employment D(InSEMP)				
Variables	Coefficients	Std. Error	t-Statistics	Probability*
D(InAI)	-0.090709	0.000452	-5.567009	0.0928*
D(InWGS)	0.082337	0.024373	3.378220	0.0021***
D(INF)	-0.025670	0.005569	-4.609156	0.0001***
GDP	-0.963005	0.000347	-0.278953	0.7823
DUMMY2015Q4	-0.012987	0.005919	-2.194054	0.0364**
DUMMY 2020Q1	-0.003333	0.001442	-2.311464	0.0281**
COINTEQ	-0.718876	0.058663	-12.25441	0.0000***

deviation.

5.7. Estimated ARDL results with structural breaks

Following the structural break of the study, the ARDL model is re-estimated to further bring insight to the study. Including dummy variables in the ARDL model allows capturing and accounting for structural breaks, which may lead to differences in the estimated coefficients compared to the model without dummy variables. It provides a more nuanced understanding of the relationship between the variables over time. The dummy variables take on the values 0 and 1; this allows for the representation of categorical data within regression models while maintaining the numerical nature of the variables required for analysis.

Table 10 reveals that the coefficient for the change in Artificial intelligence investment (AI) is negative when dummy variables are included in the re-estimated short and long-run ARDL result (-0.012037, -0.090709), indicating a negative impact on skilled employment. Conversely, Tables 8 and 9 indicate a positive coefficient for AI investment (0.010715, 0.074738) when no dummy variables are included. This suggests that the relationship between Artificial intelligence investment (AI) and skilled employment differs when accounting for structural breaks.

The negative coefficient for AI adoption in the model with dummy variables suggests that the increasing prevalence of AI technology may reduce skilled employment. As AI systems become more sophisticated, they can automate tasks that traditionally require human expertise, potentially displacing certain skilled jobs. This displacement can result in job loss and changes in the skill requirements within the workforce. Workers affected by AI-driven automation may need to acquire new skills to remain competitive in the job market (Barbieri, et al., 2020).

Additionally, the negative impact of AI on skilled employment may cause long-term changes in the job market. Industries and occupations that rely heavily on AI-driven automation are likely to see changes in employment patterns and job hierarchies, which could lead to income inequality, reduced social mobility, and a lack of economic opportunities (Zarifhonarvar, 2023). To ensure a smooth transition for affected workers and promote a strong and inclusive job market, policymakers must anticipate and adapt to these structural changes.

Furthermore, despite structural breaks, the coefficients for wages, inflation, and Gross Domestic Product (GDP) per capita remain consistent across both the ARDL models. Specifically, the positive and significant coefficient for wages suggests a continued positive impact on skilled employment. Similarly, the negative and significant coefficient

Table 11
Diagnostic results without structural breaks.

Tests	Type of Test	F-Statistic	p-value	Decision
Auto Correlation	Breusch-Godfrey	2.3002	0.1249	Fail to reject H_0
Heteroscedasticity	Breusch-Pagan Godfrey	1.3063	0.2822	Fail to reject H_0
Normality	Jarque-Bera	0.3906	0.8225	Fail to reject H_0

Source: Calculation by the authors through EViews 13 software.

Table 12
Diagnostic results with structural breaks.

Tests	Type of Test	F-Statistic	p-value	Decision
Auto Correlation	Breusch-Godfrey	4.4123	0.5492	Fail to reject H_0
Heteroscedasticity	Breusch-Pagan Godfrey	3.4895	0.4865	Fail to reject H_0
Normality	Jarque-Bera	1.8974	0.4545	Fail to reject H_0

Source: Calculation by the authors through EViews 13 software.

Note: Significance levels are 1 %, 5 %, and 10 %, denoted by ***, **, and *, respectively.

for inflation indicates a persistent negative influence on skilled employment. Moreover, the positive and significant coefficient for GDP per capita underscores its ongoing positive effect on skilled employment. Therefore, despite any structural shifts, these variables maintain their respective impacts on skilled employment, highlighting their robust and enduring relationships over time.

