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# MACROECONOMIC DETERMINANTS OF POVERTY IN SOUTH AFRICA: THE ROLE OF INVESTMENTS IN ARTIFICIAL INTELLIGENCE

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**ABSTRACT**
***Objectives:*** *This study marks a departure from conventional research that predominantly focuses on AI's impact on economic growth. Instead, it uniquely centers on the interplay among fiscal policy, AI investment, monetary policy, and poverty alleviation in South Africa, a nation recognized for its extreme income inequality. In doing so, this research distinguishes itself from the prevailing macro-level studies by scrutinizing the intricate relationship between artificial intelligence, poverty, monetary policy, and fiscal policy, particularly within the South African context.*
***Methods/Approach:*** *It employs the Praise-Winsten model and other econometrics diagnostics for the empirical analysis.*
***Results:*** *The findings reveal that government expenditure on education and investments in artificial intelligence only stimulate household consumption and, therefore, reduce poverty when they are interacted. A one-unit rise in the interaction term increases household consumption by 0.031. Additionally, a unit increase in government national expenditure and broad money growth results in a 0.007 and 0.014 decrease in poverty, respectively. Similarly, gross capital formation positively affects household consumption, thereby reducing poverty in the country by 1.022 due to a one-point increase. In general, taxes on goods and services and the repo rates exert a non-statistically significant effect on the level of poverty in the country.*
***Conclusions:*** *To effectively address these findings, it is imperative to conduct a thorough evaluation of government spending on education to ensure prudent resource allocation and prevent the mismanagement of public funds.*

**Keywords:** Artificial Intelligence, Household consumption, Government expenditure, money supply

**JEL classification:** E52, H3, H5, I3, O3
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## INTRODUCTION

Characterizing developing economies is the prevalence of low living standards among their citizens. For example, according to Statistics South Africa (Stats SA) in 2017 and Trading Economics in 2018, as cited in Musara et al. (2020), South Africa, despite being one of Africa's largest economies, continues to grapple with high unemployment rates, reaching 26.7% in the fourth quarter of 2017, with youth unemployment at 52.20%. Poverty and inequality further afflict the country, reflected in a Gini coefficient of 0.69 (World Bank, 2017), as cited in Musara et al. (2020). In 2015, approximately 736 million individuals lived below the global poverty line of US$1.90/day. By 2018, approximately 8% of workers and their children were living on less than US$1.90 per individual per day globally. Additionally, about 10% of the global population struggles to access basic needs such as education, health, sanitation, and clean water (United Nations, 2020), as cited in Solarin

(2022). The United Nations' Sustainable Development Goal 17 for 2030 prioritizes the eradication of poverty in all its forms (Griggs et al., 2013), as cited in Zhou & Liu (2022). Africa has been described as the global last frontier in the fight against extreme poverty (Hamel et al., 2019).

According to STATS SA 2018, cited in Dunga (2019), over half of South Africa's population lives in poverty. Dunga (2019), citing STATS SA (2018) and based on a report covering the period 2006 to 2015, states that 30.4 million individuals, or 55.5% of the population, live in poverty. This is an increase from 53.2% or 27.3 million individuals reported in 2011. Various factors contribute to poverty in Africa, including income inequality, geographic location, conflicts, natural disasters, and inheritance of poverty, ill health, disability, gender discrimination, education, and skills (Kabuya, 2015). Africa, the world's second-most populous continent with 1.3 billion people, is predominantly composed of youth, constituting a significant portion of the global population at 16.72%. Economic growth in Africa has shown variation, with an average real output growth of 1.8% annually from 1980 to 1989, 2.6% from 1990 to 2000, and a significant increase to 5.3% from 2000 to 2010 (UNCTAD, 2014). The exponential growth in technology and its impact on industries can influence productivity, employment, poverty levels, and overall living standards. For instance, Harari (2018) emphasizes the importance of skills like critical thinking, collaboration, communication, and creativity in the age of technology. The combination of these skills can expedite productivity and alleviate poverty. The Fourth Industrial Revolution (4IR) is expected to enhance productivity across industries, but it also poses challenges, particularly in developing countries like those in Sub-Saharan Africa. The rapid technological advancements of the 4IR have raised concerns about job displacement and skills gaps (Naudé, 2017; World Economic Forum Africa, 2016). The fear of job loss due to technological advancement has been a major concern globally (Shank, 2016), as cited in Shava & Hofisi (2017). In parallel with these global trends, upper-income economies have seen accelerated innovation and technological change (Signé, 2022).

