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The mediating role of governance in creating a nexus between investment in artificial intelligence (AII) and human well-being in the BRICS countries

Saba Charles[1], Pretorius Marinda[1]

1 *University of Johannesburg (South Africa)*

Corresponding author: Charles Saba (sabacharlesshaaba@yahoo.com)

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Abstract

The BRICS countries (Brazil, Russia, India, China, and South Africa) aim to achieve Sustainable Development Goals 3 and 16, which involve promoting human well-being for all and building strong institutions and governance. This study examines the AII-HWBG nexus contingent on governance indicators within the BRICS nations in 2012-2022 using the Cross-Sectional Augmented Autoregressive Distributed Lag (CS-ARDL) technique. Its findings reveal a long-term relationship among variables with varied causality directions and point to the necessity of integrating governance quality into AII to boost HWBG in both the short- and long-term perspective. Since AII has not so far been used to support HWBG there is a dire need for caution when considering AII's interaction with institutional governance, economic governance, control of corruption, political stability, regulatory quality and voice and accountability. The paper highlights the crucial role of governance quality in shaping the way AI investment impacts the human well-being. To ensure an overall improvement of well-being, priority should be given to strategies that promote positive synergy between AI investment and governance while mitigating possible harmful effects. Carefully targeted measures in governance areas can create an environment conducive to AI development where it will significantly benefit the citizens of the BRICS countries.

Keywords

Artificial intelligence investment; governance dimensions; human well-being; CS-ARDL technique; BRICS countries.

Аннотация

Страны БРИКС (Бразилия, Россия, Индия, Китай и Южная Африка) стремятся достичь Целей устойчивого развития 3 и 16, которые направлены на содействие человеческому благополучию для всех и построение сильных институтов и управления. В этом исследовании рассматривается взаимосвязь AII-HWBG в зависимости от показателей управления в странах БРИКС в 2012-2022 годах с использованием метода перекрестной расширенной авторегрессии с распределенным лагом (CS-ARDL). Его результаты показывают долгосрочную связь между переменными с различными направлениями причинно-следственной связи и указывают на необходимость интеграции качества управления в AII для повышения HWBG как в краткосрочной, так и в долгосрочной перспективе. Поскольку AII до сих пор не использовался для поддержки HWBG, существует острая необходимость проявлять осторожность при рассмотрении взаимодействия AII с институциональным управлением, экономическим управлением, контролем над коррупцией, политической стабильностью, качеством регулирования, правом голоса и подотчетностью. В документе подчеркивается решающая роль качества управления в формировании того, как инвестиции в ИИ влияют на благосостояние человека. Чтобы обеспечить общее улучшение благосостояния, приоритет следует отдавать стратегиям, которые способствуют положительной синергии между инвестициями в ИИ и управлением, одновременно смягчая возможные вредные последствия. Целенаправленные меры в сфере управления могут создать среду, благоприятствующую развитию ИИ, где он принесет значительную пользу гражданам стран БРИКС.

Ключевые слова

Инвестиции в искусственный интеллект; аспекты управления; благополучие человека; методика CS-ARDL; страны БРИКС.

JEL: O3, O43, O47.

1. Introduction

Until the middle of the 20th century, economic growth and income levels were primarily used to gauge a country's development. However, in recent times, the focus has shifted towards measuring human well-being or human development (Mishra & Nathan, 2014). This shift stems from the realization that economic growth and income levels alone may not accurately reflect a society's standards of living, human well-being, health and educational standards that need to be raised if we are to reduce poverty, create jobs, increase government revenues and improve the nation's competitiveness (Howarth, 2012; Bedir & Yilmaz, 2016). Since the 1960s, numerous countries have increasingly focused on improving the well-being of their citizens. According to Alatartseva and Barysheva (2016) and Veenhoven (2009), many nations now prioritize human well-being as a central element in their strategic and regional goals, aligning with UNDP's sustainable development goals. This shift underscores the growing recognition of the importance of well-being.

Both developed and developing countries have been the subjects of research into the drivers of their well-being, with the aim of helping nations achieve desirable levels of sustainable development in the context of globalization. To this day, economists disagree about how to define and measure human well-being. Alatartseva and Barysheva (2016) define well-being as *"subjective, multivalent, multifunctional, multi-aspected, contextual, situational, and polysemantic"* phenomenon. According to Rogers et al. (2012), the concept of human well-being encompasses various dimensions of individual and social well-being reflecting the holistic assessment of living conditions, happiness, and fulfilment. These dimensions are interrelated and together provide a comprehensive view of human welfare and societal progress that involve political voice, health, education, material living standards and other parameters (Rogers et al., 2012). The concept of human well-being has both subjective and objective dimensions. According to Kahneman et al. (1999), subjective well-being refers to an individual's feelings and self-perception, while, as noted by Clark (2014), objective well-being is linked to observable external factors such as education, physical health, the quality of one's surroundings and some others.

The primary goal of development is to enhance human well-being, which is closely linked to sustainable development (Steinberger & Roberts, 2010). Education (Ulucak et al., 2020), technological progress (Qin et al., 2023), and improvements in environmental quality and awareness ultimately contribute to human well-being and socioeconomic development. Balancing these aspects is crucial for any country's healthy and sustainable development. The relevant literature frequently employs the Human Development Index (HDI) as a yardstick for evaluating human and social well-being (United Nations Development Programme, 2021); this study follows suit by adopting it as a proxy for human well-being. HDI, a composite index incorporating life expectancy, education, and per capita income, serves as an effective measure of a country's overall well-being (Wang et al., 2019; Barrington-Leigh & Escande, 2018). A high HDI signifies superior health, education, and income levels. In essence, HDI plays a crucial role in assessing enhancements in human health and educational policies while providing insights into a nation's endeavors to foster skill development for technological progress (Badri et al. 2019). Scholars have increasingly examined the drivers of human well-being, including income, health, and education, which have dramatically grown in importance during the past century. This increased significance, however, has put pressure on the technological sphere that is closely tied to human activities and society as a whole (Qin et al., 2023). Previous research often focused on macro and micro economic variables, such as trade, foreign direct investment or employment; today, the scholars' attention is shifting to factors like investment in artificial intelligence and its implications for the human well-being.

Information and communication technologies (ICTs) have a profound impact on various aspects of human societies, including health, education, employment and many others. (Maiti & Awasthi, 2020). They influence the HDI through two primary mechanisms or channels. *First*, ICTs promote economic growth, enhance energy efficiency, and result in tangible productivity improvements in the real world (Zheng & Wang, 2022). *Second*, ICTs have powerful impact on people's daily lives. Sen (1999) defines human development as the *"expansion of freedoms that individuals* *experience*.", implying that ICTs are a predominant means by which people achieve their objectives and live meaningful lives (Robeyns, 2005). Time-saving, knowledge sharing, information accessibility, improved transparency and governance, and AI-driven automation are some of the ways in which advances in information and communication technologies (ICTs) have impacted human well-being (Maiti & Awasthi, 2020; Asongu & Nwachukwu, 2016). Artificial intelligence, with its rapid advancements in recent years, has the potential to transform industries, societies, and economies as it encompasses a range of technologies and applications that simulate human intelligence and perform tasks autonomously. Its potential benefits in areas such as automation, data analysis, and decision-making, may turn it into a powerful tool for enhancing productivity, efficiency, and innovation (Makridakis, 2017).

AI is revolutionizing human interactions and business practices, paving the way for the fourth industrial revolution (Lu, 2021). AI is becoming a vital technical tool for daily support in social and economic activities; its significant role in economic growth and sustainable economic development is increasingly recognized by business, academia, and government (Heylighen, 2017; Aghion et al., 2018). However, it does not guarantee human development for several reasons: (i) AI systems can inherit biases from their training data, possibly reinforcing existing inequalities and discrimination, (ii) AI-driven automation may result in job losses, particularly among low-skilled workers, potentially aggravating unemployment and inequality, and (iii) unequal access to AI and digital technologies can widen the digital divide, leaving marginalized communities behind. So, on the one hand, the expansion of economic activities boosts incomes and, consequently, human development. On the other hand, the growing concerns caused by AI deployment may exacerbate such problems as inequality, unemployment and thus have a detrimental impact on many aspects of people's existence.

To mitigate the adverse impact of AI on human development, governments can use a number of mechanisms: they can (i) enact regulations and establish oversight bodies to ensure that AI development conforms to ethical and safety standards; (ii) enhance transparency and accountability; (iii) design ethical frameworks for AI development and usage; (iv) invest in public awareness campaigns and educational programs to inform citizens about AI technologies, their benefits, and potential risks (Maiti & Awasthi, 2020). Governments could play a significant role in promoting investment in AI and its development as it will in its turn improve the human well-being (Davis, 2017; Sharma et al., 2020). Furthermore, good governance contributes to the creation of new job opportunities, thereby reducing poverty (Eichhorst et al., 2009; Kwon & Kim, 2014) and also raising living standards.

Conversely, poor governance is sure to have a negative impact on human well-being. According to Asongu and Nwachukwu (2016) and Davis (2017), to promote human development, it is crucial to establish good governance in economic, political, and institutional domains and that such governance should empower the populace and ensure accountability among decision-makers. The BRICS countries (Brazil, Russia, India, China, and South Africa) represent a diverse group of developing economies characterized by rapid technological advancements, varying levels of growth, and governance and institutional development. They often work together to address economic challenges, promote trade, and collaborate on global issues like climate change, security, and development (Khan, et al., 2017). As these nations strive for sustained economic growth and development, the interplay between artificial intelligence (AI) investment, governance, and their impact on human well-being (human development) becomes a topic of significant interest and importance.

This paper uses six governance indicators suggested by Kaufmann et al.'s (2010, 2011) (see Table 1). These indicators refer to (i) ''institutional governance", (ii) "political governance", and (iii) ''economic governance". Asongu and Nwachukwu (2016) define each dimension in accordance with Kaufmann et al.'s (2010, 2011) study as follows: "(i) institutional governance which is the respect of the State and citizens of institutions that govern interactions between them (measured with corruption-control and the rule of law); (ii) political governance which is the election and replacement of political leaders (proxied with political stability/no violence and voice and accountability) and (iii) economic governance, which is defined as the formulation and implementation of policies that deliver public commodities (measured with government effectiveness and regulation quality)" (p. 135).

According to Asongu and Odhiambo (2021) "(i) Political governance can affect human development because the principles of political stability, no violence", and "voice & accountability" contribute to the equitable distribution of constituents of the HDI. In the presence of political instability and violence, some conditions of human development, e.g. life expectancy, education or public wealth, are likely to be negatively affected. Moreover, "voice & accountability" principle is essential to enable the population to choose leaders that can improve the general well being. (ii) Economic governance (proxied with regulation quality and government effectiveness) is the formulation and implementation of policies which deliver public commodities that include education and health services. (iii) Institutional governance, related to control of corruption and the rule of law, concerns interactions between the State and the citizens. Its prime objectives should be supplying the public goods, first of all education and health services, and boosting economic prosperity, which reflects the income dimension of the HDI" (p. 75).

Figure 1 below is a graphical representation of the time paths of our main variables in the period of study, which, as one can see, are rather different. This fact indicates the need to investigate their interrelationships.

