РОЗДІЛ 1.
ЕКОНОМІКА ТА МЕНЕДЖМЕНТ

1.FEJEZET.
GAZDÁLKODÁS ÉS MENEDZSMENT

CHAPTER 1.
ECONOMICS AND MANAGEMENT

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Felix ABERU
PhD, Department of Business Management,
College of Economics and Management Sciences,
University of South Africa (UNISA)
South Africa
ORCID ID: 0000-0002-6098-6591
e-mail: aberuf@unisa.ac.za
(Corresponding author)

Botha TERSIA
Professor, Department of Business Management,
College of Economics and Management Sciences,
University of South Africa (UNISA)
South Africa
ORCID ID: 0000-0003-4701-1009

ARTIFICIAL INTELLIGENCE, DISAGGREGATED UNEMPLOYMENT, AND SUSTAINABLE DEVELOPMENT IN SOUTH AFRICA: DOES THE ROUTINE-BIASED TECHNOLOGICAL CHANGE HYPOTHESIS EXPLAIN THE DYNAMICS?

Анотація. *У цьому дослідженні вивчається взаємозв'язок між впровадженням штучного інтелекту (ШІ) та дезагрегованим безробіттям у контексті визначення сталого розвитку Південної Африки на основі теоретичної концепції рутинно-зміщеного технологічного прогресу (RBTC). З використанням річних часових рядів за період 2003–2024 років та методу авторегресійних розподілених лагів (ARDL) у дослідженні одночасно оцінюються короткострокові та довгострокові коефіцієнти з метою відображення повної динаміки розвитку. Емпіричні результати підтверджують існування довгострокової рівноважної залежності між впровадженням ШІ, дезагрегованим за рівнем освіти безробіттям та сталим розвитком. У короткостроковому періоді впровадження ШІ негативно впливає на розвиток внаслідок витрат адаптації, пов'язаних із заміщенням рутинних завдань, жорсткістю ринку праці та невідповідністю навичок. У довгостроковому* *періоді ШІ робить позитивний і статистично значущий внесок у розвиток завдяки зростанню продуктивності та інноваційним ефектам після завершення структурних перетворень. Щодо безробіття за кваліфікаційними групами, безробіття серед висококваліфікованих працівників стабільно стримує розвиток в обох часових горизонтах, відображаючи витрати продуктивності від неефективного використання людського капіталу з високим рівнем освіти. Безробіття серед менш освічених працівників демонструє позитивну довгострокову залежність, що свідчить про ефекти структурного перерозподілу праці, узгоджені з положеннями концепції RBTC. Сукупне безробіття виявляється статистично незначущим, підтверджуючи, що агреговані показники приховують суттєві розподільчі відмінності між кваліфікаційними групами та валідуючи ключову теоретичну тезу про те, що рутинно-зміщений технологічний прогрес діє через гетерогенні канали, які залишаються невидимими на агрегованому рівні. Отримані результати є особливо актуальними для органів державної політики країн із ринками, що розвиваються, які стикаються з подвійним викликом прискорення технологічних трансформацій та стійкого структурного безробіття. Дослідження рекомендує впровадження інтегрованих політичних механізмів, що поєднують стимули для розвитку ШІ, реформування ринку праці та вдосконалення системи освіти, з метою забезпечення того, щоб технологічний прогрес сприяв інклюзивному та сталому розвитку.*

Ключові слова: *штучний інтелект, дезагреговане безробіття, сталий розвиток, Південна Африка.*

JEL Classification: J23, J24, O11, O33

Absztrakt. *A tanulmány a mesterséges intelligencia (MI) alkalmazása és a dezaggregált munkanélküliség közötti kapcsolatot vizsgálja Dél-Afrika fenntartható fejlődésének összefüggésében, a rutin jellegű feladatokra irányuló technológiai változás (Routine-Biased Technological Change, RBTC) elméleti keretére építve. A kutatás a 2003–2024 közötti időszak éves idősoros adatait, valamint az autoregresszív osztott késleltetésű modell (Autoregressive Distributed Lag, ARDL) módszerét alkalmazza, amely lehetővé teszi a rövid és hosszú távú együtthatók egyidejű becslését a fejlődési dinamika teljesebb feltárása érdekében. Az empirikus eredmények megerősítik a hosszú távú egyensúlyi kapcsolat fennállását a MI alkalmazása, az iskolai végzettség szerint dezaggregált munkanélküliség és a fenntartható fejlődés között. Rövid távon a MI alkalmazása negatív hatást gyakorol a fejlődésre, ami a rutinfeladatok kiváltásával, a munkaerőpiaci merevségekkel és a készségek közötti eltérésekkel összefüggő alkalmazkodási költségekkel magyarázható. Hosszú távon ugyanakkor a MI pozitív és statisztikailag szignifikáns módon járul hozzá a fejlődéshez a termelékenységnövekedés és az innovációs tovagyűrűző hatások révén, miután a strukturális alkalmazkodási folyamatok lezárulnak. A képzettségi csoportok szerinti munkanélküliség tekintetében a magasan képzett munkavállalók munkanélkülisége mindkét időhorizonton tartósan fékezi a fejlődést, ami a magas szintű humán tőke nem megfelelő hasznosításából eredő termelékenységi veszteségeket tükrözi. Az alacsonyabb iskolai végzettségű munkavállalók munkanélkülisége pozitív hosszú távú kapcsolatot mutat, ami a munkaerő strukturális átrendeződésének hatásaira utal, összhangban az RBTC-elmélet megállapításaival. Az összesített munkanélküliség statisztikailag nem bizonyult szignifikánsnak, ami megerősíti, hogy az aggregált mutatók elfedik a képzettségi csoportok közötti lényeges eloszlási különbségeket, és igazolja azt az alapvető elméleti tételt, hogy a rutin jellegű feladatokra irányuló technológiai változás heterogén csatornákon keresztül fejti ki hatását, amelyek aggregált szinten nem láthatók. Az eredmények különösen relevánsak azon feltörekvő gazdaságok szakpolitikai döntéshozói számára, amelyek egyszerre szembesülnek a technológiai átalakulás felgyorsításának és a tartós strukturális munkanélküliség kezelésének kettős kihívásával. A tanulmány olyan integrált szakpolitikai keretek bevezetését javasolja, amelyek ötvözik a MI fejlesztését ösztönző intézkedéseket, a munkaerőpiaci reformokat és az oktatási rendszer fejlesztését annak érdekében, hogy*

a technológiai fejlődés inkluzív és fenntartható fejlődési eredményekhez vezessen.
Kulcsszavak: *mesterséges intelligencia, dezaggregált munkanélküliség, fenntartható fejlődés, Dél-Afrika.*