Growth theories, including neoclassical, classical, and endogenous growth theory, all underscore the role of technology in a nation's development. Advanced technology can internalize the law of diminishing returns (Jeffrey, 2013; Oyewale & Osadola, 2018). The continuous technological revolution worldwide has the potential to accelerate productivity and improve living standards, although its impact on employment may vary. To this end, can South Africa effectively utilize investment in artificial intelligence to significantly reduce poverty? How effective is the government's fiscal policy in poverty reduction? Investing in Artificial Intelligence (AI) raises questions about its potential to impact poverty through various channels: (i) AI investment can create jobs in fields like AI research, software development, data science, and administration, reducing unemployment and alleviating poverty (OECD, 2021); (ii) AI boosts productivity in sectors like manufacturing, healthcare, and agriculture, spurring economic growth, higher wages, and improved living standards (Ernst, 2022); (iii) AI fosters innovation and competitiveness, making businesses more profitable, generating tax revenue for poverty reduction (Lu, 2021); (iv) AI education equips individuals with job-relevant skills, enhancing employability and income, reducing poverty risk (Mena-Guacas et al., 2023). Fiscal policy, managed by governments, involves taxation and public spending to shape economic conditions. It can directly impact poverty through targeted social spending, like welfare programs and public health services, helping vulnerable populations. Tax policies can also redistribute wealth, ensuring the affluent pay more, reducing income inequality. Additionally, government investment in education and job training can enhance skills, employability, and income for citizens, lifting them out of poverty. Moreover, well-executed fiscal policies can stimulate economic growth, generating more job opportunities and increasing overall income levels, which in turn can alleviate poverty. Fiscal policy, managed by governments, involves taxation and public spending to shape economic conditions. It can directly impact poverty through targeted social spending, like welfare programs and public health services, helping vulnerable populations (Jouini et al., 2018). Tax policies can also redistribute wealth, ensuring the affluent pay more, reducing income inequality (Jouini et al., 2018). Additionally, government investment in education and job training can enhance skills, employability, and income for citizens, lifting them out of poverty (Mokoena and Mazenda, 2023). Moreover, well-executed fiscal policies can stimulate economic growth, generating more job opportunities and increasing overall income levels, which in turn can alleviate poverty.

This study contributes to the empirical literature by examining the impact of artificial intelligence, as a technology of the 4IR, on the achievement of Sustainable Development Goal 1, considering the macroeconomic role of fiscal policy in South Africa over the period 2016q1 to 2022q1. Given the limited empirical studies on the impact of artificial intelligence, this research extends the existing literature by using quarterly transformed time series data to quantify the effect of artificial intelligence investments on poverty in South Africa. The study's empirical findings provide quantitative insights, complementing the predominantly qualitative approach found in academic literature. Additionally, the research offers policy recommendations for the South African government regarding the use of fiscal policy and artificial intelligence investments as measures for poverty reduction in the economy.

The organization of this paper is as follows: Section 2 presents the literature review. Section 3 presents the methodology and data. Results from the empirical analysis are presented and discussed in Section 4, while finally, Section 5 concludes the study.

## LITERATURE REVIEW

This section compiles pertinent theoretical explanations and empirical studies related to this research.

### *2.1 Theoretical Review*

#### *The Classical and Neoclassical Theory*

The concept of poverty is a development issue having varying conceptual measures. The study of Davis (2014) provides some information on the classical perspective of poverty. According to the theory, it is assumed that efficiency characterizes the exchanges that occurs in the market, implying that wages reflect individual output. Poverty is therefore observed as the outcome of choices of individuals which undermines productivity. “Poverty or welfare” trap may arise due to the “wrong” choices of individuals. It was asserted that the intervention of state is an avenue for economic inefficiency in the scenario beyond a minimum level to avoid destitution; by creating misaligned incentives between poor persons and the generality of a society, programs that are welfare based have the possibility of resulting in the reinforcement of penury. It was observed that most of the policy prescriptions in this context concentrates on efforts to promote productivity of impoverished persons towards making them to participate in the labour force while certain persons in the class of the young, the old, the sick cannot join, and alternative assistance would be needed.

The neoclassical perspective establishes a connection between ICTs and the participation of vulnerable groups in viable economic activities (Kwan & Chiu, 2015). According to Ofori et al. (2021), this theory contends that ICTs play a vital role in helping low-income economies transition out of persistent poverty, as evidenced by the experiences of economies like China, Hong Kong, and Japan. Davis and Sanchez-Martinez's study (2015) further expands on neoclassical theories, offering a broader scope that considers factors contributing to poverty beyond individuals' control. These factors encompass the depletion of social and private assets, obstacles to education, employment challenges faced by single-parent households, immigrant status, market failures that exclude the impoverished from accessing credit markets, leading to seemingly irrational choices, and health deterioration alongside aging.

*Keynesian/Neoliberal*

As evident from Davis and Sanchez-Martinez's study (2015), the neoliberal ideology, led by the new-Keynesians, shares a focus on individual-oriented perspectives regarding poverty. However, the distinctive feature lies in the emphasis placed on the government's role, which leads to a heightened focus on public goods and inequality. According to these authors, this perspective implies that achieving a more equitable income distribution could facilitate the inclusion of disadvantaged individuals in essential activities within the broader context of poverty.

Further insights into Keynesian philosophy were derived from Alamanda's research (2020), which delves into the Keynesian theory of employment, interest, and money, shedding light on the intricate relationship between income inequality, poverty, and government expenditure. According to Keynesian philosophy, government intervention can enhance the prospects of attaining a crucial equilibrium among saving, consumption, and investment. Alamanda (2020) observed that the level of employment, a pivotal factor in assessing income inequality, hinges on the demand for goods and services. Citing Stack (1978), Alamanda (2020) highlighted that "demand is a function of the relative propensity to consume and the propensity to save. If the amount of money saved by income recipients is greater than the amount required by those responsible for investment, then total demand will be insufficient to sustain full employment." Consequently, excessive saving is deemed detrimental to an economy as it curtails job creation, leading to unemployment and exacerbating income inequality (Stack, 1978).