This paper aims to investigate the impact of AI investment on human well-being taking into account the mediating role of various dimensions of governance in the BRICS countries over the period of 2012-2022, which is important for several reasons. First, the BRICS countries represent some of the world's fastest-growing economies. They have been actively investing in AI technologies to improve performance of various sectors, from healthcare to manufacturing. Research into the governance dynamics in these economies is essential to understand how AI investments impact their socioeconomic development. Second, the BRICS nations exhibit diverse governance

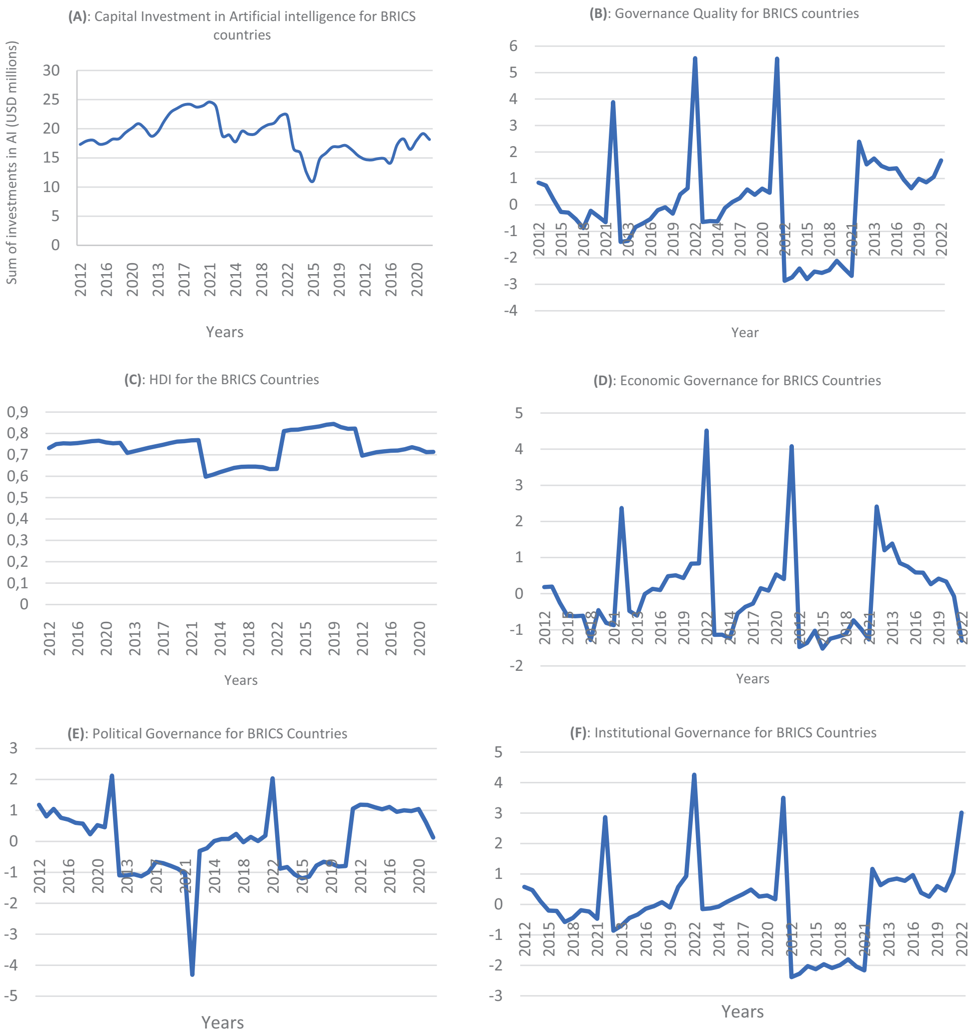

Figure 1. (**A**): Capital Investment in Artificial intelligence for BRICS countries (OECD database); (**B**): Governance Quality for BRICS countries (WGI database); (**C**): HDI for the BRICS Countries (UN database); (**D**): Economic Governance for BRICS Countries; (**E**) Political Governance for BRICS Countries; (**F**) Institutional Governance for BRICS Countries (B, D, E and F – Authors' estimations from PCA).

models, ranging from democratic to authoritarian systems. Studying the governance mediating role in AI investment allows us to find out how different governance indicators and structures influence the relationship between AI adoption and human well-being. This may also provide valuable insights into the global AI landscape with particular regard to developing countries. Third, AI investment is expected to substantially affect the human well-being through changes in employment, healthcare, education, and overall quality of life. Understanding how governance mechanisms mediate this impact is critical for policymakers who need to make informed decisions about AI adoption and regulation. Fourth, research focusing on the BRICS countries can generate ideas on how to address governance gaps and promote responsible AI deployment, which may subsequently be used to create policies that will maximize the benefits of AI, minimize potential harms and ultimately enhance the well-being of their populations. Fifth, as the BRICS countries are some of the major players in the global economy, their AI policies and practices have far-reaching implications for the global AI industry. Insights gained from studying these nations can therefore inform international discussions on AI governance, standards, and cooperation. Focusing on BRICS can contribute to shaping the global AI landscape by promoting ethical and sustainable AI practices.

The present study addresses a significant gap in the empirical literature in several ways. Firstly, it is the first endeavor to examine the impact of AI investment on the human well-being while considering various dimensions of governance. Secondly, although researchers have explored the influence of governance on human development, such studies are relatively scarce, and none could be found that specifically focused on the G-7 economies. Lastly, the study makes use of the novel Cross-Sectional Autoregressive-Distributed Lag (CS-ARDL) technique proposed by Chudik and Pesaran (2015), that helps to analyze the impact of AI investment on human well-being in relation to various governance dimensions over both short- and long-term periods.

This paper is structured as follows: Section 2 offers a literature review. The methodology and data are outlined in Section 3. Section 4 presents and discusses the findings of the empirical analysis. Section 5 outlines the policy implications. The study is brought to a conclusion in Section 6.

2. Literature Review

In empirical literature, researchers have examined the factors that influence the human well-being or human development, with some studies specifically concentrating on the role of governance. Human well-being has often been proxied using the Human Development Index (HDI). For instance, in a study focusing on the role of technological progress and ICT development, Qureshi et al. (2020) used the quantile-on-quantile regression technique to examine the technological innovation-human well-being nexus. Their findings confirmed that technological innovation had a positive impact on human well-being. Similarly, for the case of Indonesia, Haseeb et al. (2020) explored the globalization-income inequality-human well-being nexus between 1990 and 2016, with the results suggesting that globalization enhances human well-being. For the case of five South Asian countries, Iqbal et al. (2019) conducted a case study examining ICT- human development nexus in 1990-2016. Their panel results indicated that both internet and mobile phone usage contribute positively to human development. Using the Two-step system-GMM (SGMM) technique, Mirza et al.'s study (2020) explored the effects of ICT on inclusive human development, alongside other variables, across

81 developing countries in 2010 -2014. Its findings substantiate the positive influence of ICT on inclusive development. Using the non-linear ARDL technique for the case of India, Behera and Sahoo (2022) examined the ICT-globalization-human development nexus over the period of 1991-2019. The results revealed that the long-term human development benefited from increasing mobile phone density but suffered from declining internet density. Positive shocks in internet density from the previous year are advantageous in the short term, while those from the previous two years are detrimental. Negative shocks, with varying lags, affect human development in different ways.

Research has also delved into the impact of emerging technologies, including artificial intelligence (AI), on economic growth, human development, governance, employment and total factor productivity (TFP). As economic growth is closely linked to human well-being (Can et al., 2022), though not exclusively indicative of well-being improvement, it is crucial to review the studies exploring the AI-growth/development nexus. For example, Graetz and Michaels (2018) identified TFP as a significant transmission channel through which AI affects growth. The recent study of Lu (2021) developed the three-sector endogenous growth model to examine the growth and *welfare* effect of AI. Their findings show that the advancement of AI has the potential to enhance growth during the transitional dynamics phase and can contribute to short-term utility gains for households when AI accumulation results from increased productivity in the goods sector or AI sector. However, if AI accumulation is primarily driven by firms substituting human labor with AI, it may have adverse effects on short-term household utility.

Qin et al. (2023) conducted an analysis using evolutionary investigation and systematic review approaches, which examined papers related to the connection between AI and economic development. The study reveals that dedicated researchers in this field have established robust networks for collaboration and communication. Content analysis indicates that the predominant research areas are innovation, labor and capital, Industry 4.0, social governance, and intelligent decision-making. Smith and Neupane's (2018) paper investigates AI-human development nexus, highlighting three critical areas that require attention in the Global South to harness AI for development, namely: policies and regulations, inclusive and ethical AI applications, and infrastructure and skills. Benvenuti et al. (2023) explored the AI-human development nexus, particularly in the context of education acquisition. Their findings suggest that AI has the potential to support educators in nurturing creativity, fostering critical thinking, and promoting problem-solving skills within educational settings, contributing to some components of human well-being. Sharma et al. (2020) examine AI applications across various government sectors. They conducted a systematic review of 74 papers from relevant sources and found a relative lack of attention to AI's practical implementation in healthcare, ICT, education, social and cultural services, and the fashion sector.

Using the SGMM approach for the case of Sub-Saharan Africa (SSA), Asongu and Nwachukwu (2016) explored the governance-inclusive human development nexus related to mobile phone usage. Their findings suggest that governance indicators contribute to the convergence of inclusive human development and play a significant and positive mediating role in the impact of mobile phone usage on inclusive human development. Nam and Ryu (2023) analyzed the influence of governance on FDI-human development nexus in the Association of Southeast Asian Nations (ASEAN) member countries, and found that governance played a positive and significant mediating role in the nexus between FDI and human development. According to Sarkodie and Adams (2020), political system environment reduces human development in SSA. Park and Dreamson (2023), however, were able to establish that both HDI and governance played significant and positive roles in the ICT penetration in the economy of SSA. Asongu and Odhiambo (2021) employed SGMM and Tobit methods to investigate the income-governance-inclusive human development for SSA from 2000 to 2012. The results demonstrate that governance influenced by 'middle income' has a more significant impact on inclusive human development compared to governance driven by 'low income.'

It appears that so far there has been no study on the relationship between AI investment and the human well-being determined by the quality of governance, its dimensions or indicators. Nor has it been shown how general governance quality, dimensions or indicators affect human well-being in the BRICS countries. The present paper is looking into these issues with a view to identifying policy measures that could help the BRICS countries achieve the SDG 3 & 16, thus promoting human well-being for all and building strong institutions and governance.

3. Methodology and data

3.1 Empirical strategy

The initial empirical methodology employed in this research comprises various techniques, such as the principal components analysis (PCA), descriptive analysis, and scatter plot visualization. It also includes tests for panel unit root (both first- and second-generation), tests for slope homogeneity and cross-sectional dependence (CD), as well as CIPS panel unit root tests. The study also uses first- and second-generation panel cointegration tests, fully modified ordinary least squares (FMOLS), dynamic OLS (DOLS), and Dumitrescu-Hurlin (Dumitrescu & Hurlin, 2012) panel causality tests. To save space, given the word limitation of the journal, we do not include all the estimated equations for these econometric techniques because they are readily available in other empirical works. We focused our attention on the CS-ARDL econometric model which is our main estimation technique. Fig. 2 provides a visual representation of the methodological approach used in this study for the ease of reference.

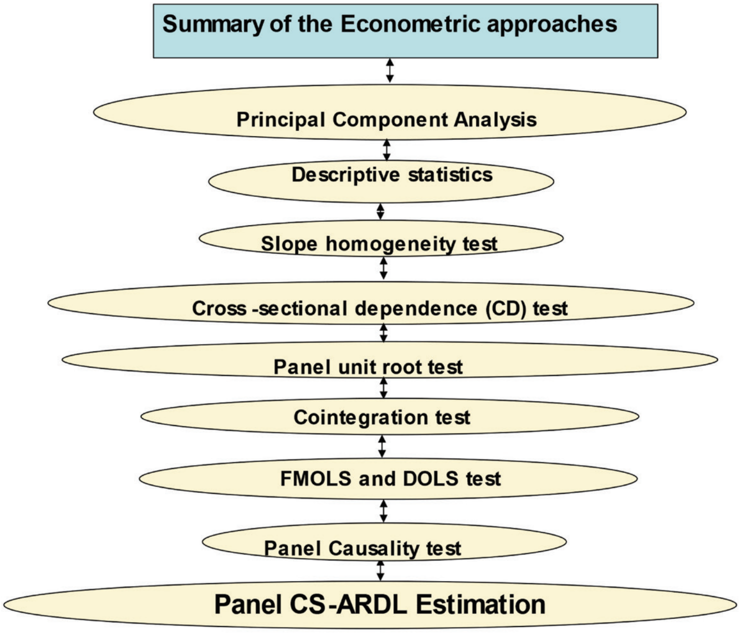

Figure 2. Summary of the Econometric Approaches

3.2 Theoretical underpinning and empirical model construction

Two normative perspectives underlie Sen's (1985) capacity assertion. Firstly, it asserts the moral necessity for individuals to possess the freedom to pursue happiness. Secondly, it contends that happiness should be assessed based on a person's capabilities and functioning. These capabilities encompass the diverse potential functions (such as actions/doings and achievements/doings) an individual can realize. Various activities and states that an individual can experience, such as maintaining good nutrition, entering into marriage, raising children, engaging in recreation, traveling, and others, are termed "functionings." Nussbaum's (2011) overarching capability approach is categorized into two groups: the first cluster concentrates on the comparative assessment of quality of life, while the second cluster addresses theories of justice. Both clusters emphasize human potential and adhere to five guiding principles: regarding each individual as a means, not merely an end; giving precedence to freedom and choice over accomplishments; valuing diversity of perspectives/values; addressing societal inequalities; and assigning certain powers to the government. On the one hand, the theory suggests that government plays a role in enhancing an individual's capabilities and functioning (Asongu & Nwachukwu, 2016) and so it is imperative to empirically investigate its impact on the Human Development Index, which serves as a proxy for human well-being in this study. On the other hand, human-AI collaboration theory argues that AI complements human capabilities rather than replaces them (Mateja & Heinzl, 2021). Human-AI collaboration can enhance productivity and problem-solving, contributing to improved human development outcomes (Mateja & Heinzl, 2021). The Capability Approach, developed by Amartya Sen, emphasizes that human well-being should be assessed based on an individual's capabilities and freedoms. Therefore, AI, when used effectively, can enhance people's capabilities by providing access to information, education, healthcare, and other essential services (Smith and Neupane, 2018; Järvelä et al. 2023; Benvenuti et al. 2023). This, in turn, can lead to improvements in human development (Smith & Neupane, 2018). The idea of "human development" draws from the capabilities approach and underscores practical implementation. Human development encompasses the expansion of individuals' opportunities and the level of their achieved well-being. Sen (2010) highlights that technological progress is pivotal in enhancing human freedoms and capabilities by increasing the productivity of people's work. To explore the impact of AI investment (AII) on human well-being, considering different governance dimensions in panel of BRICS nations from 2012 to 2022, we adapted empirical models from prior studies (see Pradhan, 2011; Asongu & Nwachukwu 2016; Njoh, 2018; Davis, 2017; Tran et al., 2021; Can et al., 2022; Behera & Sahoo, 2022; Uddin et al., 2023, among others) with appropriate adjustments. Therefore, the nexus between AII, OGV, and the Human Development Index (HDI) is represented in the following functional form. The fundamental econometric models, which were subsequently transformed into the CS-ARDL model and estimated, can all be found below:

$$HDI = f(AII, OGV) \tag{1a}$$

Where *HDI = Human Development Index proxy for human wellbegin* (*HWBG*).

AII = Artificial intellegence investment.

OGV = Over governance quality.

The functional form equation above can be linearized and augmented by incorporating other factors influencing human well-being, as indicated in the previously mentioned studies.

Model 1:

$$\begin{aligned} LHWBG_{i,t} = \beta_1 + \beth_1 LAII_{i,t} + \beth_2 LGDPPC_{i,t} + \beth_3 LEMPL_{i,t} + \beth_4 LHMN_{i,t} + \\ + \beth_5 \mathrm{OGVi,t} + \beth_6 \mathrm{LAII}_{i,t} * \mathrm{OGV}_{i,t} + \varepsilon_{1i,t} \end{aligned} \tag{1b}$$

Where □, $\beth_1$, ..., $\beth_4$, and ε_{it} represents the constants, coefficient and the error term, respectively. Model 1 excludes the interaction terms between: LAII and OGV; LAII and POLG; LAII and INSTG; LAII and ECOG; LAII*CRT; LAII*POLV; LAII*GEF; LAII*RQE; LAII*RLW; and LAII*VCAC while the rest of the models (that is, model 2-5) does in a systemic manner one after the other.

Model 2: *Capturing the interaction between* LAI and OGV

$$\begin{aligned} LHWBG_{i,t} = \beta_1 + \beth_1 LAII_{i,t} + \beth_2 LGDPPC_{i,t} + \beth_3 LEMPL_{i,t} + \beth_4 LHMN_{i,t} + \\ + \beth_5 OGV_{i,t} + \beth_6 LAII_{i,t} * OGV_{i,t} + \varepsilon_{1i,t} \end{aligned} \tag{2}$$

Model 3: *Capturing the interaction between* LAI and POLG

$$LHWBG_{i,t} = \beta_1 + \beth_1 LAII_{i,t} + \beth_2 LGDPPC_{i,t} + \beth_3 LEMPL_{i,t} + \beth_4 LHMN_{i,t} + \\ + \beth_5 POLG_{i,t} + \beth_6 LAII_{i,t} * POLG_{i,t} + \varepsilon_{1i,t} \tag{3}$$

Model 4: *Capturing the interaction between* LAI and ECOG

$$LHWBG_{i,t} = \beta_1 + \beth_1 LAII_{i,t} + \beth_2 LGDPPC_{i,t} + \beth_3 LEMPL_{i,t} + \beth_4 LHMN_{i,t} + \\ + \beth_5 ECOG_{i,t} + \beth_6 LAII_{i,t} * ECOG_{i,t} + \varepsilon_{1i,t} \tag{4}$$

Model 5: *Capturing the interaction between* LAI and INSTG

$$LHWBG_{i,t} = \beta_1 + \beth_1 LAII_{i,t} + \beth_2 LGDPPC_{i,t} + \beth_3 LEMPL_{i,t} + \beth_4 LHMN_{i,t} + \\ + \beth_5 INSTG_{i,t} + \beth_6 LAII_{i,t} * INSTG_{i,t} + \varepsilon_{1i,t} \tag{5}$$

We specify the CS-ARDL model below which took its bearing from the above equations:

$$\Delta LHWBG_{i,t} = \mathfrak{F}_i + \xi_i(LHWBG_{i,t-1} - \beth_i X_{i,t-1} - \beta_{1i}\overline{LHWBG}_{t-1} - \beta_{2i}\overline{X}_{t-1}) + \\ \sum\nolimits_{j=0}^{p-1} \gamma_{i,j}\Delta LHWBG_{i,t-j} + \sum\nolimits_{j=0}^{v-1} \Gamma_{i,j}\Delta X_{i,t-j} + \o_{1i}\Delta\overline{LHWBG}_t + \o_{2i}\overline{X}_t + u_{it} \tag{6}$$

Where $\Delta LHWBG$, $X_{i,t}$, $\overline{LHWBG}_{t-1}$ & $\overline{X}_{t-1}$, $\Delta LHWBG_{i,t-j}$ & $\Delta X_{i,t-1}$, $\Delta\overline{LHWBG}_t$ & $\Delta\overline{X}_t$ and u_{it} are dependent variable, all independent variables during the long-run, mean of the dependent and explanatory variables in the long-run, dependent and independent variables in the short-run, mean dependent and independent variables during the short-run and the error term, respectively. Furthermore, where j, t, $\beth_{1i}$, γ_{1i}, $\Gamma_{i,j}$, $\o_{1i}$ and $\o_{2i}$ denotes cross-sectional dimension, time, coefficients of the independent variables, short-run coefficient of the dependent variable, short-run coefficients of the independent variables, mean of dependent variables and mean of independent variables in the short-run, respectively. The details of the dependent and independents variables regressors can be found in *Table 1*. The justification for including the regressors in the model is explained briefly below:

3.3 Data and variables description

This research study employed annual panel data encompassing the Group of BRICS countries, namely Brazil, Russia, India, China, and South Africa, for the period spanning from 2012 to 2022. The data sources included three primary databases which can be found in Table 1. The selection of the time frame and countries was based on data availability. The variable representing governance quality was derived from the six indicators specified in Tables 1 and 2, utilizing Principal Component Analysis (PCA). Table 1 provides a comprehensive list of the variables employed in this research study.

Table 1. Variable description and data sources

Variables	Description	Sources	
Dependent variable			
HWBG	*Log of* human development index (HDI) serves as proxy for human well-being	UN database	
Independent variables			
LAII	*Log* of capital investments in artificial intelligence (AI) serves as proxy for AI investment	OECD database	
LGDPPC	*Log* of GDP per capita (constant 2015 US$) proxy for levels of income	WDI database	
LEMPL	*Log* of employment to population ratio, 15+, total (%) serves as proxy for employment	WDI database	
LHMN	*Log* of School enrollment, secondary (% gross) serves as proxy for human capital	WDI database	
LAII* OGV	Computed interaction between AI and Overall governance	Authors	
LAII* POLG	Computed interaction between AI and political governance	Authors	
LAII*INSTG	Computed interaction between AI and institutional governance	Authors	
LAII*ECOG	Computed interaction between AI and economic governance	Authors	
LAII*CRT	Computed interaction between AI and control of corruption	Authors	
LAII*POLV	Computed interaction between AI and political stability and absence of violence/terrorism	Authors	
LAII*GF	Computed interaction between AI and government effectiveness	Authors	
LAII*RG	Computed interaction between AI and regulatory quality	Authors	
LAII*RLW	Computed interaction between AI and Rule of law	Authors	
LAII*VACC	Computed interaction between AI and voice and accountability	Authors	
General/Overall governance (OGV) variable computed via PCA using the six governance indicators below		Authors	Authors
CRT	*Log* of Control of Corruption	WGI database	
POLV	Political stability and absence of violence/terrorism	WGI database	
GF	*Log* of government effectiveness	WGI database	
RG	*Log* of regulatory quality	WGI database	
RLW	*Log* of rule of law	WGI database	
VACC	*Log* of voice and accountability	WGI database	
POLG	It represents political governance which is computed via PCA using the voice and accountability and political stability and absence of violence/terrorism	Authors	
INSTG	It represents institutional governance which is computed via PCA using the rule of law and control of corruption	Authors	
ECOG	It represents economic governance which is computed via PCA using the regulatory quality and government effectiveness	Authors	

Note: WDI represents World Bank's World Development Indicators. OECD represents The Organization for Economic Cooperation and Development database. WGI represents World Bank's World Governance Indicators. There were very few missing data, but this was handled by means of interpolation and extrapolation of data. * is multiplication sign.

4. Empirical results and discussion

4.1 Preliminary Analysis

4.1.1 Principal component and summary statistics analysis

Table 2 displays the results of PCA for overall governance quality and its political, institutional, and economic dimensions. Initial tests assessed the links between the indicators used to construct the indexes. The results shown in Table 2 confirm significant correlations between the indicators, validating the prerequisite for conducting principal component analysis (PCA) (Saba & Ngepah, 2022a, 2022b). To construct composite indexes, we selected the first principal component, explaining 3.289% (overall governance), 1.151% (political governance), 1.903% (institutional governance), and 1.537% (economic governance) of the total variation, based on the eigenvalue criterion. Figure 3's scree plots further support these findings. Table 3 summarizes the variables, including HWBG, LGDPPC, LAII, LEMPL. These variables exhibit mean (or median) values of approximately -0.3125 (-0.3011), 8.6993 (9.0392), 18.6243 (18.2463), and 3.9756 (4.0355), respectively. Variable ranges span from approximately 24.5859 to -4.3384. Skewness analysis reveals that negatively skewed distributions correspond to variables with negative skewness values, while positively skewed distributions correspond to variables with positive skewness values.

Table 2. Principal component method results

Panel A: Overall governance							
Principal component results							
Compnnt	Eigenvalue	Difference	Proportion	Cumulative			
Compnnt 1	**3.2890**	1.9194	0.5482	0.5482			
Compnnt 2	1.3697	0.4856	0.2283	0.7764			
Compnnt 3	0.8840	0.6146	0.1473	0.9238			
Compnnt 4	0.2694	0.1372	0.0449	0.9687			
Compnnt 5	0.1322	0.0765	0.0220	0.9907			
Compnnt 6	0.0557		0.0093	1.0000			
Principal components eigenvectors results							
Variables	Compnnt 1	Compnnt 2	Compnnt 3	Compnnt 4	Compnnt 5	Compnnt 6	Unexplained
CRT	0.5095	-0.1061	-0.0384	0.5855	-0.4555	0.4213	0.131
GF	0.3811	-0.5119	0.3439	-0.0998	0.6296	0.2610	0.1634
POLV	0.0210	0.6257	0.7017	0.2931	0.1704	-0.0269	0.4624
RG	0.4774	0.1699	0.2358	-0.7190	-0.4110	0.0418	0.2109
RLW	0.5327	-0.0088	-0.1466	0.1917	0.1138	-0.8031	0.0665
VACC	0.2883	0.5534	-0.5574	-0.0876	0.4305	0.3270	0.3072

Table 2. Continued

Panel B: Political governance						
Compnnt	Eigenvalue	Difference	Proportion	Cumulative		
Compnnt 1	**1.1506**	0.3012	0.5753	0.5753		
Compnnt 2	0.8494		0.4247	1.0000		
Principal components eigenvectors results						
Variables	Compnnt 1	Compnnt 2	Unexplained			
POLV	0.7071	0.7071	0.4247			
VACC	0.7071	-0.7071	0.4247			
Panel B: Institutional governance						
Compnnt	Eigenvalue	Difference	Proportion	Cumulative		
Compnnt 1	**1.9034**	1.8068	0.9517	0.9517		
Compnnt 2	0.0966		0.0483	1.0000		
Principal components eigenvectors results						
Variables	Compnnt 1	Compnnt 2	Unexplained			
CRT	0.7071	0.7071	0.0483			
RLW	0.7071	-0.7071	0.0483			
Panel C: Economic governance						
Compnnt	Eigenvalue	Difference	Proportion	Cumulative		
Compnnt 1	1.5366	1.0733	0.7683	0.7683		
Compnnt 2	0.4634		0.2317	1.0000		
Principal components eigenvectors results						
Variables	Compnnt 1	Compnnt 2	Unexplained			
RG	0.7071	0.7071	0.2317			
GEF	0.7071	-0.7071	0.2317			
Panel A: Correlation matrix results for the governance variable						
	i	ii	iii	iv	v	vi
(i) CRT	1.000					
(ii) GF	0.6537*** (0.0000)	1.000				
(iii) POLV	-0.0443*** (0.5136)	-0.1932*** (0.0040)	1.000			
(iv) RG	0.6795*** (0.0000)	0.5366*** (0.0000)	0.2588*** (0.0001)	1.000		
(v) RLW	0.9034*** (0.000)	0.6219*** (0.0000)	-0.0428*** (0.5274)	0.7586*** (0.0000)	1.000	
(vi) VACC	0.3896*** (0.0000)	-0.1532*** (0.0230)	0.1506*** (0.0255)	0.4596*** (0.0000)	0.5580*** (0.0000)	1.000

Note: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$, p-value in parentheses. Where compnnt is component. *Source:* Author's computation using WDI, WGI and ITU data.