Abstract. *This study examines the relationship between artificial intelligence (AI) adoption and disaggregated unemployment in determining sustainable development in South Africa, grounded in the Routine-Biased Technological Change (RBTC) framework. Using annual time-series data from 2003–2024 and the Autoregressive Distributed Lag (ARDL) modelling approach, the study simultaneously estimates short- and long-run coefficients to capture full developmental dynamics. Empirical results confirm a long-run equilibrium relationship among AI adoption, skill-disaggregated unemployment, and sustainable development. In the short run, AI adoption negatively impacts development due to adjustment costs from routine-task substitution, labour market rigidities, and skill mismatches. In the long run, AI contributes positively and significantly through productivity gains and innovation spillovers once structural adjustments are completed. Regarding skill-specific unemployment, highly educated workers' unemployment consistently impedes development across both horizons, reflecting the productivity costs of underutilised advanced human capital. Unemployment among less-educated workers shows a positive long-run relationship, suggesting structural labour reallocation effects consistent with RBTC predictions. Total unemployment proves statistically insignificant, confirming that aggregate measures mask critical distributional differences across skill groups, and thus validating the core theoretical proposition that skill-biased technological change operates through heterogeneous channels that remain invisible at the aggregate level. The findings are particularly relevant for policymakers in emerging economies facing the dual challenge of accelerating technological transformation and persistent structural unemployment. The study recommends integrated policy frameworks combining AI development incentives, labour market reform, and education strategies to ensure that technological progress translates into inclusive and sustainable development outcomes..*
Keywords: *Artificial Intelligence, Disaggregated Unemployment, Sustainable Development, South Africa.*

Problem description. South Africa faces persistent unemployment, high inequality, and slow structural changes coupled with the disproportionate impact of the introduction of technology, which are capable of challenging and threatening the progress of sustainable development goals such as decent work (SDG 8), reduced inequalities (SDG 10), and inclusive economic growth. For example, the exponential swift of Artificial Intelligence technologies is not unconnected to the reshaping pattern in the labour markets globally. Giving the Routine-Biased Technological Change (RBTC) hypothesis, technological innovations has the tendency to displace workers in routine, low to medium-skilled jobs, potentially increasing unemployment and inequality, if adequate adaptive measures are not in place. In South Africa, where a substantial portion of the workforce is engaged in routine or semi-skilled occupations, the proliferation of AI technologies presents a significant developmental challenge. The debate regarding whether AI will exacerbate labour market vulnerabilities or facilitate more sustainable and inclusive development pathways remains unresolved.

South Africa's development trajectory has been marked by high unemployment with a large share of the population employed in routine or semi-skilled work. Adoption of AI technologies at a labour force with high concentration in routine employment may result in developing countries falling into what can be described as a

Premature Automation Trap; automation of labour-intensive sectors before the country reaches optimal levels of income, institutional completeness, and workforce readiness. Labour-intensive sectors such as agriculture, logistics, and manufacturing are some of the last hopes of employment for low-skilled workers. Automation of these sectors before South Africa reaches comparable levels of development to advanced economies could lead to growing unemployment with no alternative source of employment. Such a rapid adoption of technology could grow the gap between the realities of the labour force and the level of technological readiness seen within the economy, therefore, capable of impeding development in the long-run.

Despite the increasing policy discussions, there is a paucity of empirical evidence on how AI-driven routine-biased technological change (RBTC) dynamics are manifesting within the unique socio-economic context of South Africa and Africa. [5] argued that there is a significant negative relationship between AI adoption and. Low-skilled employment, meaning that routine-task displacement is already observable in the labour market. AI, robotic process automation, and generative AI tools are increasingly replacing routine administrative [20]; apparently, this is generating concerns about potential job losses and the need for extensive workforce framework. It has also been argued by [16], that AI adoptions promote operating efficiency and product quality, but needs a workforce with more advanced technological competencies. Furthermore, [11] highlighted that in the automotive sector, AI adoption generates a continuum of job loss and job creation, this assertion also reflect the complex dynamics of automation-driven structural change. Therefore, the literature is limited in the documentation of the degree of disaggregated unemployment and AI influence on sustainable development most especially in Africa, and these has the propensity to inform policy identification problem which will in turn constrain South Africa's ability to design forward-looking employment, education, and innovation policies that align technological progress with sustainable development objectives.

Literature review. Existing scholarship on artificial intelligence, employment dynamics and sustainable development in South Africa is theoretically grounded, empirically diverse and conceptually rich, yet it remains fragmented in ways that open an important opportunity for novel research. Much of the work draws on the Routine-Biased Technological Change (RBTC) theory, originally advanced by [3], argues that technological progress particularly computerisation and automation tends to substitute tasks that are routine while complementing non-routine analytical or interactive tasks. AI technologies promote automation by enabling machines to perform both physical and cognitive routine tasks, thereby altering the distribution of employment and wages [2]. In the same vein, [6] adopted the RBTC framework and empirically shown that routine-intensive, middle-skilled jobs has long-run declines between 1997 and 2015 as technology became more prevalent. Their results aligned with international RBTC theory.

Supporting this theoretical strand, the majority of the extant literature captures the influence of AI rather than general automation on employment. [15], argues that robot introduction, is connected with displacement effects in manufacturing sector, though, further argued that jobs losses are balanced out by gains elsewhere, reflecting the central predictions of RBTC theory and reinforcing concerns about the future of work in developing economies. [13], uses quarterly data from 2012 to 2021, he found a significant negative long-run relationship between AI adoption and low-skilled employment in South Africa, and that AI-driven technological change is increasing the substitution of routine and low-skill labour. These empirical insights demonstrate that South Africa is not exempted from the associated labour-market disruptions informed by the technological change. Noticeably, the extant literature remains widely restricted to exploring employment effects without linking them to broader developmental implications. Furthermore, the labour-market literature, examines separate conceptual and empirical body on the role of AI in promoting sustainable development.