According to Alamanda (2020), this theory implies that government participation in an economy can contribute to a reduction in income inequality and poverty through three channels. Firstly, the nature of government expenditure can mitigate obstacles and enhance the living standards of impoverished households. Secondly, increased job opportunities resulting from public works projects reduce unemployment,

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subsequently lowering inequality and poverty levels. Lastly, the multiplier effects of programs promoting job creation have the potential to stimulate economic activities and a cascade of reinvestments.

### 2.2 Empirical Review

Many economists in developing economies view the prospects of the fourth industrial revolution (Thailand Board of Investment, 2017) as influenced by the earlier adoption of this revolution by advanced economies like the UK, USA, South Korea, and China (Ciszewska-Mlinaric, 2009). While industrial growth occurred in Great Britain and continental Europe in the eighteenth and nineteenth centuries, Africa mainly focused on generating agricultural items and raw materials such as rubber, cocoa, coffee beans, sugar cane, cotton, tobacco, copper from Northern Rhodesia, and gold and diamonds from South Africa (Amin, 1972). Many Sub-Saharan African countries heavily rely on rain-fed agriculture and primary activities (Adekunle et al., 2016; Bachewe et al., 2018). The adoption of technology and the utilization of technical progress are significant drivers of output growth in most developed economies, leading to substantial advancements in social and economic development (World Economic Forum, 2017). Observers and analysts widely agree that fourth industrial technologies hold significant promise for stimulating ongoing economic growth and development processes in Africa (Banga et al., 2020; Signé, 2022).

According to a World Bank (2018) report cited in Dunga's work (2019), although extreme poverty levels appear to have declined, the problem has shifted and concentrated in specific regions. Dunga (2019) highlights that poverty levels have risen in sub-Saharan Africa. Between 1990 and 2015, the number of individuals living in extreme poverty increased from 278 million to 413 million, making the region home to more extremely poor individuals than the rest of the world combined. Prisecaru (2016) observes that the digitalization stemming from the Fourth Industrial Revolution exacerbates global inequalities, particularly affecting weaker and poorer states, which struggle to adapt to these technological changes from the second and third industrial revolutions. Mesnard (2016) suggests that revolutionary technologies that dramatically transform industrial production can put employment at risk, as the Fourth Industrial Revolution may lead to reduced demand for labor or necessitate new educational prerequisites. Borg (2016) argues that widespread changes in technical capabilities in areas such as digitalization, connectivity, big data, and robotics could disrupt labor markets significantly. The World Bank (2018) further emphasizes the shifting nature of poverty despite reductions in extreme poverty levels.

Zahonogo (2017) applies the system GMM technique to a panel of 42 Sub-Saharan African economies spanning from 1980 to 2012. He finds that financial development contributes to a reduction in poverty, with a specific threshold level of 1.19% necessary for financial development to have a significant impact on poverty. Mumtaz and Ali (2022) examines the impact of exchange rates and their volatility on domestic consumption in India and Pakistan, covering the period from 1980 to 2018. They find that a rise in real exchange rates stimulates consumption, while a rise in nominal exchange rates decreases consumption in India. Mushtaq and Bruneau (2019) analyzed the role of ICT in poverty alleviation using a panel of 61 countries from 2001 to 2012. They find that financial inclusion facilitates the impact of ICT diffusion in reducing poverty and

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inequality. Recently, financial technology has emerged as a significant tool for reducing poverty and driving domestic economic development (McKinsey Global Institute, 2016, as cited in Bateman et al., 2019).

The McKinsey Global Institute (2016) employs McKinsey's proprietary general equilibrium macroeconomic model and predicts that digital finance could boost GDP levels in emerging economies by 6%, or $3.7 trillion, by 2025. To achieve this, emerging markets must stimulate digital payments at a rate equal to that of the top quartile of advanced economies over the long term and ensure that 91% of adults have access to financial services, on average. Ofori et al. (2021) investigates the impact of ICT diffusion and financial development on poverty reduction in SSA using data spanning from 1980 to 2019. They employ dynamic system GMM and panel corrected standard errors and find that, unlike financial access, ICT usage, access, and skills have a pronounced impact on reducing both the severity and intensity of poverty. This impact is further enhanced when there is strengthened financial development. Batrancea et al. (2021) analyze the determinants of economic growth across seven economies from 1990 to 2019. They find that economic growth is significantly affected by the bank capital-to-assets ratio. Rami´Reza et al. (2017) identifies a causal and declining effect of property tax revenues on poverty headcount ratio and gap, with considerable spillovers across municipalities. Mehmood and Sadiq (2010) examine government expenses on poor individuals from 1976 to 2010 and find that government expenditures have a negative and significant impact on poverty. Kazungu and Cheyo's (2014) study examines the impact of government expenses on strategic growth and poverty reduction in Tanzania from 2005 to 2013. They found that government expenditures aimed at stimulating growth do not necessarily lead to poverty reduction, as these expenses are often concentrated on social investments. Oriavwote and Ukawe (2018) investigates the impact of government expenditure on poverty reduction in Nigeria from 1980 to 2016. Their analysis, using the ECM model and cointegration techniques, suggests that government expenditure on health and education positively affects per capita income, albeit with low elasticity. Meanwhile, government expenditure on building and construction also has a direct and significant effect on per capita income, albeit with low elasticity. The study finds no evidence of causation between government expenditure on health and education. In many African economies, particularly in Sub-Saharan Africa, low employment transformation and widespread informal employment are prevalent (Fox et al., 2020, as cited in Fox and Signé, 2021).