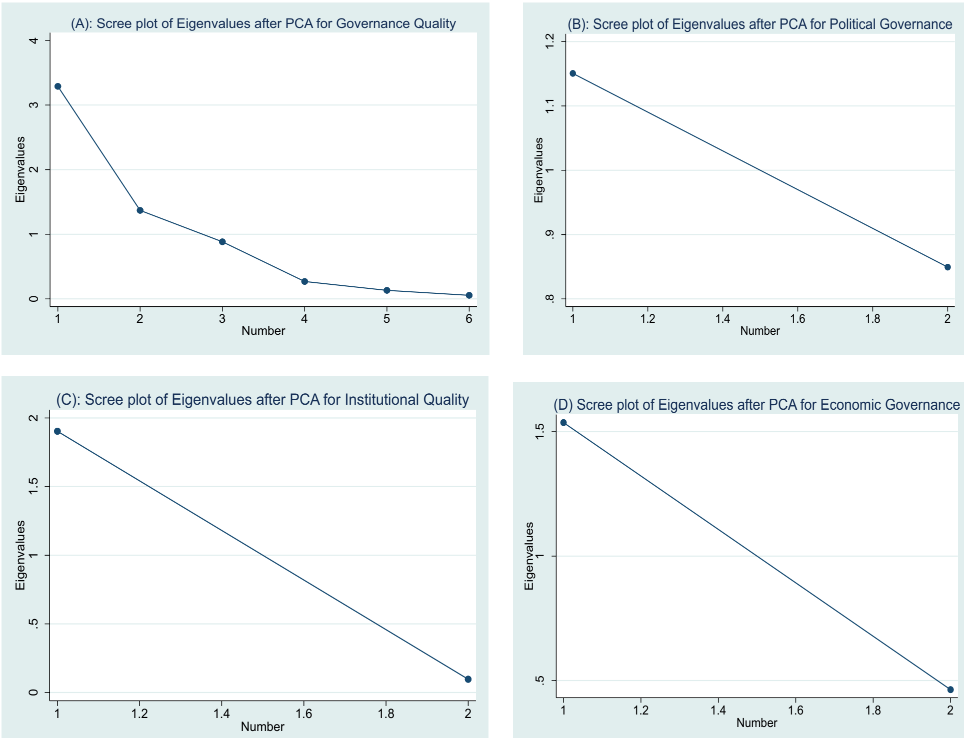

Figure 3. (**A**) Scree plot for governance quality; (**B**) Scree plot for political governance; (**C**) Scree plot for institutional governance; (**D**) Scree plot for economic governance

Table 3. Discriptive Statistics results

	Mean	Median	Max	Mini	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Prob.
LHDI	-0.3125	-0.3011	-0.1684	-0.5142	0.0903	-0.4597	2.4931	10.1044	0.0064
LGDPPC	8.6993	9.0392	9.3227	7.1985	0.6596	-1.2762	3.0224	59.7256	0.0000
LAII	18.6243	18.2463	24.5859	11.0021	3.0930	0.0820	2.6718	1.2335	0.5397
LEMPL	3.9756	4.0355	4.2075	3.6818	0.1608	-0.2460	1.5889	20.4736	0.0000
LHMN	4.6281	4.6255	4.7034	4.5622	0.0382	0.2947	2.0422	11.5930	0.0030
OGV	1.82E-09	-0.1151	5.5839	-2.8866	1.8136	0.8177	4.5900	47.6917	0.0000
ECOG	-5.45E-09	-0.0746	4.5463	-1.5332	1.2396	1.6153	6.4278	203.378	0.0000
INSTG	1.27E-08	0.0745	4.2903	-2.4014	1.3796	0.6032	4.3330	29.6303	0.0000
POLG	3.27E-08	0.0815	2.1391	-4.3384	1.0727	-0.9342	5.9449	111.5028	0.0000
VACC	-0.2072	0.2954	1.1127	-1.6608	0.8994	-0.4972	1.5660	27.9135	0.0000
RLW	-0.1843	-0.1360	1.0352	-0.8698	0.4072	0.4442	4.0956	18.2357	0.0001
RG	-0.1303	-0.1852	0.9212	-0.5600	0.3432	1.2540	4.4014	75.6580	0.0000
POLV	-0.5565	-0.5226	1.0747	-4.2696	0.6563	-2.9610	19.7817	2903.041	0.0000
GF	0.0995	0.0689	1.8407	-0.5336	0.4300	1.5651	6.8065	222.6350	0.0000
CRT	-0.2897	-0.2890	1.0537	-1.0516	0.4372	0.8568	4.7053	53.5753	0.0000

4.1.2 Slope homogeneity, cross-sectional dependence (CD) and panel unit root analysis

We began by conducting a slope homogeneity test following Pesaran and Yamagata's (2008) suggestion. The results in Table 4 reveal significant evidence of country heterogeneity in the examined variables, especially in the long run, as we rejected the homogenous slope coefficient assumption at the 1% significance level. Likewise, the Pesaran (2021) and Breusch and Pagan (1980) LM tests presented in Table 5 indicate cross-sectional dependence in the series, with p-values for the statistic being statistically significant at 1%. The first-generation (Levin-Lin-Chu (LLC) and Im-Pesaran-Shin (IPS)) and second- generation panel unit root tests in Tables 6 and 7 confirm that the series are integrated of order 1, at least at a 1% significance level (except for HWBG and LGDPPC whose results were mixed in Table 6). This implies that we can proceed to examine the long-run equilibrium relationship between the series using the second-generation cointegration approach. These estimates and the unit root and cross-dependency tests mentioned earlier justify the use of the panel CS-ARDL estimator to explore potential relationships among all the variables under consideration.

Table 4. Slope homogeneity results

Test statistics (Delta)	Value	p-value
Δ_{delt}	11.971***	0.000
$\Delta_{adj\ delt}$	13.054***	0.000

Note: ***, ** and * denote significance at 1%, 5% and 10%, respectively. *Source*: Author's Computations.

Table 5. Cross-sectional dependence (CD) test results

	Pesaran test		Breusch-Pagan LM test	
Variables	Statistic	P-value	Statistic	P-value
HWBG	17.39***	0.000	150.725***	0.000
LGDPPC	-1.02	0.309	192.510***	0.000
LAII	12.42***	0.000	85.780***	0.000
LEMPL	13.67***	0.000	65.855***	0.000
LHMN	-2.74***	0.006	101.260***	0.000
OGV	13.85***	0.000	240.249***	0.000
POLG	-3.97***	0.000	283.476***	0.000
ECOG	3.82***	0.000	309.340***	0.000
INSTG	18.82***	0.000	244.938***	0.000
CRT	18.35***	0.000	291.576***	0.000
GF	2.67***	0.008	178.136***	0.000
POLV	-4.26***	0.000	267.838***	0.000
RG	4.84***	0.000	240.343***	0.000
RLW	16.27***	0.000	271.125***	0.000
VACC	5.23***	0.000	142.674***	0.000

Note: *** p<0.01, ** p<0.05, and * p<0.1 are significance level respectively at denote rejection of null hypothesis. *Source*: Author's computations.

Table 6. Panel unit root test results

Series	Model	Levels	First Difference
HWBG	LLC	-3.4510*** (0.0003)	-8.1866*** (0.0000)
	IPS	-1.9719** (0.0243)	-8.8373*** (0.0000)
LGDPPC	LLC	-1.5217* (0.0640)	-7.7317*** (0.0000)
	IPS	0.4820 (0.6851)	-9.0149*** (0.0000)
LAII	LLC	-0.9696 (0.1661)	-6.5198*** (0.0000)
	IPS	0.5063 (0.6937)	-7.7185*** (0.0000)
LEMPL	LLC	0.1874 (0.5743)	-3.2116*** (0.0007)
	IPS	0.0059 (0.5024)	-7.3500*** (0.0000)
LHMN	LLC	0.8661 (0.8068)	-7.8598*** (0.0000)
	IPS	1.4207 (0.9223)	-7.3869*** (0.0000)
OGV	LLC	3.9196 (1.0000)	-9.2173*** (0.0000)
	IPS	2.7555 (0.9971)	-7.5137*** (0.0000)
POLG	LLC	5.0740 (1.0000)	-9.3104*** (0.0000)
	IPS	3.3999 (0.9997)	-7.6536*** (0.0000)
ECOG	LLC	4.6239 (1.0000)	-8.9634*** (0.0000)
	IPS	3.6116 (0.9998)	-7.8113*** (0.0000)
INSTG	LLC	5.2553 (1.0000)	-8.7998*** (0.0000)
	IPS	3.4401 (0.9997)	-7.6270*** (0.0000)
CRT	LLC	5.0740 (1.0000)	-9.3104*** (0.0000)
	IPS	3.3999 (0.9997)	-7.6536*** (0.0000)
GF	LLC	3.8799 (0.9999)	-7.5759*** (0.0000)
	IPS	2.9365 (0.9983)	-7.7854*** (0.0000)
POLV	LLC	4.8784 (1.0000)	-8.5996*** (0.0000)
	IPS	3.7380 (0.9999)	-7.7717*** (0.0000)
RG	LLC	4.4832 (1.0000)	-8.5459*** (0.0000)
	IPS	3.2718 (0.9995)	-7.7101*** (0.0000)
RLW	LLC	4.4047 (1.0000)	-8.3746*** (0.0000)
	IPS	2.8854 (0.9980)	-7.5409*** (0.0000)
VACC	LLC	2.1604 (0.9846)	-8.9917*** (0.0000)
	IPS	2.3327 (0.9902)	-7.7901*** (0.0000)

Notes: Null: Unit root (assumes common unit root process): Levin, Lin & Chu (t*). Null: Unit root (assumes individual unit root process): Im, Pesaran and Shin (W-stat). *** $p<0.01$, ** $p<0.05$, and * $p<0.1$ are significance level respectively. Levin-Lin-Chu (LLC) (Levin et al., 2002) and Im-Pesaran-Shin (IPS) (Im et al., 2003)) *Source*: Author's computations.

Table 7. CIPS Panel unit root test results

Variables	Levels	1st Difference
HWBG	-1.553	-6.187***
LGDPPC	-1.223	-6.190***
LAII	-1.915	-6.188***
LEMPL	-1.709	-6.185***
LHMN	-0.762	-6.193***
OGV	-1.380	-6.194***
POLG	-0.459	-6.186***
ECOG	-1.454	-6.188***
INSTG	-1.292	-6.179***
CRT	-1.688	-6.182***
GF	-1.709	-6.183***
POLV	-1.303	-6.189***
RG	-1.669	-6.184***
RLW	-1.127	-6.188***
VACC	-0.517	-6.191***

Note: *, ** and *** denote statistically significant at the 1%, 5%, and 10% level respectively. The critical values of CIPS test at 10%, 5% and 1% significance levels are: -2.21, -2.33 and -2.55 for no intercept nor trend, respectively. Pesaran (2007) (CIPS) panel unit root tests. *Source*: Author's computations.