5.8. Diagnostic test result

The diagnostic tests conducted in this study encompass autocorrelation, heteroscedasticity, and a normality test. Autocorrelation, which measures the similarity between a time series and a lagged version of itself over successive time intervals, is employed with the null hypothesis positing the presence of autocorrelation. Heteroscedasticity characterizes situations where the variability of errors (residuals) in a regression model is not constant across all independent variable(s) levels – artificial intelligence, wages, inflation and GDP per capita. The null hypothesis here is the presence of heteroscedasticity. Lastly, the normality test determines whether the dataset adheres to a normal distribution, with the null hypothesis assuming the distribution of residuals is not normal (Gujarati, 2022).

The results of these diagnostic tests are presented in Table 11 and 12. The auto correlation, heteroscedasticity, and normality test results indicate the absence of defects in the model, with probability values exceeding the 10 % significance level. This robustness in diagnostic test outcomes enhances the reliability and validity of the model's results, instilling confidence in the study's findings and conclusions.

Source: Calculation by the authors through EViews 13 software.

Furthermore, the Cumulative Sum (CUSUM) test is conducted to test structural breaks or changes in the parameters of a time series model. Also, The CUSUM test is used to assess whether the parameters of a model remain stable over time or if there are significant deviations from stability. The CUSUM test results without and with structural breaks are presented in Figs. 2 and 3.

The CUSUM test result indicate that both the result for without and with structural breaks reflect normal stability at 5 %. This result reveal that the time series model do not show any defects in stability.

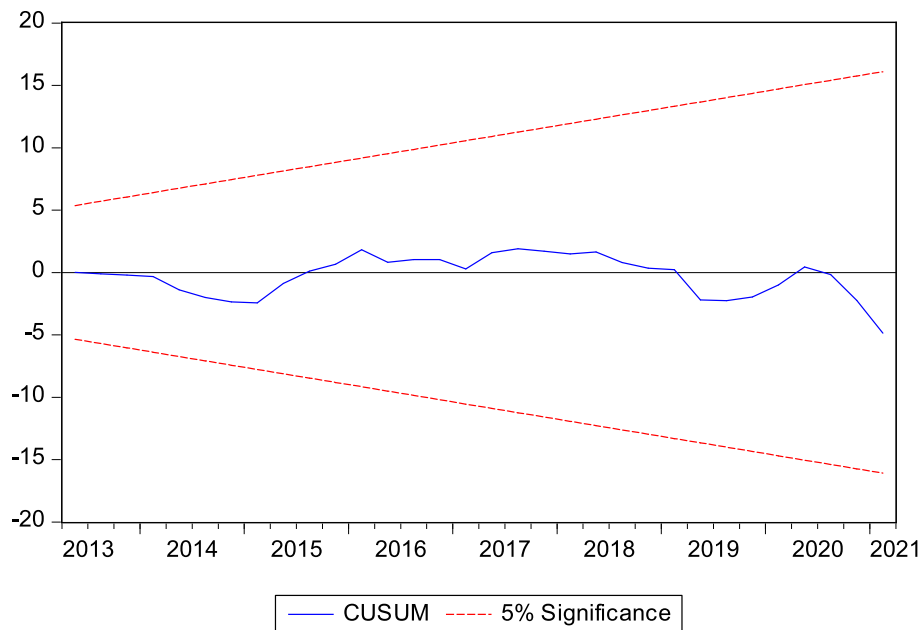


Fig. 2. CUSUM result without structural breaks.