According to [18], AI can improve educational quality and institutional capacity within South Africa's higher education system; similarly, [25] affirmed that AI adoption improves resource efficiency and environmental performance, [12] found that many employees perceive AI as a threat to job security, with approximately 70% of white-collar workers showing concern over possible displacement. Furthermore, routine-intensive jobs in South Africa are vulnerable to automation, with potential associated threats to social inclusion and sustainable development [4]. More so, the reports of the [21] indicate that AI could increase South Africa's economic output by 6% over the next decade, but achieving this result depends on broad-based digital inclusion and effective labour market policies. [9] presented a conceptual investigation by exploring the possibility of AI accelerating SDG achievement in energy, healthcare, environmental management and governance, but with a caution on ethical risks and inequality.

Using a Vector Error Correction Model (VECM), [5] found a significant long-run negative relationship between AI adoption and low-skilled employment, implying that routine-task displacement is already observable in the labour market. Additionally, [20] examined the perceptions of senior human resource managers and reported that AI, robotic process automation, and generative AI tools are increasingly replacing routine administrative tasks, raising concerns about potential job losses and the need for extensive workforce upskilling. Although AI adoption enhances operational efficiency and product quality in the manufacturing sector, it also requires a workforce with more advanced technological competencies [16], thereby indicating the dual nature of AI's impact on employment. Similarly, the dynamics of AI adoption in South Africa's automotive sector may generate both job creation and job losses [11].

While these studies highlighted the risk of unemployment, they are limited to cover broader unemployment spectrum in line with sustainable development outcomes. Additionally, there exist limited understandings on how AI driven labour market transformations informs multidimensional development impacts, this is crucial in aligning technological adoption with the Sustainable Development Goals. More so, the extant literature ignores the dynamic and mediated pathways through which AI affects development. For example, [11], and [4] examined routine-job displacement; their study do not empirically model how such displacement interacts with unemployment dynamics to affect broader sustainable development indicators. Additionally, these studies show how Artificial Intelligent technologies is continually conceptualising sustainable development discourse; however, they fail to consider how labour-market disruptions stemming from AI-driven RBTC can offset or complicate these developmental benefits.

Therefore, this study increases the body of literature by looking at how AI, in conjunction with disaggregated unemployment influences work pattern and how these changes in the labour market impact sustainable development in South Africa. This integrated approach supports a genuinely innovative approach which reflects the reality on how AI affects development not only through innovation and productivity gains but also through its disruptive effects on work, livelihoods and economic opportunity in South Africa. Against this backdrop, this study examines the impacts of AI adoption and related labour market dynamics on sustainable development in South Africa.

Goals of the article. The aim of the study is to examine the extent to which AI adoption, and unemployment dynamics, affects sustainable development in South Africa, with a research question of how does AI adoption, unemployment dynamics influences sustainable development outcomes in South Africa?

Methods and methodology. The Routine-Biased Technology Change (RBTC) theory by [3] tries to explain how new technologies affect people. The RBTC theory says that technological progress has different effects on different types of jobs and tasks. This causes changes to be made to the differences in wages and jobs. The plan stresses how important daily work is for changing how the job market works. The RBTC theory says that automation is a great step forward in technology for everyday jobs that need both mental and physical work. Individuals may not be needed to do routine tasks that do not take a lot of skill if automation happens. This theory says that new technology changes different jobs and tasks in different ways. It changes the way daily jobs are done. This is easy to do because there are clear steps on how to use computers and other tools for everyday tasks. It is common to do things like work on a production line, enter data, and does office work. The theory argued that new technology usually makes it easier to do things that need imagination, problem-solving, and making tough choices. Jobs that pay more and require more knowledge, like management, creative, and professional duties, often come with tasks that are not done every day [22]. As technology gets better, it gets easier to automate daily tasks. For the jobs, this means that fewer people are needed to do them. People with routine jobs could lose their jobs or become unemployed if tasks are automated [14].

Furthermore, the theory says that the labour market might split into two groups because people do their daily jobs in different ways. Highly trained people whose jobs are in high demand and make more money because they are good at using new technology. But as machines take over, low-skilled workers who do the same things every day are losing their jobs and seeing their pay stay the same or go down. This split may make the wealth gap bigger because people with more skills get paid more quickly than people with less skill. The theory says that middle-skill jobs with repetitive tasks, like office and industrial jobs are more likely to be lost to technology [8]. The theory further buttresses that job specifications set the rules for the manufacturing process. There are three things that decide whether a job is given to a person or a computer: how automated it is; how easy it is to separate it from other tasks, and how much it costs to hire a machine instead of a person. "Machines" in this case can mean a lot of different kinds of technology, like hardware, software, and robots that do both. One important part of this way of thinking is the difference between skills and jobs.

The authors [1], say that a task is any work that leads to the creation of things and services. Additionally, they think that a skill is a group of abilities that let a person do many different things. As technology improves and wage costs rise or fall in relation to capital, people may change the work they do. The Routine-Biased Technological Change (RBTC) theory says that jobs can be put into two groups: routine and non-routine, and that change in technology affect the way different kinds of work are done. This splits the job market and changes the skills that are needed. This theory further argued that machines are more likely to do mental and physical jobs that people do all the time.

Non-routine chores, on the other hand, are less likely to be automated and more likely to be helped by technology [23]; Production function equation can be changed to take into account how new technologies affect the job market;

$$Y = \int_0^1 y \, \frac{\sigma-1}{\sigma} di \qquad (1)$$

Eq. 1 implies that AI increases sustainability in rule-based tasks; however, jobs can be done by labour or AI, hence; total output in the economy is a function of the tasks performed, considering the efficiency of labor and capital (AI) in different tasks

$$y\,(i) = \max[a_s(i)\, l_s(i), A\,(i)\, K\,(i)] \qquad (2)$$

Eq 2 shows that routine administrative, clerical and call-centre tasks can be automated, therefore AI can replace labour when automation is cheaper. Furthermore output from a task i is determined by the maximum of labour or AI-based production, depending on which is more efficient.

$$\frac{w_s}{a_s(i)} > \frac{r}{A(i)} \qquad (3)$$

Eq 3 implies that as AI improves, routine middle-skill jobs becomes more likely to be automated, hence, the share of tasks done by middle-skill workers starts shrinking, More so, comparing the cost of labour with the cost of AI for a given task, if AI becomes cheaper than labour, automation will take place

$$\frac{\partial I_M}{\partial A\,(i)} < 0 \qquad (4)$$

Eq 4 shows that automation reduces the number of tasks assigned to routine workers, thus, middle-skill wages are likely to fall; As AI improves, middle-skill (routine) jobs decrease in number, reflecting the shift away from these roles due to automation.