4.2 The cointegration, fully Modified Least Squares (FMOLS) and dynamic OLS (DOLS) long run analysis

Tables 8 and 9 present the outcomes of the Johansen-Fisher and Westerlund (Westerlund, 2007) panel cointegration tests, conducted to determine the enduring equilibrium associations between the dependent variable, human well-being, and the independent variables. Optimal lag length, identified as 1 based on the AIC, SIC, and HQIC indicators shown in Table 10, was established prior to the estimations. The findings in Table 8 from the Johansen-Fisher panel cointegration test indicate the existence of ten cointegrating vectors, with an equal number derived from both the trace and maximum eigenvalue statistics, confirming a long-standing equilibrium link among the variables under examination. The null hypothesis of no cointegration was dismissed with at least 1% significance for both tests, thus strongly affirming the presence of cointegration. In pursuit of methodological solidity, to manage the cross-sectional dependence among countries we used the Westerlund (2007) panel cointegration test, which is esteemed for its dependability as noted by Khan et al. (2020). According to the results documented in Table 9, all four test statistics (, , and statistics) report p-values under 1%. Rejecting the null hypothesis in at least one of these tests endorses the existence of a long-term equilibrium association between the variables, taking into account the inter-country linkages.

For the estimation of the long-run coefficients of the explanatory variables, this study employed the FMOLS and DOLS methods as advocated by Pedroni (2001, 2004), which are better suited than OLS for addressing concerns of serial correlation and endogeneity. The R-squared and Adjusted R-squared figures, exceeding 70% for both methods, confirm the correct specification of our models. With this validation, we are well-positioned to interpret and discuss the estimated results. In Table 11, Panels A and B present the results of the FMOLS and DOLS, respectively. The impact of the explanatory variables on human well-being (HWBG) appears to be similar in terms of sign, coefficient, and significance for both FMOLS and DOLS models. Therefore, we will focus on interpreting and discussing our main variables to save space. In Panel A and B of Table 11, in the long-run, especially for the results in Column 2, AI investment significantly and positively impact human well-being for the BRICS countries, while overall governance quality (OGV) significantly and negatively impacts human well-being. A 1% increase in AI investment and OGV increased human well-being by 0.002% and reduced it by 0.003% for the FMOLS model, and by 0.003% and 0.005% for the DOLS model, respectively. The result regarding the impact of overall governance quality on human well-being contradicts the findings of Woodward (2010) and Nam and Ryu (2023). This implies that good governance may not consistently enhance human well-being in a society, a notion supported by Rapley's (2013) arguments.

In Column 2 of Table 11, the interaction between AI investment and governance quality has a significant and positive impact on human well-being for both the FMOLS and DOLS models. A 1% increase in the interaction between AI investment and governance quality increased human well-being by 0.0003% and 0.003% for the FMOLS and DOLS models, respectively. This implies that the interaction between AI investment and governance quality plays a significant role in promoting human well-being in the BRICS countries. In Column 3 of Table 11, the interaction between AI investment and other explanatory variables such as political governance (POLG), institutional governance (INSTG), economic governance (ECOG), control of corruption (CRT), political stability and absence of violence/terrorism (POLV), government effectiveness (GF), regulatory quality (RG), rule of law (RLW) and voice and accountability (VACC) exhibits a significant positive impact on human well-being for both FMOLS and DOLS models. Specifically, a 1% increase in the interaction between AI investment and variables such as POLG, INSTG, ECOG, CRT, POLV, GF, RG, RLW and VACC increases human well-being by 0.004%, 0.003%, 0.003%, 0.009%, 0.003%, 0.004%, 0.013%, 0.012% and 0.008% for FMOLS and increases it by 0.005%, 0.004%, 0.004%, 0.012%, 0.007%, 0.010%, 0.017%, 0.014% and 0.006% for DOLS models, respectively. In the DOLS results, which we think are more reliable because of its advantages over FOLS, it is evident that the interaction between AI investment and variables such as POLG, INSTG, ECOG, CRT, POLV, GF, RG, RLW and VACC significantly contributed to the human well-being in the BRICS countries.

Table 8. Johansen-Fisher Panel cointegration test results

		Trace test				Maximum Eigenvalue test	
H_0	H_1	λ-trace statistic	p-value	H_o	H_1	λ-max statistic	p-value
$r = 0$	$r \geq 1$	0.000	1.0000	$r = 0$	$r \geq 1$	0.000	1.0000
$r \leq 1$	$r \geq 2$	214.1	0.0000	$r \leq 1$	$r \geq 2$	166.9	0.0000
$r \leq 2$	$r \geq 3$	245.7	0.0000	$r \leq 2$	$r \geq 3$	217.6	0.0000
$r = 3$	$r \geq 4$	156.1	0.0000	$r = 3$	$r \geq 4$	136.3	0.0000
$r \leq 4$	$r \geq 5$	78.85	0.0000	$r \leq 4$	$r \geq 5$	73.24	0.0000
$r \leq 5$	$r \geq 6$	32.01	0.0004	$r \leq 5$	$r \geq 6$	32.01	0.0004

Notes: *Rejection of the null hypothesis of no cointegration at least at the 10% level of significance. Probabilities are computed using asymptotic Chi-square distribution. *Source*: Author's computations.

Table 9. Westerlund panel cointegration tests

Statistic	Value	Z-value	P-value	Robust P-value
G_t	-1.367***	3.002	0.099	0.000
G_a	-3.787***	3.035	0.099	0.000
P_t	-2.871***	2.253	0.088	0.000
P_a	-3.118***	2.200	0.086	0.000

Note: *, ** and *** represent significance at the 1%, 5%, and 10% levels respectively; number of replications to obtain bootstrapped p-values is set to 100; bandwidth is selected according to the data depending rule recommended by Newey and West (1994); Barlett is used as the spectral estimation method. *Source*: Author's Computations.

Table 10. Optimum lag length selection results

Lag	AIC	SIC	HQIC
0	0.8342	0.9349	0.8750
1	-22.1541	-21.4492*	-21.8687
2	-21.8515	-20.5423	-21.3214
3	-21.5855	-19.6720	-20.8108
4	-21.4374	-18.9197	-20.4180
5	-23.4418*	-20.3199	-22.1778*

Note: * indicates lag order selected by the criterion. AIC is Akaike information criterion; SIC is Schwarz information criterion; Hannan-Quinn information criterion. *Source*: Author's computations.

Table 11. FMOLS and DOLS estimates

PANEL A: FMOLS											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Variables	Coeff	Coeff	Coeff	Coeff	Coeff	Coeff	Coeff	Coeff	Coeff	Coeff	Coeff
LGDPPC	0.1509***	0.1409***	0.1294***	0.1239***	0.1187***	0.1271***	0.1205***	0.1135***	0.1243***	0.1197***	0.1306***
	(0.0166)	(0.0076)	(0.0014)	(0.0013)	(0.0013)	(0.0011)	(0.0013)	(0.0011)	(0.0014)	(0.0015)	(0.0012)
LAII	**0.0017***	**0.0014*****	**-0.0041*****	**-0.0022*****	**-0.0062*****	**0.0002*****	**-0.0050*****	**-0.0071*****	**-0.0040*****	**-0.0006***	**-0.0002**
	(0.0010)	**(0.0004)**	**(0.0003)**	**(0.0003)**	**(0.0002)**	**(0.0003)**	**(0.0003)**	**(0.0002)**	**(0.0003)**	**(0.0003)**	**(0.0003)**

Table 11. Continued

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
LEMPL	-0.1090**	-0.1068	-0.0224***	-0.0519***	0.0360***	-0.0457***	0.0584***	0.0718***	0.0169***	-0.0352***	-0.0477***
	(0.0462)	(0.0000)	(0.0074)	(0.0071)	(0.0058)	(0.0056)	(0.0053)	(0.0047)	(0.0063)	(0.0078)	(0.0077)
LHMN	-0.0394	-0.0406	-0.2739***	-0.2481***	-0.2972***	-0.2717***	-0.3255***	-0.3143***	-0.3004***	-0.2627***	-0.2708***
	(0.0551)	(0.1150)	(0.0046)	(0.0043)	(0.0036)	(0.0031)	(0.0030)	(0.0031)	(0.0037)	(0.0047)	(0.0060)
OGV	**-0.0026****	-0.0076***									
	(0.0010)	(0.0024)									
LAII* OGV		**0.0003****									
		(0.0001)									
POLG			-0.0976***								
			(0.0039)								
LAII* POLG			**0.0044*****								
			(0.0002)								
INSTG				-0.0782***							
				(0.0028)							
LAII* INSTG				**0.0034*****							
				(0.0001)							
ECOG					-0.0576***						
					(0.0030)						
LAII* ECOG					**0.0027*****						
					(0.0001)						
CRT						-0.2201***					
						(0.0072)					
LAII*CRT						**0.0094*****					
						(0.0004)					
POLV							-0.0728***				
							(0.0064)				
LAII* POLV							**0.0031*****				
							(0.0003)				
GF								-0.0841***			
								(0.0092)			
LAII* GF								**0.0038*****			
								(0.0004)			
RG									-0.2640***		
									(0.0109)		
LAII*RG									**0.0126*****		
									(0.0006)		
RLW										-0.2673***	
										(0.0106)	

Table 11. Continued

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
LAII* RLW										**0.0118*** **	
										(0.0005)	
VACC											-0.1688***
											(0.0043)
LAII* VACC											**0.0080*** **
											(0.0002)
R-squared	0.9864	0.9869	0.9043	0.9187	0.8921	0.9122	0.8812	0.8785	0.9043	0.9180	0.9237
Adj. R-squared	0.9858	0.9863	0.9020	0.9168	0.8895	0.9101	0.8783	0.8756	0.9021	0.9161	0.9219
Obs	215	215	215	215	215	215	215	215	215	215	215
					PANEL B: DOLS						
Variables	Coeff	Coeff	Coeff	Coeff	Coeff	Coeff	Coeff	Coeff	Coeff	Coeff	Coeff
LGDPPC	0.1809***	0.1266***	0.1312***	0.1263***	0.1243***	0.1335***	0.1306***	0.1165***	0.1275***	0.1199***	0.1264***
	(0.0441)	(0.0051)	(0.0061)	(0.0050)	(0.0066)	(0.0054)	(0.0079)	(0.0073)	(0.0062)	(0.0046)	(0.0040)
LAII	**0.0029*** **	**-0.0007**	**-0.0014**	**-0.0000**	**-0.0021** **	**0.0022**	**0.0013**	-0.0028**	-0.0009	0.0019	-0.0005
	(0.0011)	**(0.0010)**	**(0.0011)**	**(0.0011)**	**(0.0011)**	**(0.0014)**	**(0.0016)**	**(0.0015)**	**(0.0011)**	**(0.0012)**	**(0.0011)**
LEMPL	0.1180**	-0.0640**	-0.0248	-0.1035***	-0.0143	-0.1185***	0.0139	0.0256	-0.0095	-0.0547*	-0.0120
	(0.0572)	(0.0276)	(0.0351)	(0.0283)	(0.0298)	(0.0283)	(0.0335)	(0.0395)	(0.0271)	(0.0295)	(0.0328)
LHMN	-0.1149	-0.2492***	-0.2859***	-0.2177***	-0.2820***	-0.2297***	-0.3322***	-0.2984***	-0.2965***	-0.2570***	-0.2914***
	(0.0728)	(0.0181)	(0.0225)	(0.0171)	(0.0207)	(0.0166)	(0.0207)	(0.0290)	(0.0178)	(0.0189)	(0.0272)
OGV	**-0.0046*** **	-0.0709***									
	(0.0013)	(0.0096)									
LAII* OGV		**0.0032*** **									
		(0.0005)									
POLG			-0.1115***								
			(0.0195)								
LAII* POLG			**0.0053*** **								
			(0.0009)								
INSTG				-0.0985***							
				(0.0121)							
LAII* INSTG				**0.0044*** **							
				(0.0006)							
ECOG					-0.0941***						
					(0.0179)						
LAII* ECOG					**0.0043*** **						
					(0.0009)						

Table 11. Continued

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
CRT						-0.2652***					
						(0.0409)					
LAII*CRT						**0.0118*** **					
						(0.0020)					
POLV							-0.1628***				
							(0.0429)				
LAII* POLV							**0.0074*** **				
							(0.0020)				
GF								-0.2285**			
								(0.0871)			
LAII* GF								**0.0100*** **			
								(0.0041)			
RG									-0.3472***		
									(0.0543)		
LAII*LRG									**0.0169*** **		
									(0.0029)		
LRLW										-0.3135***	
										(0.0435)	
LAII *RLW										**0.0141*** **	
										(0.0022)	
VACC											-0.1344***
											(0.0218)
LAII* VACC											**0.0062*** **
											(0.0011)
R-squared	0.9956	0.9682	0.9623	0.9701	0.9578	0.9638	0.9492	0.9415	0.9658	0.9693	0.9669
Adj. R-squared	0.9922	0.9405	0.9295	0.9440	0.9209	0.9322	0.9051	0.8905	0.9360	0.9425	0.9381
Obs	205	205	205	205	205	205	205	205	205	205	205

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Standard Error in parenthesis, while the dependent variable is human development index proxy for human well-being (HWBG). *Source*: Author's Computations.