Nuru and Zeratsion (2022), identified shocks to government spending using a vector autoregression model based on Cholesky identification. Their study found that shocks to government spending had a direct and significant impact on labor share in the first quarter.

The research presented in this section reveals a critical gap in the existing literature as it provides information on the interactive impact of investments in artificial intelligence and government expenditure on education on poverty in South Africa. To the best of our knowledge, no such empirical interaction has been observed in the specific context of South Africa between 2016q1 and 2022q1. Therefore, to address this research gap and contribute to the body of knowledge in this area, this study employs the Prais-Winsten AR(1) regression which takes care of the problem serial autocorrelation and heteroscedasticity in the error terms. The primary aim of this research is to provide policy recommendations that can assist South Africa in achieving the Sustainable Development Goal (SDG) of poverty eradication.

## METHODOLOGY

### 3.1 Empirical strategy

The empirical strategy that was employed in this study includes descriptive analysis, unit root test, matrix of correlations, normality indicators, Cusum stability test, and the Prais-Winsten Regression Model. The Prais-Winsten model becomes appropriate for this study considering its robustness in empirical estimation. For instance, according to Anarfo et al. (2017), Prais-Winsten estimation helps to eliminate the incidence of autocorrelation of type AR(1) in a linear model as well as heteroscedasticity in the error terms, mostly for time series regression analysis. The Prais-Winsten model is a modification of Cochrane-Orcutt model because it does not forfeit the first observation, thus creating more efficiency, reflecting a special scenario of feasible generalized least squares.

### 3.1 Empirical model specification

In order to empirically investigate the relationship between poverty and fiscal policy in South Africa, given investments in artificial intelligence, the following functional relation is specified

$$lhfc = f(pge\ lgai\ tgs\ gne\ bmg\ repo\ lgcf\ aie) \quad (1)$$

Subsequently, the econometric model takes the following:

$$lhfc = \alpha_0 + \alpha_1 pge + \alpha_2 lgai + \alpha_3 tgs + \alpha_4 gne + \alpha_5 bmg + \alpha_6 repo + \alpha_7 lgcf + \alpha_8 aie + \epsilon_t \ldots \quad (2)$$

### 3.2 Data

We collected annual time series data from four sources: The World Development Indicators (WDI), the Organization for Economic Cooperation and Development (OECD) database, the South African Reserve Bank (SARB) and the African Development Bank (AFDB). Specifically, data on the percentage of GDP spent on education (pge), household final consumption expenditure (lhfc), and gross capital formation (lgcf) were obtained from the AFDB. Additionally, data on investments in artificial intelligence (lgai) was obtained from the OECD, while taxes on goods and services (% of revenue) (tgs), broad money (%of GDP) (bmg) and Gross national expenditure (% of GDP) (gne) were obtained from the WDI. A missing data point for 2022 in respect of tgs was obtained through interpolation before quarterly transformation. Studies that have used this technique include those of Saba and Ngepah (2019, 2022a, 2022b, 2022c). Finally, repo rates were obtained from the SARB. The central focus of the study, among others, is to evaluate the effect of investments in artificial intelligence on the poverty level in South Africa. Consequently, the data sets across the variables were selected based on the data availability on investments in artificial intelligence in which South Africa has data running from 2016. Therefore, data covers the period from 2016 to 2022. However, given the limited range of data, a quarterly transformation of all the variables was done through the use of e-views, which resulted in 25 observations each.

## EMPIRICAL RESULTS AND DISCUSSION

Table 1 presents the summary statistics for the variables under consideration. The series of lhfc, pge, lgai, tgs, gne, bmg, repo, lgcf and the interaction term, aie exhibit the mean of 11.381, 5.987, 7.691, 33.414, 97.758, 68.785, 5.73, 10.748 and 46.179 respectively. The variables' minimum and maximum values range between 3.5 and 99.549, respectively. Skewness analysis reveals that all the variables are negatively skewed except pge and bmg. Among the negatively skewed distribution, lhfc, tgs, gne, repo, lgcf and aie are relatively normally distributed as well as the positively skewed variables of pge and bmg.

Table 2 presents the results of the unit root tests for all the variables under investigation. This step is crucial in empirical studies to prevent the issue of spurious regression. The study specifically utilized the Augmented Dickey-Fuller test (ADF) evaluated on the basis of the constant option. Upon examination of the table, the variables exhibit a combination of the I (1) and I (0) series, and the variables are therefore relevant for examining the relationship between artificial intelligence and poverty in South Africa.