$$W_{s = \int_{iEI_s}^1 P\,(i)} a_s(i) \; \frac{\sigma-1}{\sigma} di \qquad (5)$$

The wages for middle-skill workers depend on the tasks assigned to them, influenced by the degree of automation in their roles. The disappearance of routine tasks informed Eq 6;

$$\frac{\partial W_M}{\partial A\ (i)} < 0 \qquad (6)$$

In Eq 6, middle-skill wages fall as AI replaces their tasks; however, high skill wages has the propensity to rise, while low skill wages is likely to remain unchanged. As automation increases, middle-skill wages decline due to fewer routine tasks being available for human workers.

$$\frac{\partial w_H}{\partial A\ (i)} > 0, \frac{\partial w_L}{\partial A\ (i)} \approx 0 \qquad (7)$$

From Eq 7, AI benefited high skill workers while offering limited gains for low skill workers, therefore. High-skill wages tend to rise with AI, while low-skill wages remain largely unchanged, reflecting the differential impact of automation.

$$E_{s=} \int_{iEI_s}^{1} l_s\ (i)\ di \qquad (8)$$

As routine task decline, middle skill employment decreases, low skill and high skill employment rises, and this implication would inform the shift of job opportunities to shift away from the middle skill workers, which will in turn integrates to impact sustainable development outcomes, therefore, employment in each skill group depends on the number of tasks assigned to that group, with middle-skill jobs shrinking as automation rises

$$SDG = \alpha E_L + \beta E_M + \gamma E_H \qquad (9)$$

Sustainable development outcomes (SDGs) are influenced by the employment levels of low, middle, and high-skill workers, weighted by their contribution to the economy

$$\frac{\partial SDG}{\partial AI\ (i)} = \alpha(+)+ \beta(-)+ \gamma(+) \qquad (10)$$

Eq 10 implies that the impact of AI on SDGs is mixed: it boosts high-skill employment, reduces middle-skill jobs, and has limited effects on low-skill workers, leading to mixed outcomes in terms of income inequality and unemployment.

Considering the objective of this study, the [3], model is adopted, this supported technological progress mostly computerisation and automation having the propensity to impact on routine tasks while complementing the non-routine tasks, thereby influencing the general employment pattern. Sustainable development (SD) is considered the dependent variable in the model, while AI and the disaggregated unemployment are the independent variables in the model.

The study covers 2003 to 2024; these periods capture AI advancement from research to widespread use, and also to investigate its hypothesis of boosting productivity and its adverse effects on reshaping jobs and skill demands. Hence, studying these relationship shows how technological progress can support growth while addressing unemployment, inequality, and skills gaps in South Africa. Using the Routine-Biased Technological Change (RBTC) framework in this study, makes it crucial to classify unemployment by educational level since technology is assumed to affect skill groups differently.

Workers with advanced education tend to perform abstract, non-routine tasks are complemented by new technologies, while those with basic education are more likely to be in routine or routine-manual jobs that are prone to automation. Using unemployment measures by education therefore allows the study to capture how technological change shifts labour demand unequally across group's dynamics that aggregate unemployment would hide.

The disaggregation also addresses a major gap in the existing literature, which often relies on total unemployment and overlooks how technological change can affects workers with different educational backgrounds. This can mask groups' experience of displacement or gains, which would impede policymakers in designing more targeted responses in retraining, skill upgrading, and education policy. In the study, SDG Index is used as a proxy for Sustainable development because it combines all 17 Sustainable Development Goals into a single measure, capturing economic, social, and environmental dimensions and thus reflecting the multidimensional nature of sustainable development. Furthermore, in the literature, ICT experience has been significantly argued to influence AI adoption. ICT acquaintance directly and indirectly boosts AI acceptance by shaping expectations [27].

Furthermore, [27] emphasises that both ICT experience and AI exposure predict adoption intention. Integrated AI-specific questions into ICT usage surveys, enables policymakers to track AI diffusion alongside digital infrastructure indicators. Robust ICT infrastructure, cloud platforms, broadband, are proxies for AI [17].

National AI strategies consistently identify ICT capacity as a prerequisite for AI diffusion [24]. Recent industry reports confirm that cloud readiness and secure networks are critical enablers for enterprise AI, [7]; [10].

Thus; the functional relationship among the variables is specified as follows:

$$lnSD_t = \beta_0 + \beta_1 AI_{t-1} + \beta_2 UNEWAE_{t-2} + \beta_3 UNEWBE_{t-3} \; UNETL_{t-4} + \varepsilon_t \quad (11)$$

Where:

$lnSD$ = Sustainable development is proxy by Sustainable development Index

AI = ICT Access and usage by industries

$UNEWAE$ = Unemployment with advanced education (% of total labour force with advanced education)

$UNEWBE$= Unemployment with basic education (% of total labour force with basic education)

$UNETL$= Unemployment, total (% of total labour force, national estimate)

β_0 = Intercept coefficient

$\beta_1 \ldots \beta_4$ = Slope coefficient

ε = Disturbance term

From Eq 1, the autoregressive distributed lag (ARDL) approach is used to determine the relationship among the variables. Thus, the model is expressed as follows;

$$SD_t = \delta_0 + \sum_{j=1}^{N_1} \emptyset_j \,\Delta SD_{t-j} + \sum_{j=0}^{N_2} \omega_j \,\Delta AI_{\,t-j} + \sum_{j=0}^{N_3} \eta_j \,\Delta UNEWAE_{t-j} + \sum_{j=0}^{N_4} \tau_j \,\Delta UNEWBE_{t-j}$$
$$+ \sum_{j=0}^{N_5} \vartheta_j \,\Delta UNETL_{t-j} + \delta_1 SD_{t-1} + \delta_2 AI_{t-1} + \delta_3 UNEWAE_{t-1} + \delta_4 UNEWBE_{t-1}$$
$$+ y_5 UNEWBE_{t-1} + \alpha ECT_{t-1} + \mu_t \qquad (12)$$