4.3 Panel causality and CS-ARDL estimates analysis

This section examines the causative links between the series under consideration. Based on whether their p-values were below or above the 10% significance threshold, we either dismissed or upheld the null hypothesis asserting the absence of causality for each Chi-square statistic. To begin with, the outcomes of the panel causality tests are depicted in Table 12. In Table 12, focusing on our variables of interest, unidirectional causality runs from: (i) CRT to HWBG; (ii) GF to HWBG; (iii) RG to HWBG; (iv) RLW to HWBG; (v) POLV to HWBG; (vi) POLG to HWBG; (vii) ECOG to HWBG; (viii) OGV to HWBG; (ix) CRT to AI investment; (x) GF to AI investment; (xi) RG to AI investment; (xii) RLW to AI investment; (xiii) POLV to AI investment; (XIV) POLG to AI investment; (XV) ECOG to AI investment; (XVI) INSTG to AI investment; and (XVII) OGV to AI investment. This implies that investment in AI and HWBG are dependent on control of corruption, regulatory quality, government effectiveness, rule of law, political stability, political governance, economic governance and overall governance quality. Secondly, bidirectional causality runs between: (i) HWBG and AI investment; (ii) institutional governance and HWBG. This implies that these variables are dependent on each other and further highlights their importance to the BRICS economies. Thirdly, no causality exists between: (i) HWBG and voice and accountability; and (ii) investment in AI and voice and accountability. These causality findings underscore the significance of adopting a comprehensive approach to promote AI development, taking into account economic, political, institutional and governance dimensions.

Table 12. Dumitrescu and Hurlin (2012) panel causality test results

Model	Null hypothesis	W-statistic	Zbar-statistic	p-value	Direction of relationship observed	Conclusion
1	HWBG LAII	1.9724*	-0.1418	0.0873	HWBG ↔ LAII	Bidirectional causality
	LAII HWBG	0.8779**	-1.2349	0.0169		
2	CRT HWBG	0.2689*	-1.8431	0.0653	CRT → HWBG	Unidirectional causality
	HWBG CRT	0.4888	-1.6236	0.1045		
3	GF HWBG	0.4254*	-1.6868	0.0916	GF → HWBG	Unidirectional causality
	HWBG GF	0.6336	-1.4789	0.1392		
4	RG HWBG	0.3443*	-1.7678	0.0771	RG → HWBG	Unidirectional causality
	HWBG RG	0.6879	-1.4246	0.1543		
5	LRLW HWBG	0.3162*	-1.7959	0.0725	RLW → HWBG	Unidirectional causality
	HWBG RLW	0.4704	-1.6419	0.1006		
6	VACC HWBG	0.5825	-1.5299	0.1260	HWBG VACC	No causality
	HWBG VACC	0.6856	-1.4270	0.1536		
7	POLV HWBG	0.2675*	-1.8445	0.0651	POLV → HWBG	Unidirectional causality
	HWBG POLV	0.4896	-1.6227	0.1046		
8	POLG HWBG	0.2010*	-1.9110	0.0560	POLG→ HWBG	Unidirectional causality
	HWBG POLG	0.4863	-1.6261	0.1039		
9	ECOG HWBG	0.3884*	-1.7239	0.0847	ECOG→ HWBG	Unidirectional causality
	HWBG ECOG	0.5288	-1.5836	0.1133		
10	INSTG HWBG	0.2922*	-1.8199	0.0688	HWBG ↔ INSTG	Bidirectional causality
	HWBG INSTG	0.4311*	-1.6812	0.0927		
11	OGV HWBG	0.3935*	-1.7187	0.0857	OGV→ HWBG	Unidirectional causality
	HWBG OGV	1.1775	-0.9357	0.3494		

Table 12. Continued

Model	Null hypothesis	W-statistic	Zbar-statistic	p-value	Direction of relationship observed	Conclusion
12	CRT LAII	0.2473*	-1.8648	0.0622	CRT→ LAII	Unidirectional causality
	LAII CRT	2.9517	0.8364	0.4030		
13	GF LAII	0.3284*	-1.7838	0.0745	GF→ LAII	Unidirectional causality
	LAII GF	1.6409	-0.4729	0.6363		
14	LRG LAII	0.4269*	-1.6853	0.0919	RG→LAII	Unidirectional causality
	LAII RG	3.1557	1.0402	0.2983		
15	RLW LAII	0.2157*	-1.8963	0.0579	RLW→LAII	Unidirectional causality
	LAII RLW	3.0466	0.9312	0.3518		
16	VACC LAII	1.6823	-0.4315	0.6661	VACC LAII	No causality
	LAII VACC	1.1274	-0.9857	0.3243		
17	POLV LAII	0.3240*	-1.7881	0.0738	POLV→LAII	Unidirectional causality
	LAII POLV	2.7830	0.6679	0.5042		
18	POLG LAII	0.2077**	-1.9043	0.0569	POLG→LAII	Unidirectional causality
	AII POLG	2.6794	0.5644	0.5725		
19	ECOG LAII	0.3309*	-1.7813	0.0749	ECOG→LAII	Unidirectional causality
	LAII ECOG	2.4297	0.3150	0.7527		
20	INSTG LAII	0.1005**	-2.0114	0.0443	INSTG→LAII	Unidirectional causality
	LAII INSTG	3.2690	1.1533	0.2488		
21	OGV LAII	0.1973**	-1.9147	0.0555	OGV→LAII	Unidirectional causality
	LAII OGV	2.8811	0.7659	0.4438		

Note: ↔ and → denote bidirectional and unidirectional causality respectively. denote does not homogeneously cause (i.e H0). *** p<0.01, ** p<0.05, * p<0.1. *Source*: Author's Computations.

Table 13 presents the panel CS-ARDL results: the estimates of the Error Correction Term (ECT) for all regression models, the values indicated in Column 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, and 11, respectively, all of which are statistically significant, at least at the 1% level of significance. These values suggest that there is a strong negative relationship between the deviations from the long-run equilibrium and the short-run changes in the human well-being variable. Specifically, the negative ECT values indicate that any deviations from the long-run equilibrium will be corrected at the values indicated in the Columns mentioned above, suggesting that the human well-being variable will adjust back towards its equilibrium level relatively quickly. The R-squared values for all the models are above 59%, which implies that our models are correctly specified.

For the first model, without the interaction term variables, in Column 1 of Table 13, the CS-ARDL results show that at a 10% level of significance, the impact of AI investment on human well-being (HWBG) is insignificantly negative in both the short and long run, while the impact of governance quality on HWBG is significantly positive in both short and long run. Specifically, a 1% increase in governance quality promotes HWBG by 0.001% both in the short and long run. This suggests that in both the short and long run, the impact of governance quality on HWBG remained consistently positive in both time frames and the opposite was true for AI investment. This suggests that AI investment alone cannot boost human well-being (HWBG), while the influence of overall governance quality is more pronounced. The result regarding the impact of overall governance quality on human well-being aligns with the studies of Woodward (2010), Medina-Morala and Montes-Gan (2018) and Nam and Ryu (2023) showing that good governance may consistently enhance human well-being in BRICS.

In Column 2, 3, 8, and 10 of Table 13, the results indicate that the interaction between AI investment and explanatory variables such as overall governance, political governance, government effectiveness and rule of law has a positive and significant impact on HWBG at a 10% level of significance in both the short and long run. These findings highlight the potential benefits of AI technologies within a well-governed framework, which can contribute to the well-being of individuals and society as a whole. The positive interactions between AI investment and governance indicators such as overall governance, political governance, government effectiveness and rule of law highlight the interconnected nature of these variables. Therefore, investment in AI is not a standalone solution to improved HWBG; its effectiveness depends on the broader governance environment such as overall governance, political governance, government effectiveness and rule of law in BRICS economy. The studies by Kim et al. (2008) and Bankole et al. (2011) also suggest that technological investment has the potential to enhance various aspects of human development. However, the effect of AI investment in conjunction with overall governance appears to have a minimal impact on HWBG when compared to political governance, government effectiveness and rule of law - probably because it takes time for the governance quality to reap the substantial AI benefits and then translate them into improvements in HWBG. There are numerous approaches through which the BRICS countries can leverage governance quality alongside AI investment to enhance HWBG. For example, they can prioritize the demand for high-quality education, subsidize healthcare services, and enhance or expand social protection facilities that positively influence education outcomes and life expectancy. When these services are consistently delivered by the government or private sector and enhanced by governance quality reforms, both AI industry investors and the citizens of these countries stand to gain (Asongu & Odhiambo, 2021).

The interaction between AI investment and explanatory variables such as institutional governance, economic governance, control of corruption, political stability and absence of violence, regulatory quality and voice and accountability has a negative and significant impact on HWBG at a 10% level of significance in both the short and long run (see Column 4, 5, 6, 9 and 11 of Table 13). A 1% increase in the interaction between AI investment and these variables resulted in decreases of HWBG by 0.0004%, 0.0002%, 0.0003%, 0.0001% and 0.0022% in the short run, and by 0.0004%, 0.0002%, 0.0003%, 0.0001% and 0.0022% in the long run.

These findings do not align with the studies conducted by Davis (2017) and Mombeuil and Diunugala (2021). Davis's research centered on sub-Saharan Africa, Mombeuil and Diunugala (2021) concentrated on 10 former European colonies; they both show

how crucial governance indicators are to human development. This suggests that when AI is leveraged in conjunction with improvements in institutional governance, economic governance, control of corruption, political stability and absence of violence, regulatory quality and voice and accountability, there are negative effects on HWBG both in the short and long term. These findings highlight the potential negative side effect of AI technologies within a poor-governed framework, which could retard well-being of individuals and society as a whole.

Although good governance is often viewed as a crucial factor in promoting human well-being, it is important to recognize that there are situations in developing countries where some dimensions or indicators of good governance may not consistently lead to the expected improvements in human well-being. The reasons why it is so may include the following: (i) the BRICS countries differ in size, economic structure, and social dynamics so governance indicators and policies may have different effects (Soyyiğit, 2019). Differences in regional development, income distribution, and historical legacies can all impact the relationship between some of the governance indicators and well-being (Ferraz et al., 2022); (ii) in some of the BRICS countries, bureaucratic inefficiencies, corruption, or regulatory hurdles can hinder the translation of good governance principles into the improvements in people's lives (Pradhan, 2011); (iii) HWBG is a multidimensional concept that encompasses various aspects of life, including income, education, health, social inclusion and others. While some governance indicators or dimensions can contribute to improvements in income, education, health or social inclusion, it may not address all aspects equally or simultaneously; (iv) the BRICS countries are not immune to external shocks, such as economic crises, regional wars leading to sanctions, natural disasters or global pandemics. These shocks can disrupt governance processes and erode people's well-being (Dauda & Iwegbu, 2022); (v) while some governance indicators may imply overall improvements in the well-being, they may not address income inequality or disparities in access to opportunities. In some cases, governance reforms may inadvertently exacerbate inequality by favoring certain groups or regions (Khan & Naeem, 2020; Topuz, 2022).

It is obvious that, for example, effective control of corruption typically leads to more efficient and transparent government processes (Davis, 2017). When AI technologies or ICT technologies are introduced in environments with low corruption, they are more likely to be deployed and managed efficiently and lead to better public services and improved resource allocation, all of which contribute to higher well-being. AI can enhance the quality and accessibility of public services, such as healthcare, education, and transportation (Asongu & Le Roux, 2017; Smith & Neupane, 2018; Neogi, 2020; Behera & Sahoo, 2022). The BRICS countries, however, are believed to have rather high levels of corruption and so the benefits from AI are less likely to reach the intended beneficiaries. In Column 7 of Table 13, the results indicate that the interaction between AI and political stability and absence of violence or terrorism has a negative and insignificant impact on HWBG at a 10% level of significance in both the short and long run. The negative and insignificant impact of the interaction of AI investment and political stability on HWBG in the BRICS economies could be attributed to the possibility that, although there might be relative political stability, the actual implementation of AI-related policies could be absent or ineffective. This limitation might hinder the realization of the positive effects of the interaction between AI investment and political stability on HWBG.