**Table 1.** Descriptive Statistics

| Variables | Obs | Mean | Std. Dev. | Min | Max | p1 | p99 | Skew. | Kurt. |
|---|---|---|---|---|---|---|---|---|---|
| lhfc | 25 | 11.381 | .032 | 11.311 | 11.416 | 11.311 | 11.416 | -.713 | 2.284 |
| pge | 25 | 5.987 | .404 | 5.444 | 6.562 | 5.444 | 6.562 | .259 | 1.551 |
| lgai | 25 | 7.691 | .484 | 6.146 | 8.332 | 6.146 | 8.332 | -1.309 | 5.268 |
| tgs | 25 | 33.414 | .509 | 32.436 | 34.167 | 32.436 | 34.167 | -.447 | 2.08 |
| gne | 25 | 97.758 | 1.903 | 94.119 | 99.549 | 94.119 | 99.549 | -.649 | 1.834 |
| bmg | 25 | 68.785 | 2.712 | 66.145 | 74.117 | 66.145 | 74.117 | .431 | 1.655 |
| repo | 25 | 5.73 | 1.482 | 3.5 | 7 | 3.5 | 7 | -.723 | 1.634 |
| lgcf | 25 | 10.748 | .056 | 10.622 | 10.816 | 10.622 | 10.816 | -.529 | 2.327 |
| aie | 25 | 46.179 | 5.549 | 33.461 | 54.678 | 33.461 | 54.678 | -.136 | 2.428 |

*Source:* Authors' computation

**Table 2.** Unit root test results

| Series | Levels | First Difference |
|---|---|---|
| Pge | | -1.846** (0.0412) |
| Lhfc | -2.639*** (0.0083) | |
| Ltd | | -1.975** (0.0324) |
| Pg | -2.620*** (0.0087) | |
| Lgcf | -1.746** (0.0489) | |
| Lgai | -1.969** (0.0323) | |
| Tgs | -2.796*** (0.0060) | |
| Bmg | | -2.666*** (0.0081) |
| repo | | -1.959** (0.0333) |
| Gne | -2.239** (0.0190) | |

*Source:* Authors' computation

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Table 3 displays the matrix of correlations as this becomes crucial in order to evaluate the level of associations among the variables. The metric of poverty, lhfc has a direct association with government expenditure on education, investments in artificial intelligence, taxes on goods and services, gross capital formation, and the interacted term, aie. On the other hand, lhfc negatively correlates with gne, bmg, and the repo rates. The level of correlations of lhfc and the foregoing variables are relatively minimal. Other variables also show various combinations of associations. For instance, pge directly relates with lgai,tgs, bmg and aie but negatively relates with gne, repo rates, and lgcf. A direct association is the field day between investments in artificial intelligence and tgs, bmg, and aie while inversely relates with gne, repo rates, and lgcf. While Taxes on goods and services negatively correlate with gne and repo rates, it however positively relates with bmg, lgcf, and aie. The association between gne, bmg, and aie is also negative but gne has a positive association with repo rates and gross capital formation. Broad money growth directly relates with aie but inversely relates with repo rates and gross capital formation. Moreover, repo rates directly relate with gross capital formation but inversely relate with aie, while gross capital formation negatively correlates with the interaction term aie. The lag length of the respective variables occupied Table 4 which shows all the variables exhibited a lag length of 2 each. The unit root was consequently evaluated on the basis of the lags.

**Table 3.** Matrix of correlations

| Variables | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| (1) lhfc | 1.000 | | | | | | | | |
| (2) pge | 0.351 | 1.000 | | | | | | | |
| (3) lgai | 0.611 | 0.722 | 1.000 | | | | | | |
| (4) tgs | 0.706 | 0.447 | 0.488 | 1.000 | | | | | |
| (5) gne | -0.029 | -0.857 | -0.681 | -0.083 | 1.000 | | | | |
| (6) bmg | -0.124 | 0.841 | 0.558 | 0.181 | -0.862 | 1.000 | | | |
| (7) repo | -0.337 | -0.916 | -0.705 | -0.335 | 0.865 | -0.724 | 1.000 | | |
| (8) lgcf | 0.436 | -0.670 | -0.283 | 0.075 | 0.787 | -0.939 | 0.593 | 1.000 | |
| (9) aie | 0.502 | 0.941 | 0.913 | 0.492 | -0.844 | 0.763 | -0.892 | -0.532 | 1.000 |

*Source:* Authors' computation

**Table 4.** Lag length

| Variables | Length |
|---|---|
| Pge | 2 |
| Lhfc | 2 |
| Lgcf | 2 |
| Lgai | 2 |
| Bmg | 2 |
| Tgs | 2 |
| Repo | 2 |
| Gne | 2 |

*Source:* Authors' computation

### 4.1 Prais Winsten AR (1) regression

Table 5 displays the empirical estimates of the effect of the respective variables on household consumption, a proxy for poverty. Our findings show that government expenditure on education, investment in artificial intelligence, gross national expenditure, broad money growth, gross capital formation, and the interacted term of aie significantly affect household consumption and, therefore, the poverty level in South Africa.