Here, the optimal lag lengths are denoted by N_1, N_2, N_3, and N_4, $N_5$with μ representing the disturbance term. The long-run estimates of the intercept and the independent variables are then derived as follows:

$$\varphi_0 = -\frac{\gamma_0}{\gamma_1}, \omega_1 = -\frac{\partial_2}{\partial_1}, \delta_2 = -\frac{\vartheta_3}{\vartheta_1}, \tau_3 = -\frac{\vartheta_4}{\vartheta_1}, \sigma_4 = -\frac{\vartheta_3}{\vartheta_1}\rho_5, \; and\; \theta_{ni} = -\frac{\sigma_5}{\sigma_1}$$

Given that

$$\Delta SD_{t-k} = \Delta AI_{\,t-j} = \Delta UNEWAE_{t-j} = \Delta UNEWBE_{t-j} = \Delta UNETL_{t-j} + \delta_1 = 0$$

occurs in the long term, hence, the error correction term for each variable is given as

$$ECT_{t-1} = SD_{t-k} - \theta_1 AI_{\,t-j} - \theta_2$$
$$Exch_{RATE\,t-1} - \theta_4 UNEWAE_{t-j} - \theta_5 UNEWBE_{t-j} - \theta_5 UNETL_{t-j}$$

which estimate the speed of adjustment to the long run equilibrium which can be confirmed when the coefficient of the error correction term, α, is negative and significant SDSN stands for Sustainable Development Solutions Network.

Table 1

Measurement and Variables Sources

Variable		Source(s)
Sustainable Development (SD)	Sustainable development is measured using the SDG Index, which combines normalised indicators across the 17 SDGs into a composite score from 0 to 100, where higher values indicate better performance.	(SDSN, WDI,OECD)
Artificial Intelligence (AI)	This is ICT access and usage by industries	(OECD)
Unemployment with advanced education (UNEWAE)	This are the categories of unemployment rate among people whose highest completed level of education is advanced (BSc, MSc, PhD, and Equivalent higher-education qualifications) in South Africa who are willing to work but not employed and are still searching for job, this is measured in percentage of total labour force	(WDI)
Unemployment with basic education (UNEWBE)	This is the category of unemployment rate among people whose highest level of education is basic education, usually primary education or lower secondary education in South Africa who are without job and are willing to work. It is measured in percentage of total labour force	(WDI)
Total Unemployment (UNETL)	This is the classes of the overall people who are unemployed in South Africa, regardless of their education levels. It measures the percentage of the entire labour force including all working-age people who are working or still looking for job.	(WDI)

Source: authors compilations

SDG Index that is provided by SDSN is internationally accepted as the most holistic representation of country level achievements of SDGs. It combines information from various indicators to provide an overall score on the performance against SDGs. OECD stands for Organisation for Economic Co-operation and Development. OECD has provided internationally comparable and reliable data on ICT use and access across industries to understand its adoption.

Since AI technology use is an important component of technological transformation across industries, the data has been taken from OECD.

WDI stands for World Development Indicators.

The World Bank's [26] WDI is used as it is one of the most commonly accessed databases for labour market statistics, specifically unemployment rates across the world. It has the most detailed and comparable data for various kinds of unemployment present for the countries. Data from these sources were extracts of different years up to 2023.

Results and discussions. This section discussed the empirical results of the study; starting from the pre-estimation descriptive, unit root, multicollinearity tests, main estimation (ARDL techniques) and the post-estimation (Breusch–Godfrey LM, Breusch–Pagan–Godfrey, CUSUM, CUSUMSQ tests).

Table 2

Descriptive Statistics

	SD	AI	UNEWAE	UNEWBE	UNEWTL
Mean	16.12934	76.98875	11.51381	36.23800	29.44400
Median	15.61793	77.86000	11.32750	35.68450	28.84250
Maximum	19.16876	78.08000	14.78300	40.73600	34.00700
Minimum	12.34554	72.80000	7.333000	29.21100	24.56100
Std. Dev.	1.910993	1.674626	2.736729	4.266655	3.729082
Skewness	-0.197517	-1.410390	-0.174300	-0.117729	-0.025790
Kurtosis	2.608731	3.580337	1.443669	1.402325	1.273575
Jarque-Bera	0.412190	11.05812	3.391583	3.477343	3.977603
Probability	0.813756	0.003970	0.183454	0.175754	0.136859
Sum	516.1389	2463.640	368.4420	1159.616	942.2080
Sum Sq. Dev.	113.2088	86.93555	232.1802	564.3347	431.0877
Observations	32	32	32	32	32

Source: authors compilations

The descriptive statistics show that sustainable development (SD) indicators in South Africa remain relatively stable over the study's period, with moderate variability, as reflected by a mean of 16.13 and a standard deviation of 1.91.

Artificial intelligence (AI) usage performed consistently high levels, although its strong negative skewness and significant Jarque–Bera test indicate a non-normal distribution, suggesting uneven or rapid shifts in AI uptake over the years. Unemployment patterns reveal a clear skills-based divide: unemployment among individuals with basic education (UNEWBE) is significantly higher (mean 36.24%)

and more volatile than unemployment among those with advanced education (UNEWAE), which averages 11.51%.

Table 3

Summary Statistics (Levels)

Variable	Mean	Median	Maximum	Minimum	Stand Dev	Skew	Kurt
SD	7.65	2.61	19.17	12.35	1.91	-0.20	2.61
AI	35.63	11.06	78.08	72.80	1.67	-1.41	3.58
UNEWAE	5.84	3.39	14.78	7.33	2.74	-0.17	1.44
UNEWBE	16.79	4.27	40.74	29.21	4.27	-0.12	1.40
UNEWTL	13.99	3.98	34.01	24.56	3.73	-0.03	1.27

Source: authors compilations

The total unemployment (UNEWTL) also remains high at a mean of 29.44%, implying persistent structural labour-market challenges. Most unemployment variables approximate normal distributions and show mild negative skewness, implying that higher unemployment values occur more frequently. Overall, the descriptive results align with the routine-biased technological change hypothesis, as AI adoption appears to affect low-skilled workers more severely, while sustainable development outcomes show moderate fluctuation possibly influenced by labour-market dynamics.