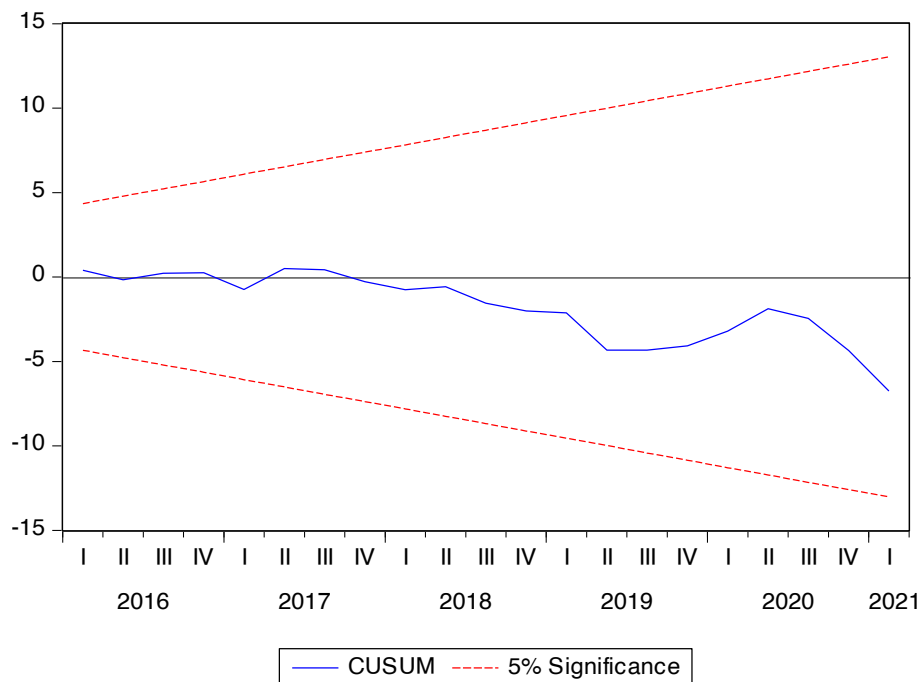


Fig. 3. CUSUM result with structural breaks.

6. Conclusion and policy implication

As the fourth industrial revolution continues to permeate South Africa, it becomes imperative to explore how the increasing prevalence of artificial intelligence (AI) contributes to the economy and, in turn, impacts skilled employment. This paper aims to assess the dynamic effects of AI on skilled employment in the country, utilizing the Autoregressive Distributed Lag (ARDL) model and Granger causality test from 2012Q1 to 2021Q4.

In summary, the study successfully validates its hypothesis. The ARDL model reveals a positive relationship between skilled employment and artificial intelligence, persisting in the long and short run. However,

two structural breaks were identified in the data, hence a re-estimation of the ARDL model. The re-estimated ARDL model revealed a negative and significant relationship between AI and skilled employment. Additionally, the Granger causality analysis underscores the existence of a causal link, affirming that artificial intelligence significantly influences skilled employment dynamics in South Africa.

Policy recommendations stemming from this research advocate for a proactive approach. First, investing in training programs and educational opportunities is paramount to empower the workforce with the requisite skills for an AI-driven economy. This not only mitigates the risk of job displacement but also ensures that individuals are well-prepared for evolving job requirements.

Policymakers may also consider implementing regulations and labor market policies that promote the responsible deployment of AI technology while safeguarding workers' rights and job security. This could include establishing guidelines for AI deployment in the workplace, ensuring transparency and accountability in AI systems. Also, strengthening social safety nets. This could involve expanding access to vital resources such as unemployment insurance, healthcare benefits, and other social welfare programs. These measures can help mitigate the economic hardships displaced workers and their families face.

CRedit authorship contribution statement

Fiyinfoluwa Giwa: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Nicholas Ngepah:** Validation, Supervision, Funding acquisition.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: The authors assert that there are no conflicts of interest that could impact the objectivity of this research. The present study was carried out with a strong commitment to upholding integrity and transparency, ensuring that the findings' validity remained unaffected by any potential financial or personal relationships.

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Submission declaration statement

By submitting this manuscript, we confirm its originality and assert that it has not been previously published. We confirm that all authors have reviewed and endorsed the content, and any conflicts of interest have been disclosed. The submission adheres to ethical guidelines and ensures the integrity of the data.

Information on rights and permission

The data and content used in this study were obtained from publicly accessible online platforms and repositories. No permissions were necessary for their utilization, as they fall under the public domain and are subject to open-access policies.

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