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Specifically, a unit increase in government expenditure on education and investments in artificial intelligence decrease household consumption, which implies that the poverty level increases by 0.194 and 0.163, respectively. On the other hand, the poverty level respectively falls by 0.007 and 0.014 due to a point increase in gross national expenditure and broad money growth. Moreover, a one percent rise in gross capital formation was established to generate a 1.022 percent increase in household consumption, which invariably implies a decline in poverty. Finally, an effort was made to create a new variable by interacting investments in artificial intelligence and government expenditure on education with a view to assessing the probable impact of an educational system that is AI-fortified on the level of poverty in the country. Our observation on the interacted term shows that a unit increase in aie increases household consumption by 0.031 and, by implication, reduces poverty in South Africa. The overall model has an F-test of 883.666 at a p-value of 0.000 which is statistically significant.

**Table 5.** Prais-Winsten AR(1) regression

| lhfc | Coef. | St.Err. | t-value | p-value | [95% Conf | Interval] | Sig |
|---|---|---|---|---|---|---|---|
| pge | -.194 | .074 | -2.62 | .018 | -.351 | -.037 | ** |
| lgai | -.163 | .053 | -3.05 | .008 | -.276 | -.05 | *** |
| tgs | .001 | .002 | 0.55 | .589 | -.003 | .005 | |
| gne | .007 | .001 | 6.03 | 0 | .004 | .009 | *** |
| bmg | .014 | .003 | 4.30 | .001 | .007 | .021 | *** |
| repo | -.002 | .001 | -1.20 | .246 | -.005 | .001 | |
| lgcf | 1.022 | .122 | 8.37 | 0 | .763 | 1.281 | *** |
| aie | .031 | .009 | 3.36 | .004 | .011 | .051 | *** |
| Constant | -.25 | 1.229 | -0.20 | .841 | -2.854 | 2.354 | |

| | | | |
|---|---|---|---|
| Mean dependent var | 11.381 | SD dependent var | 0.032 |
| R-squared | 0.998 | Number of obs | 25 |
| F-test | 883.666 | Prob > F | 0.000 |
| Akaike crit. (AIC) | -227.687 | Bayesian crit. (BIC) | -216.717 |

*** *p<.01*, ** *p<.05*, * *p<.1*
Rho = -.005
Durbin–Watson statistic (original) = 1.957405
Durbin–Watson statistic (transformed) = 1.956524

*Source:* Authors' computation

### *5.0. Discussion of the empirical results*

This section situates the empirical findings within the ambit of the previous studies. Our findings show that increasing investments in artificial intelligence reduces household consumption. The implication of the foregoing is an increase in the level of poverty.

The effect of investment in artificial intelligence in reducing household consumption and by implication, increasing poverty may be attributed to the displacement of workers by advanced technology. Additionally, the relatively low skill levels of the population compared to advancements in artificial intelligence could hinder labor employment, resulting in reduced income and constrained household consumption, thereby exacerbating poverty levels. The negative influence of artificial intelligence on household consumption in South Africa contradicts the findings of Mhlanga (2021), who examined the impact of artificial intelligence on achieving sustainable development goals, with a focus on poverty reduction, industry, innovation, and infrastructure development in emerging economies. Using content analysis, the author observed that artificial intelligence has a substantial impact on SDGs, particularly in reducing poverty and improving the reliability of infrastructure, such as transportation, leading to potential economic growth and development in emerging countries. The author noted that artificial intelligence contributes to poverty reduction by enhancing data collection for poverty-related assessments and promoting agricultural and financial sector development through financial inclusion. Furthermore, the empirical findings show that government expenditure on education reduces household consumption and thus increases poverty. This contradicts the expectation of a higher income-generating capacity arising from the acquisition of human capital through government expenditure on education. This could possibly be a result of the challenges in efficiently channeling public funds to intended projects. A comparable study is that of Sayyidina et al. (2023), which evaluated, with respect to Eastern Indonesia, the impact of government expenditure in the education sector, human development index, and economic growth on poverty rates. By utilizing multiple linear regression techniques in a panel comprising 13 provinces, the author found, among others, a negative, non-significant effect on poverty of government spending in the education sector. Furthermore, the empirical findings provide evidence that gross national expenditure and broad money growth result in an increase in household consumption and, invariably, a decline in poverty. The desirable effect of government spending could be as a result of well-organized and efficiently channeled government resources to intended projects, which boosts productivity, enhances the income of households and consumption, and consequently reduces poverty in the country. Also, the desirable effect of money supply could be a result of a well-administered money supply by the SARB, which are effectively channelled to productive uses via the commercial banks

The result corroborates the findings of Anjande et al. (2022) in terms of government expenditure but contradicts in terms of money supply. The authors analyzed the effect of government spending and money supply in the alleviation of poverty in Africa by using 48 Sub-Saharan African countries over the span of 2001 to 2017. By utilizing the techniques of one-step and two-step system GMM, it was observed that government spending and foreign direct investment exert a significant negative impact on generating a decline in poverty while money supply exerts a direct effect on poverty.