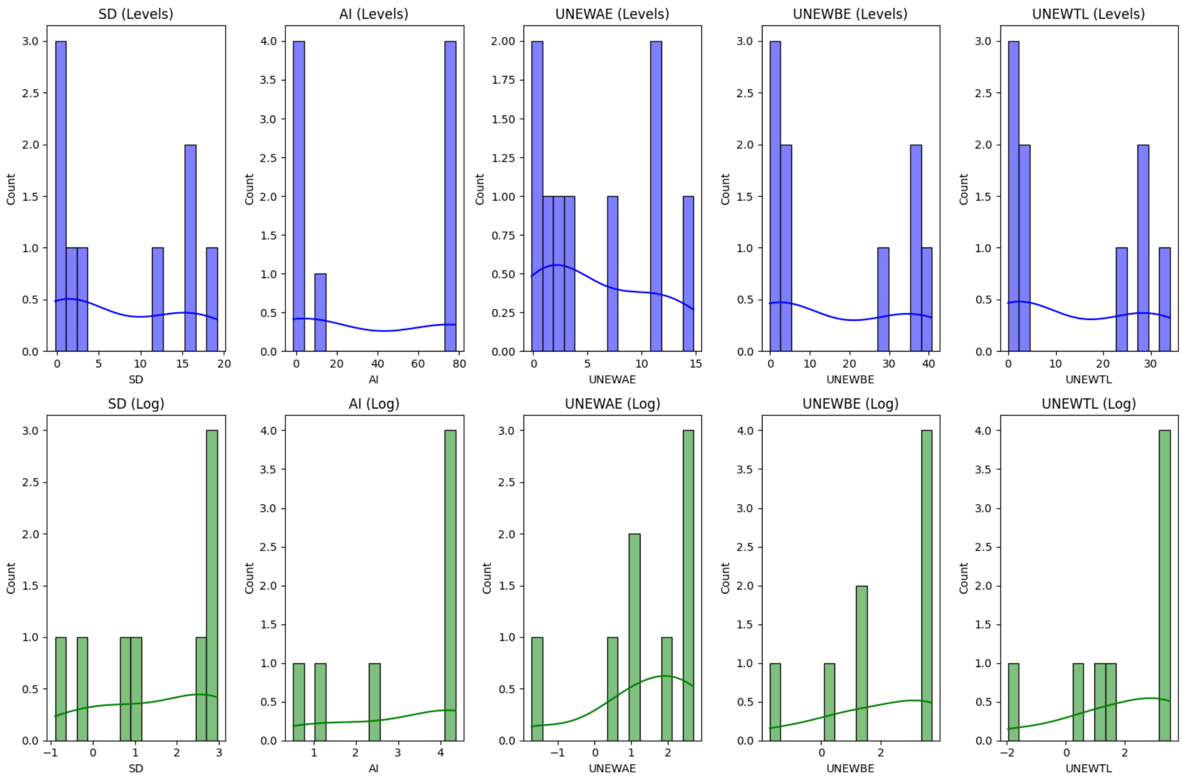

Fig. 1. Descriptive plots

Source: authors compilations

Table 5 shows the results of the unit root test for five variables: SD, AI, UNEWAE, UNEWBE, and UNEWTL. Variables such as SD, AI, and UNEWTL are I (1), which means they are not stationary at levels but become stationary after first differencing. On the other hand, UNEWAE and UNEWBE are I (0), which means they are stationary at the level and don't need to be differenced. Hence, the appropriate model of estimation is ARDL [19], thus;

$$\Delta lnD_t = \beta_0 + \sum_{g=1}^{ni} \beta_1 \, \Delta lnSD_{t-g} + \sum_{g=0}^{ni} \beta_2 \, \Delta lnAI_{t-g} + \sum_{g=0}^{ni} \beta_3 \, \Delta \, ln \, \text{UNEWAE}_{t-g} + \sum_{g=0}^{ni} \beta_4 \, \Delta \, ln \, \text{UNEWBE}_{t-g} + \sum_{g=0}^{ni} \beta_5 \, \Delta \, ln \, \text{UNEWTL}_{t-g} + \varepsilon_t \quad , \qquad (14)$$

where Δ means the first difference operator, η_i= 1...5, however, other variables assumes initial definitions.

Table 6 shows the best ways to choose the lag length. The LogL is -128.46 at lag length 0, and the FPE is 0.056, which means that the fit is not as good as it could be. The AIC and SC values are also greater. At lag length 1, the LogL goes up to 65.49, the LR statistic goes up a lot, and both the FPE and AIC decreases, which means that lag 1 is the best model fit. Hence, based on the selection criteria, lag 1 is the best choice.

Table 6

Optimal Lag Length Selection Criteria

Lag Length	LogL	LR	FPE	AIC	SC	HQ
0	-128.457	NA	0.056	8.137	8.3952	8.211
1	65.493	315.721*	8.45e-09*	-1.247	* 0.560*	-0.775*

Source: authors compilations

The Bound Test Approach

The Bound Test Approach (ARDL) helps in this study to check for long-term correlations and cointegration across variables in the model, irrespective of level of integration orders, and preferred to standard tests like Johansen or Engle-Granger. The test utilises an F-statistic compared to critical bounds [19]. Thus;

H_0: β_1= β_2= β_3= β_4= β_5 = 0. This implies that there is no cointegration among variables

H_1: $\beta_1 \neq \beta_2 \neq \beta_3 \neq \beta_4 \neq \beta_5 \neq 0$. Cointegration exists among variables in this case

Table 7

Bound Test Result

F-Statistic	1% Lower Bound	1% Upper Bound	5% Lower Bound	5% Upper Bound	10% Lower Bound	10% Upper Bound
6.681599	2.89	4.12	2.18	3.42	1.99	3.10

Source: authors compilations

Since the F-statistic in Table 7 exceeds the upper bound at all significance levels (1%, 5%, and 10%), we can conclude that there is cointegration between the variables in the regression model, indicating a long-run relationship**.**

Table 8

Long-Run Relationships (ARDL)
Dependent Variable: δSD

Variable	Coefficient	Std. Error	t-Statistic	Prob.
$\delta\Delta ln$ AI	1.040	3.067	-0.339	0.043
$\delta\Delta ln$UNEWAE	-2.215	1.647	-1.345	0.010
$\delta\Delta ln$ UNEWBE	1.611	2.363	0.682	0.050
$\delta\Delta ln$ UNEWTL	2.317	4.166	0.556	0.583
Constant	-0.463	0.087	-5.299	0.000

*Note: *(**) (***) means 1% (5%) (10%) significance level respectively*
Source: authors compilations

Artificial intelligence maintains a statistically significant long-run association with sustainable development, with a coefficient of 1.040 (p = 0.043). Nevertheless, the level of significance suggests the persistent influence of AI on sustainable development, conditioned upon the structural and institutional factors. Therefore, without adequate absorptive capacity in South Africa, AI-driven growth may not automatically transform into sustainable development outcomes.