Table 13. Panel CS-ARDL estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Variables											
Short Run Est.											
ΔLGDPPC	-0.0193**	-0.0392**	0.0868**	-0.0167*	0.0101*	0.1255***	0.1357***	0.1277***	0.1265***	0.0551**	0.0980*
	(0.0093)	(0.0176)	(0.0336)	(0.0093)	(0.0056)	(0.0351)	(0.0415)	(0.0328)	(0.0360)	(0.0243)	(0.0524)
ΔLAII	**-0.0000**	**0.0005**	**0.0028**	**-0.0003**	**-0.0011**	**-0.0008*** **	**-0.0002*** **	**-0.0003**	**-0.0004*** **	**0.0004**	**0.0000**
	(0.0002)	**(0.0012)**	**(0.0028)**	**(0.0002)**	**(0.0008)**	**(0.0002)**	**(0.0001)**	**(0.0002)**	**(0.0001)**	**(0.0006)**	**(0.0001)**
ΔLEMPL	0.0417***	-0.1821	0.0726**	-0.0254	0.0536**	0.0190***	0.0062**	0.0255	0.0204**	0.0268	-0.0158
	(0.0139)	(0.1708)	(0.0373)	(0.0336)	(0.0233)	(0.0090)	(0.0027)	(0.0218)	(0.0092)	(0.0328)	(0.0216)
ΔLHMN	-0.1257	0.1478***	-0.0850	0.0917*	0.0958	0.0871***	0.1180**	0.0807***	0.0861***	0.1333***	0.1236**
	(0.2452)	(0.0251)	(0.0851)	(0.0533)	(0.0716)	(0.0267)	(0.0460)	(0.0269)	(0.0274)	(0.0478)	(0.0555)
ΔOGV	**0.0014***	0.0125**									
	(0.0008)	(0.0057)									
Δ LAII*OGV		**0.0003***									
		(0.0002)									
Δ POLG			-0.1040***								
			(0.00357)								
Δ LAII*POLG			**0.0058*** **								
			(0.0016)								
ΔINSTG				0.0082*							
				(0.0047)							
ΔLAII*INSTG				**-0.0004*** **							
				(0.0001)							
ΔECOG					0.0057*						
					(0.0033)						
ΔLAII*ECOG					**-0.0002** **						
					(0.0001)						
ΔLCRT						0.0005					
						(0.0004)					
ΔLAII*LCRT						**-0.0003*** **					
						(0.0001)					
ΔPOL							0.0027*				
							(0.0014)				
ΔLAII*POLV							-0.0000				
							(0.0000)				
ΔLGF								-0.0333***			
								(0.0127)			

Table 13. Continued

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
ΔLAII*LGF								0.0020**			
								(0.0009)			
ΔLRG									0.0002		
									(0.0006)		
ΔLAII*LRG									-0.0001***		
									(0.0000)		
ΔLRLW										-0.0308***	
										(0.0131)	
ΔLAII*LRLW										0.0016**	
										(0.0008)	
ΔLVACC											0.0378***
											(0.0133)
ΔLAII*LVACC											-0.0022***
											(0.0008)
Adjust. Term											
ECT	-1.0434***	-0.6978***	-1.1475***	-1.0440***	-1.0552***	-1.0218***	-1.0169***	-1.0300***	-1.0232***	-1.0294***	-1.0202***
	(0.0489)	(0.1051)	(0.0623)	(0.0172)	0.0121	(0.0133)	(0.0125)	(0.0144)	(0.0145)	(0.0120)	(0.0158)
Long Run Est.											
LR_LGDPPC	-0.0195**	-0.0724**	0.0798***	-0.0156**	0.0096*	-0.0002***	0.1332***	0.1243***	0.1235***	0.0538**	0.0950*
	(0.0094)	(0.0323)	(0.0319)	(0.0088)	(0.0054)	(0.0001)	(0.0406)	(0.0321)	(0.0353)	(0.0238)	(0.0511)
LR_LAII	-0.0001	0.0009	0.0030	-0.0003	-0.0011	-0.0008***	-0.0002***	-0.0003	-0.0004***	0.0004	0.0001
	(0.0002)	(0.0017)	(0.0027)	(0.0002)	(0.0008)	(0.0002)	(0.0001)	(0.0002)	(0.0001)	(0.0007)	(0.0007)
LR_LEMPL	0.0393***	-0.2430	0.0604*	-0.0235	.00508**	0.0184**	0.0060**	0.0242	0.0198**	0.0256	-0.0145
	(0.0128)	(0.2975)	(0.0328)	(0.0325)	(0.0223)	(0.0086)	(0.0027)	(0.0207)	(0.0090)	(0.0316)	(0.0203)
LR_LHMN	-0.1098	0.2299***	-0.0671	0.0901*	0.0926	0.0853***	0.1161**	0.0785***	0.0845***	0.1295***	0.1227**
	(0.2437)	(0.0594)	(0.0700)	(0.0534)	(0.0689)	(0.0268)	(0.0455)	(0.0267)	(0.0274)	(0.0466)	(0.0566)
LR_OGV	0.0014**	0.0194**									
	(0.0007)	(0.0096)									
LR_LAII*OGV		0.0005*									
		(0.0003)									
LR_POLG			-0.0977***								
			(0.0387)								
LR_ LAII*POLG			0.0048****								
			(0.0017)								
LR_INSTG				0.0080*							
				(0.0045)							
LR_ LAII*INSTG				-0.0004***							
				(0.0001)							
LR_ECOG					0.0055*						
					(0.0031)						

Table 13. Continued

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
LR_ LAII*ECOG					-0.0002**						
					(0.0001)						
LR_LCRT						0.0005					
						(0.0004)					
LR_LAII*LCRT						-0.0003***					
						(0.0001)					
LR_POL							0.0027**				
							(0.0015)				
LR_ LAII*POL							-0.0000				
							(0.0000)				
LR_LGF								-0.0320***			
								(0.0122)			
LR_ LAII*LGF								0.0020***			
								(0.0008)			
LR_LRG									0.0001		
									(0.0006)		
LR_LAII*LRG									-0.0001***		
									(0.0000)		
LR_LRLW										-0.0296**	
										(0.0124)	
LR_ LAII*LRLW										0.0016**	
										(0.0008)	
LR_LVACC											0.0375***
											(0.0135)
LR_ LAII*LVACC											-0.0022***
											(0.0008)
Observation	210	210	210	210	210	210	210	210	210	210	210
R-squared	0.60	0.94	0.61	0.84	0.81	0.89	0.91	0.90	0.89	0.87	0.91

Note: Standard errors in parentheses; *, ** and *** represent significance at the 1%, 5%, and 10% levels respectively.
Source: Author's Computations.

5. Policy implications

Firstly, the study shows that, on the one hand, unconditional AI investment did not enhance human well-being (HWBG) in both the short- and long-run; on the other hand, unconditional overall governance quality impacts HWBG. Therefore, while prioritizing AI-related initiatives to boost HWBG, the policymakers should not neglect governance quality as it also produces certain effect. This suggests that a balanced policy approach, focusing on both AI investment and governance quality, can contribute to comprehensive improvements in HWBG.

Secondly, when investment in AI and overall governance quality jointly have a positive and significant impact on HWBG in the BRICS countries, it suggests that quality of governance plays a crucial role in harnessing the benefits of AI for the well-being of citizens. It means that governments should prioritize the development and enforcement of robust governance and regulatory frameworks specifically tailored to investment in AI technologies. This should include clear guidelines for ethical AI development, data privacy, accountability mechanisms and some others. Governments should devise and enact policies that foster continued support and encouragement for AI research, development, and adoption. Such support can manifest itself through mechanisms like grants, tax incentives, and partnerships with private sectors, aiming to promote innovation within the AI industry while simultaneously reinforcing political governance structures, government effectiveness and rule of law in the BRICS countries both in the short- and long-run. Policymakers should prioritize enhancing economic governance by reducing bureaucracy, streamlining regulations, and ensuring fair competition within the AI industry. Effective economic governance fosters an environment conducive to AI innovation, thereby promoting both short-term and long-term improvements in human well-being.

Thirdly, when the interaction between investment in AI and institutional governance has a negative and significant impact on human well-being in the BRICS countries, it suggests that certain aspects of institutional governance may weaken the positive effects of AI investments both in the short- and long-run. To address this issue, it will be necessary to streamline the institutional governance regulations related to AI investments and applications. Policies that establish institutional regulatory environment that fosters innovation while incorporating essential safeguards to maximize the benefits of AI for human well-being should be promoted. Given that institutional governance structures often entail lengthy decision-making processes that could hinder the timely implementation of AI investment programs with societal benefits, governments and policymakers should proactively identify and address issues causing delays at the institutional level. Policymakers should prioritize policies that streamline complex bureaucratic procedures, which can otherwise impede AI initiatives at the institutional level. This is because simplifying processes for obtaining approvals, licenses, or funding for AI investment projects could accelerate the delivery of AI-driven services, promoting human well-being. Institutional governance decisions about resource allocation should prioritize AI investment initiatives that directly contribute to well-being.

Fourthly, the interaction between investment in AI and control of corruption making a negative and significant impact on human well-being in BRICS countries suggests that control of corruption has not played a crucial role in harnessing the benefits of AI for citizens' well-being. Therefore, policies should strengthen anti-corruption measures and enforcement to maintain a clean and transparent investment environment for AI and other technologies in BRICS countries. Governments and policymakers should develop and enforce ethical AI guidelines to prevent corrupt practices in AI procurement, development and deployment processes. This will ensure fairness and transparency in AI project selection and implementation. The results indicate that a peaceful and stable political environment has not played a crucial role in realizing the benefits of AI for citizens' well-being, so the governments of the BRICS countries should implement policies aimed at ensuring the continuity of political stability through effective governance, conflict resolution mechanisms, and investments in conflict prevention strategies. These measures could help minimize the risk of violence and social unrest, which could otherwise disrupt AI projects and overall economic stability. As the absence of violence reduces the need for resources and efforts to manage conflicts, governments will be able to allocate more resources to AI projects that could positively impact human well-being both in the short- and long-term. The result of the interaction between investment in AI and regulatory quality suggests that regulatory quality policies should foster innovation by providing clear rules and incentives for businesses to invest in AI research and development. This competition among AI providers can lead to improved AI technologies that have a positive impact on various aspects of human well-being, such as healthcare, education, and public services.There is a need for regulations that support innovation while safeguarding against potential negative consequences and balance safety and ethical considerations while encouraging AI research and development.

Finally, given that the BRICS countries are still classified as developing countries, the interaction between investment in AI and government effectiveness has a positive and significant impact on human well-being, which indicates the need for policies that further enhance government effectiveness by implementing reforms aimed at improving efficiency, transparency, and accountability in the use of AI investments. Since the interaction between investment in AI and the rule of law has a positive and significant impact on human well-being in BRICS countries, they are in need of policies addressing legal and regulatory bottlenecks that could hinder the development, deployment, and utilization of AI technologies effectively. Such policies should target complex or outdated legal frameworks, legal uncertainties, or inconsistent enforcement of AI-related laws and regulations, which could impede innovation and the full realization of AI's potential benefits for human well-being. The interaction between investment in AI and voice and accountability has a negative and significant impact on human well-being in BRICS countries, which may indicate that policies aimed at enhancing public participation, transparency, and accountability in AI decision-making processes are needed. These policies should encourage citizen engagement, ensure that AI applications align with societal values, and provide mechanisms for oversight and accountability in AI development and deployment in BRICS countries both in the short- and long-run. The negative impact might suggest that if these elements are lacking, AI technologies could be deployed in ways that do not fully consider the well-being and interests of the population, leading to adverse outcomes. Therefore, strengthening voice and accountability mechanisms becomes crucial in guiding AI investments and applications to benefit human well-being. Policies should promote robust collaboration among the BRICS countries to establish shared AI regulatory standards and norms aimed at enhancing human well-being. Sharing best practices and knowledge can help address BRICS AI investment challenges. BRICS governments should involve the public in AI-related decision-making processes to address concerns, build trust, and enhance government legitimacy. Policies should encourage sharing best practices and knowledge to address BRICS AI challenges, especially considering some of their prominent positions in AI development.