The empirical findings also reveal that gross capital formation significantly increases household consumption and, therefore, reduces the level of poverty in South Africa. This scenario could be due to the development of capital formation in the country that is effectively utilized to boost productivity and employment and consequently decrease the level of poverty. A comparable result is the study of Akobeng, E. (2017) that analyzed the impact of gross fixed capital formation on poverty as well as investigated if the relationship between gross fixed capital formation and poverty can be enhanced by institutions. The study covered a panel of 41 Sub-Saharan African economies over the span of 1981-2010 as well as employed the dynamic two-step system generalized technique of moment estimator. The author established that gross fixed capital formation causes a decline in poverty, while institutions stimulate the link between gross fixed capital formation and poverty.

Furthermore, an empirical outcome of our finding also shows that interacting investments in artificial intelligence and government expenditure on education (a proxy for education) increase household consumption and, by implication, decrease poverty in South Africa. This is an indication that educational investments in the country that incorporate the technological revolutions of investments in artificial intelligence, which better equip the populace, will enhance their prospects for employment and income generation and consequently cause a decline in the poverty level.

The Prais-Winsten regression produced a Durbin-Watson statistic of 1.957, which implies that the null hypothesis of no serial auto-correlation cannot be rejected. Therefore, no correlation among the residuals enhances the reliability of the estimates. Subsequently, the skewness and Kurtosis tests for normality were examined as contained in Table 6. The test resulted in a probability of 0.175, which is not statistically significant. It implies that the null hypothesis that the model is normally distributed cannot be rejected, which is also supported by the Shapiro-Wilk test in Table 7, having a p-value of 0.427 which is not statistically significant. Furthermore, the normality test was also supported by the Jarque-Bera statistic of 1.567 with a p-value of 0.457.

Also, effort was made to run the usual ordinary least squares regression in order to assess the state of heteroscedasticity. The outcome is presented in 9. The p-value of 0.406, which exceeds the critical value of 0.05, shows that the null hypothesis that the model is homoscedastic cannot be rejected, which is also corroborated by the Breusch-Pagan/Cook-Weisberg test having a chi-square of 2.24 at a p-value of 0.134.

**Table 6.** Skewness and kurtosis tests for normality

| | | | | -----Joint test ----- | |
|---|---|---|---|---|---|
| Variable | Obs | Pr(skewness) | Pr(kurtosis) | Adj chi2(2) | Prob>chi2 |
| Residual | 25 | 0.2435 | 0.1843 | 3.48 | 0.1753 |

*Source:* Authors' computation

**Table 7.** Shapiro–Wilk W test for normal data

| Variable | Obs | W | V | Z | Prob>z |
|---|---|---|---|---|---|
| Residual | 25 | 0.96061 | 1.095 | 0.185 | 0.427 |

*Source*: Authors' computation

**Table 8.** Jarque-Bera statistics

| | |
|---|---|
| Jarque-Bera normality test | 1.567 |
| Chi(2) | .4568 |

*Source:* Authors' computation

**Table 9**. Cameron & Trivedi's decomposition of IM-test

| Source | chi2 | Df | P |
|---|---|---|---|
| Heteroskedasticity | 25.00 | 24 | 0.4058 |
| Skewness | 9.89 | 8 | 0.2728 |
| Kurtosis | 2.29 | 1 | 0.1299 |
| Total | 37.18 | 33 | 0.2823 |

*Source:* Authors' computation

**Tabel 9.** Breusch–Pagan/Cook–Weisberg test for heteroskedasticity

| | |
|---|---|
| chi2(1) | 2.24 |
| Prob > chi2 | 0.1343 |

*Source:* Authors' computation

Figure 1 presents the results of the stability test based on Cusum. In this case, the stability of our model is evident as it largely lies within the 5% bound with only a mild deviation. This indicates that our model was properly specified and that the results we obtained are dependable for making policy recommendations.