Unemployment with advanced education remains negative and statistically significant in the long run, with a coefficient of −2.215 (p = 0.010). This indicates that a 1% increase in skilled unemployment reduces sustainable development by more than 2% in the long run; underscoring the severe and lasting developmental cost of underutilising educated labour. This result provides strong empirical support for the RBTC hypothesis, suggesting that routine-intensive skilled jobs are increasingly vulnerable to automation.

Furthermore, unemployment with basic education has a positive and significant long-run effect, with a coefficient of 1.611 (p = 0.050). This suggests that long-term reductions in low-skill routine employment may be associated with structural transformation and productivity upgrading, provided displaced workers are absorbed elsewhere in the economy. Total unemployment remains statistically insignificant in the long run confirming that aggregate labour-market indicators obscure critical distributional effects. Hence, the practical implications of these findings remain crucial for South Africa, for instance, the magnitude and significance of the error-correction coefficient (−0.463; p = 0.000) imply that market forces alone are insufficient to rapidly correct AI-induced disruptions. This means that the South African government needs to take the initiative to speed up the changes that will lead to sustainable growth.

The short-run negative impact of AI (−0.481; p = 0.038) signals that unregulated AI diffusion increases the risk of job displacement and inequality, thereby raising pressure on social protection systems. Without complementary labour-market policies, the government faces higher fiscal costs through unemployment benefits and social grants.

Table 9

Short-Run Relationships (ARDL)
Dependent Variable: D*ln* (SD)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DLOG(AI)	-0.481	1.427	-0.337	0.039
DLOG(UNEWAE)	-1.025	0.436	-2.350	0.027
DLOG(UNEWBE)	0.745	1.272	0.586	0.563
DLOG(UNEWTL)	1.072	1.504	0.713	0.482
CointEq(-1)	-0.463	0.087	-5.299	0.000

*Note: *(**) (***) means 1% (5%) (10%) significance level respectively*
Source: authors compilations

The particularly large and significant coefficients for unemployment among the highly educated (−1.025; p = 0.027 in the short run and −2.215; p = 0.010 in the long run) indicate a serious policy failure. These results imply inefficient returns on public investment in higher education and heighten the risk of brain drain. Consequently, the government must urgently reform education curricula toward AI-complementary skills and strengthen innovation-driven employment pathways. Although the long-run positive coefficient for low-skill unemployment (1.611; p = 0.050) may reflect structural upgrading, it also poses a governance challenge. Without reskilling and active labour-market programs, displaced low-skill workers may become permanently excluded, exacerbating inequality and social instability.

Furthermore, the insignificance of total unemployment in both the short and long run suggests that aggregate employment targets are inadequate. The government must therefore design skill-specific, technology-sensitive labour policies to ensure that AI adoption supports inclusive and sustainable development in South Africa. Hence, the results indicate that AI-driven technological change, in the absence of targeted government intervention, risks undermining sustainable development in South Africa. The magnitude and significance of the estimated coefficients emphasise the need for coordinated policies in education, labour markets, and innovation to transform AI from a source of displacement into a driver of inclusive growth.

The error correction results as shown in Table 9 confirm the presence of a stable long-run relationship among sustainable development (SD), artificial intelligence (AI), and unemployment disaggregated by education levels. The coefficient of the ECT approximately confirmed that 46% of short-run deviations in sustainable development are corrected annually, although the relatively moderate speed of adjustment informed structural rigidity in the South African economy. In the short run, artificial intelligence negatively affects sustainable development, with a coefficient of −0.481, p = 0.039). The statistically significant results suggest that a 1% increase in AI adoption leads to an approximate 0.48% decline in sustainable development outcomes in the short term. This finding shows that AI adoptions initially generate adjustment costs, such as labour displacement and skills mismatch that outweigh immediate productivity gains, which supports the Routine-Biased Technological Change (RBTC) hypothesis, that predicted automation to substitute's routine tasks before complementary job creation occurs.

Unemployment among individuals with advanced education exhibits a strong negative effect on sustainable development in the short run, with a coefficient of −1.025 (p = 0.027). This implies that a 1% increase in unemployment among highly educated workers reduces sustainable development by approximately 1.02%. This result highlight the vulnerability of the skilled workers involved in routine cognitive tasks and suggests that their displacement has a disproportionate consequence on development outcomes due to their roles in innovation, productivity, and institutional capacity.

Table 10

Breusch-Godfrey Serial Correlation LM

F-statistic	2.819	Prob. F(2,23)	0.080
Obs*R-squared	6.102	Prob. Chi-Square(2)	0.447

Source: authors compilations

By contrast, unemployment among individuals with basic education has a positive but statistically insignificant short-run coefficient of 0.745 (p = 0.563), while total unemployment also remain insignificant (1.071; p = 0.482). The results show that short-run changes in the low-skilled or overall unemployment did not have an impact on long-run development during the study periods. This demonstrates that labour market composition matters more than total unemployment rates.

The Breusch–Godfrey test indicates no significant serial correlation in the residuals, as both the F-statistic (p = 0.080) and the Obs*R^2 statistic (p = 0.447) are greater than 0.05, so we fail to reject the null hypothesis at the 5% significance level.

Table 11

Heteroskedasticity Test: Breusch-Pagan-Godfrey

F-statistic	3.373	Prob. F(5,25)	0.618
Obs*R-squared	12.489	Prob. Chi-Square(5)	0.329
Scaled explained SS	19.505	Prob. Chi-Square(5)	0.942

Source: authors compilations

The Breusch–Pagan–Godfrey test indicates no evidence of heteroskedasticity, as all p-values (F = 0.6183, Obs*R^2 = 0.3287, Scaled SS = 0.9415) are greater than 0.05, so we fail to reject the null hypothesis of constant variance.