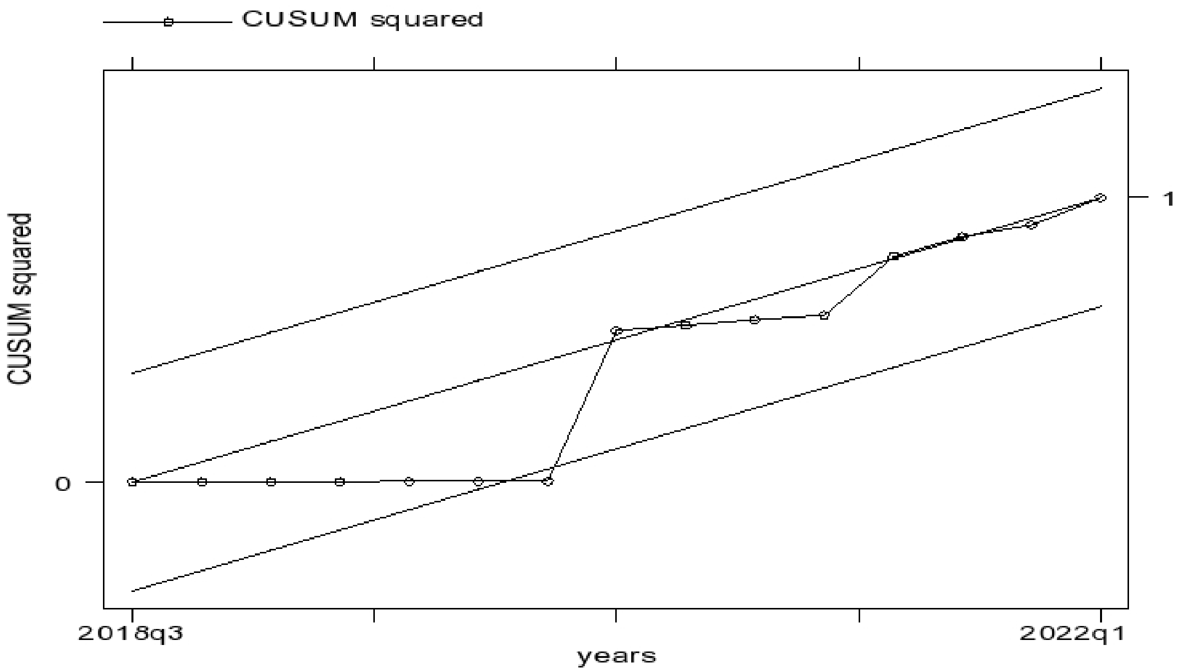


**Fig.1.** Stability test

## CONCLUSION AND POLICY RECOMMENDATIONS

The South African government is committed to achieving and sustaining Sustainable Development Goal (SDG) 1 of the United Nations, which focuses on eradicating poverty. However, the empirical research question on how to effectively harness the use of artificial intelligence (AI) and fiscal policy (especially the element of government expenditure) is yet to be addressed in the literature, particularly concerning the South African economy. Hence, this study examines the artificial intelligence investment-poverty-fiscal policy nexus for South Africa spanning 2016q1 to 2022q1. We employed the Prais-Winsten AR (1) regression. Specifically, this study used investment in artificial intelligence as a measure of the fourth industrial revolution, while also incorporating other variables such as government national expenditure, government expenditure on education, taxes on goods and services, repo rates, gross capital formation, broad money growth, household final consumption expenditure (to measure poverty) as well as the interaction of government expenditure on education and investments in artificial intelligence. We observe that government expenditure on education alone, rather than decreasing the poverty level, however, increases it. However, when government expenditure on education interacted with investments in artificial intelligence, it reduced poverty. This contributes to the literature by indicating that government expenditure on education that is AI-fortified will result in poverty reduction in the country. A similar conclusion also goes for investments in artificial intelligence, which increases the poverty level when not interacting with education in the country. We also conclude that the appropriate management of the major macroeconomic policy of fiscal and monetary policies is crucial for poverty reduction following the statistical significance of government expenditure on education, government national expenditure, and broad money growth. Moreover, we found gross capital formation to significantly increase household consumption and, therefore, reduce the poverty level in South Africa.

Based on the findings presented in this study, here are some policy recommendations within the context of South Africa: (i) address the issue of low skill levels among the population by investing in education and vocational training programs. This will help the workforce to adapt to technological advancements, including artificial intelligence, and reduce the risk of job displacement; (ii) the South African government should encourage the development and adoption of AI technologies in a way that prioritizes poverty reduction. This could involve supporting AI projects that focus on job creation and skill enhancement, particularly in sectors that are critical to South Africa's economy; (iii) sustaining the efficiency and transparency of government expenditure to ensure that public funds are channeled effectively into projects that benefit the population. This may involve enhancing governance, reducing corruption, and implementing better monitoring and evaluation mechanisms; (iv) the desirable impact of the money supply should be sustained through appropriate monetary policy by SARB that ensures commercial banks minimize to the barest minimum the incidence of asymmetric information in the management of fund supplied to the economy through the commercial banks; (v) the government should continuously monitor the impact of AI, government expenditure, and economic policies on household consumption and poverty levels. Be prepared to adapt policies as needed based on evolving circumstances and outcomes; (vi) the government should collaborate with international organizations and other countries to gain insights into effective strategies for addressing the challenges posed by AI and its impact on poverty; (vii) the government should invest in data collection and research to better understand the dynamics between AI, government expenditure, poverty, and household consumption. This is because informed policymaking relies on accurate and up-to-date information; (viii) the government should foster public awareness and participation in policy discussions and decisions related to AI and poverty alleviation. The government should engage with civil society organizations, experts, and the public to ensure that policies are well-informed and inclusive, and (ix) the government should reinforce the sustainability of capital formation that meets the productive needs of investors both in the private and public sectors.

The limitation of this study is that the availability of data on investments in artificial intelligence is of limited coverage, which was transformed to a quarterly frequency and, therefore, other variables. Therefore, with the availability of more data in years to come, future research should investigate whether the conclusions established in this study withstand empirical scrutiny within the availability of more streams of data to further enhance our current understanding of the research topic. This will be especially relevant for deriving additional policy recommendations and implications.

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