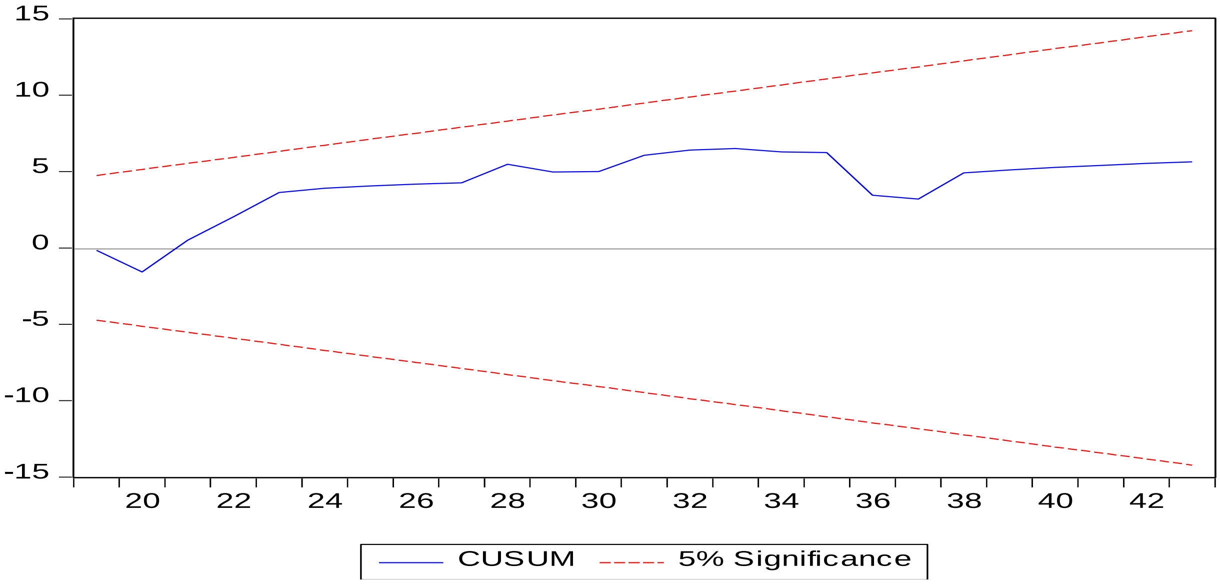

Fig 2. CUSUM test

Source: authors compilations

Fig. 2 show that there is no evidence of changes in the variability of regression residuals. This implies that the variance line remains within control limits. We can conclude that the homoscedasticity assumption has not been violated; that is, error variance has not changed over time and there have not been changes in the precision of the regression model.

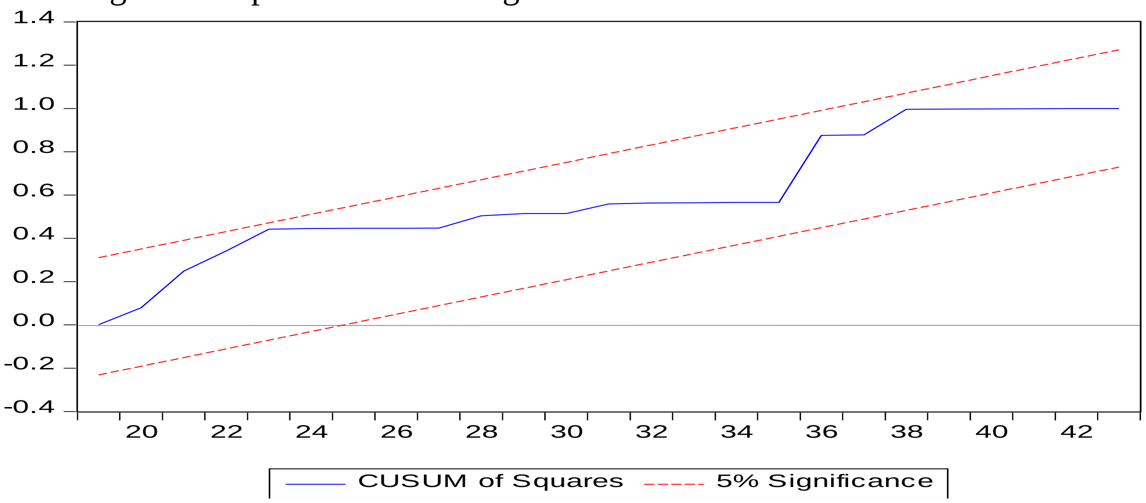

Fig 3. CUSUMSQ test

Source: authors compilations

Fig 3 shows the existence of stability in the variance of the regression residual. The CUSUM of Squares line continues to increase (since variance is only accumulating); it is contained within the control limits. This means that there is no significant increase or decrease in the variance of the model, which indicates that the predicted values of the regression model or mean are consistent with no structural break or shift in the data. Hence, there is no need for model re-specification.

Conclusions and prospects for further research. This study found that artificial intelligence is neither inherently favourable nor inherently harmful to sustainable development in South Africa; instead, its developmental impact depends critically on how labour-market transitions are managed. Anchored in the Routine-Biased Technological Change (RBTC) hypothesis, the empirical results show that AI adoption initially exerts negative impact on sustainable development through job displacement. These short-run adjustment costs are particularly severe in an economy already characterised by high unemployment and inequality. Also, AI contributes positively to sustainable development in the long run, showing that productivity gains and innovation effects can materialise once the economy adjusts with matching institutions being put in place. This study specifically aligned with the study of [5] and [4] who founds that routine-job displacement impact on growth. Furthermore, the study empirically improved the literature frontiers to demonstrates how such displacement influenced unemployment dynamics to affect broader sustainable development outcomes in South Africa

The disaggregated unemployment analysis provides deeper insight into these dynamics. Unemployment among individuals with advanced education significantly undermines sustainable development in both the short and long run, underscoring the high developmental implications of underutilising skilled labour in a technology-driven economy. The findings reflect the vulnerability of routine cognitive tasks to automation. Therefore, these findings recommend the need for a developmental strategy that explicitly integrates AI adoption with labour-market and education policies. Sustainable development cannot be achieved through technological diffusion alone; therefore, it requires deliberate policy coordination to mitigate displacement risks while enhancing the economy's absorptive capacity.

Education and training systems must therefore be reoriented toward AI-complementary skills that emphasise analytical reasoning, creativity, and problem-solving, ensuring that both current and future workers can adapt to changing task requirements. At the same time, active labour-market policies and reskilling programmes are essential to support workers displaced from routine tasks, preventing long-run exclusion and rising inequality. Additionally, AI strategies with national sustainable development objectives such as decent work, inclusive growth, and reduced inequality is therefore crucial. In this context, South Africa's ability to transform AI from a source of labour-market disruption into a driver of sustainable development depends on proactive government intervention, coordinated policy design, and sustained investment in human capital and innovation systems. Hence, future studies can deepen causality, advance measurements, and expand the theoretical and policy insights around Artificial Intelligent.

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