6. Conclusion

The BRICS countries (Brazil, Russia, India, China, and South Africa) have shown commitment to achieving and maintaining Sustainable Development Goal (SDG) 3 and 16 of the United Nations, which includes promoting human well-being for all and building strong institutions and governance. However, the empirical research question of how to leverage artificial intelligence (AI) investment to promote human well-being in the context of governance dynamics remained unexplored, especially concerning the BRICS economies; hence the need to examine the AI investment (AII) and human well-being (HWBG) nexus contingent on various dimensions or indicators of governance in the BRICS countries between 2012 and 2022. We applied the novel Cross-Sectional Augmented Autoregressive Distributed Lag (CS-ARDL) estimation and other novel econometric techniques. The research findings reveal a long-term relationship among variables, with various causality directions. Based on CS-ARDL results, policymakers should prioritize integrating governance quality into AII to boost HWBG in the short- and long-term perspective. However, caution is needed when considering AII's interaction with institutional governance, economic governance, control of corruption, political stability, regulatory quality and voice and accountability as it did not support HWBG either in the short or the long run.

Overall, these findings underscore the significance of governance quality in shaping the impact of AI investment on human well-being. Policymakers should pursue strategies that foster positive interactions between AI investment and governance dimensions while addressing potential negative impacts to ensure the overall enhancement of human well-being. In addition, targeted improvements in governance can help create an environment where AI contributes significantly to the overall well-being of citizens in the BRICS countries. Based on the CS-ARDL results, the study recommends that BRICS governments and policymakers prioritize and enhance the integration of AII into their governance systems to stimulate HWBG in both the short- and long-term perspective. However, the study cautions against overlooking the interaction between AII and variables such as institutional governance, economic governance, control of corruption, political stability, regulatory quality and voice and accountability, as it did not support HWBG either in the short or the long run. Therefore, the study recommends to develop AII-friendly governance policies within the BRICS countries, considering the nascent nature of AI as one of the technologies of the Fourth Industrial Revolution.

Future research should examine whether the conclusions of this study hold up to empirical inspection within country-specific or regional settings to further enhance our understanding of the research topic. The study acknowledges its scope and limitations, and future research is encouraged to include a broader range of variables, such as physical capital investments and other macroeconomic variables, to provide a more comprehensive analysis of the factors affecting human well-being.

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References

Aghion, P., Jones, B. F., & Jones, C. I. (2018). Artificial intelligence and economic growth. In *The economics of artificial intelligence: An agenda.* (pp. 237-282). University of Chicago Press.

Alatartseva, E., & Barysheva, G. A. (2016). What is well-being in the modern society: Objective view. *The European Proceedings of Social & Behavioural Sciences (EpSBS). Vol. 7: Lifelong Wellbeing in the World (WELLSO 2015). Nicosia, 2016*, 375-384.

Asongu, S. A., & Le Roux, S. (2017). Enhancing ICT for inclusive human development in Sub-Saharan Africa. *Technological Forecasting and Social Change*, *118*, 44-54. https://doi.org/10.1016/j.techfore.2017.01.026

Asongu, S. A., & Nwachukwu, J. C. (2016). The role of governance in mobile phones for inclusive human development in Sub-Saharan Africa. *Technovation*, *55*, 1-13. https://doi.org/10.1016/j.technovation.2016.04.002

Asongu, S. A., & Odhiambo, N. M. (2021). Income levels, governance and inclusive human development in Sub-Saharan Africa. *Applied Research in Quality of Life*, *16*, 71-103. https://doi.org/10.1007/s11482-019-09755-8

Badri, A. K., Badri, P. K., & Cham, M. (2019). ICT and human development in selected devolving countries. *International Journal of Social Sciences Perspectives*, *5*(2), 30-35. https://doi.org/10.33094/7.2017.2019.52.30.35

Bankole, F. O., Shirazi, F., & Brown, I. (2011). Investigating the impact of ICT investments on human development. *The Electronic Journal of Information Systems in Developing Countries*, *48*(1), 1-19. https://doi.org/10.1002/j.1681-4835.2011.tb00344.x

Barrington-Leigh, C., & Escande, A. (2018). Measuring progress and well-being: A comparative review of indicators. *Social Indicators Research*, *135*, 893-925. https://doi.org/10.1007/s11205-016-1505-0

Bedir, S., & Yilmaz, V. M. (2016). CO 2 emissions and human development in OECD countries: Granger causality analysis with a panel data approach. *Eurasian Economic Review*, *6*, 97-110. https://doi.org/10.1007/s40822-015-0037-2

Behera, J., & Sahoo, D. (2022). Asymmetric relationships between information and communication technology (ICT), globalization, and human development in India: evidence from non-linear ARDL analysis. *Journal of Economic Structures*, *11*(1), 1-25. https://doi.org/10.1186/s40008-022-00269-5

Benvenuti, M., Cangelosi, A., Weinberger, A., Mazzoni, E., Benassi, M., Barbaresi, M., & Orsoni, M. (2023). Artificial intelligence and human behavioral development: A perspective on new skills and competences acquisition for the educational context. *Computers in Human Behavior*, *148*, 107903. https://doi.org/10.1016/j.chb.2023.107903

Breusch, T. S., & Pagan, A. R. (1980). The Lagrange multiplier test and its applications to model specification in econometrics. *The Review of Economic Studies*, *47*(1), 239-253. https://doi.org/10.2307/2297111

Can, B., Ahmed, Z., Ahmad, M., & Can, M. (2022). Do renewable energy consumption and green trade openness matter for human well-being? Empirical evidence from European Union countries. *Social Indicators Research*, *164*(3), 1043-1059. https://doi.org/10.1007/s11205-022-02981-y

Chudik, A., & Pesaran, M. H. (2015). Common correlated effects estimation of heterogeneous dynamic panel data models with weakly exogenous regressors. Journal of econometrics, 188(2), 393-420. https://doi.org/10.1016/j.jeconom.2015.03.007

Clark, D. A. (2014). Defining and measuring human well-being. *Global environmental change. Springer, Dordrecht, Netherlands,* 833-855. http://dx.doi.org/10.1007/978-94-007-5784-4_66

Dauda, R. O., & Iwegbu, O. (2022). Human Development and Macroeconomic Shocks in Nigeria: An Empirical Investigation. *Journal of Social, Behavioral, and Health Sciences*, *16*(1), 371-391. https://doi.org/10.5590/JSBHS.2022.16.1.25

Davis, T. J. (2017). Good governance as a foundation for sustainable human development in sub-Saharan Africa. *Third World Quarterly*, *38*(3), 636-654. https://doi.org/10.1080/01436597.2016.1191340

Dumitrescu, E. I., & Hurlin, C. (2012). Testing for Granger non-causality in heterogeneous panels. Economic modelling, 29(4), 1450-1460. https://doi.org/10.1016/j.econmod.2012.02.014

Eichhorst, W., Marx, P., & Tobsch, V. (2009). Institutional arrangements, employment performance and the quality of work. *IZA Discussion Paper*, 4595.

Ferraz, D., Moralles, H. F., Costa, N. S. D., & Nascimento, D. D. (2022). Economic complexity and human development: comparing standard and slack-based data envelopment analysis models. *CEPAL Review*, 137.

Graetz, G., & Michaels, G. (2018). Robots at work. *Review of Economics and Statistics*, *100*(5), 753-768. https://doi.org/10.1162/rest_a_00754

Haseeb, M., Suryanto, T., Hartani, N. H., & Jermsittiparsert, K. (2020). Nexus between globalization, income inequality and human development in Indonesian economy: Evidence from application of partial and multiple wavelet coherence. *Social Indicators Research*, *147*(3), 723-745. https://doi.org/10.1007/s11205-019-02178-w

Heylighen, F. (2017). Towards an intelligent network for matching offer and demand: From the sharing economy to the global brain. *Technological Forecasting and Social Change*, *114*, 74-85. https://doi.org/10.1016/j.techfore.2016.02.004

Howarth, R. B. (2012). Sustainability, well-being, and economic growth. *Minding Nature*, *5*(2), 32-39.

Im, K. S., Pesaran, M. H., & Shin, Y. (2003). Testing for unit roots in heterogeneous panels. *Journal of Econometrics*, *115*(1), 53-74. https://doi.org/10.1016/S0304-4076(03)00092-7

Iqbal, K., Hassan, S. T., Peng, H., & Khurshaid. (2019). Analyzing the role of information and telecommunication technology in human development: panel data analysis. *Environmental Science and Pollution Research*, *26*, 15153-15161. https://doi.org/10.1007/s11356-019-04918-4

Järvelä, S., Nguyen, A., & Hadwin, A. (2023). Human and artificial intelligence collaboration for socially shared regulation in learning. *British Journal of Educational Technology*, 54(5), 1057-1076. https://doi.org/10.1111/bjet.13325

Kahneman, D., Diener, E., & Schwarz, N. (1999). *Well-being: Foundations of hedonic psychology*. Russell Sage Foundation.

Kaufmann, D., Kraay, A & Mastruzzi, M., (2010). The worldwide governance indicators: Methodology and analytical issues. *World Bank Policy Research Working Paper*, 5430.

Kaufmann, D., Kraay, A., & Mastruzzi, M. (2011). The worldwide governance indicators: Methodology and analytical issues. *Hague Journal on the Rule of Law*, *3*(2), 220-246. https://doi.org/10.1017/S1876404511200046

Khan, A., Siddiqui, S. H., Bukhari, S. H., & Iqbal, S. M. H. (2020). Human Development, Political Stability and Economic Growth: The way forward. *Review of Economics and Development Studies*, *6*(2), 351-361. https://doi.org/10.47067/reads.v6i2.213

Khan, H. U. R., Zaman, K., Khan, A., & Islam, T. (2017). Quadrilateral relationship between information and communications technology, patent applications, research and development expenditures, and growth factors: Evidence from the group of seven (G-7) countries. *Social Indicators Research*, *133*, 1165-1191. https://doi.org/10.1007/s11205-016-1402-6

Khan, R. E. A., & Naeem, H. M. (2020). Corruption, income inequality and human resource development in developing economies. *Asian Journal of Economic Modelling*, *8*(4), 248-259. https://doi.org/10.18488/journal.8.2020.84.248.259

Kim, Y. J., Kang, H., Sanders, G. L., & Lee, S. Y. T. (2008). Differential effects of IT investments: Complementarity and effect of GDP level. *International Journal of Information Management*, *28*(6), 508-516. https://doi.org/10.1016/j.ijinfomgt.2008.01.003

Kwon, H. J., & Kim, E. (2014). Poverty reduction and good governance: Examining the rationale of the Millennium Development Goals. *Development and Change*, *45*(2), 353-375. https://doi.org/10.1111/dech.12084

Levin, A., Lin, C. F., & Chu, C. S. J. (2002). Unit root tests in panel data: asymptotic and finite-sample properties. *Journal of Econometrics*, *108*(1), 1-24. https://doi.org/10.1016/S0304-4076(01)00098-7

Lu, C. H. (2021). The impact of artificial intelligence on economic growth and welfare. *Journal of Macroeconomics*, *69*, 103342. https://doi.org/10.1016/j.jmacro.2021.103342

Maiti, D., & Awasthi, A. (2020). ICT exposure and the level of wellbeing and progress: a cross country analysis. *Social Indicators Research*, *147*(1), 311-343. https://doi.org/10.1007/s11205-019-02153-5

Makridakis, S. (2017). The forthcoming Artificial Intelligence (AI) revolution: Its impact on society and firms. *Futures*, *90*, 46-60. https://doi.org/10.1016/j.futures.2017.03.006

Mateja, D., & Heinzl, A. (2021). Towards machine learning as an enabler of computational creativity. *IEEE Transactions on Artificial Intelligence*, *2*(6), 460-475. https://doi.org/10.1109/TAI.2021.3100456

Medina-Moral, E., & Montes-Gan, V. J. (2018). Economic freedom, good governance and the dynamics of development. *Journal of Applied Economics*, *21*(1), 44-66. https://doi.org/10.1080/15140326.2018.1526873

Mirza, F. M., Ansar, S., Ullah, K., & Maqsood, F. (2020). The impact of information and communication technologies, CO 2 emissions, and energy consumption on inclusive development in developing countries. *Environmental Science and Pollution Research*, *27*, 3143-3155. https://doi.org/10.1007/s11356-019-07131-5

Mishra, S., & Nathan, H. S. K. (2014). Measuring HDI–The Old, the New and the Elegant: Implications for multidimensional development and social inclusiveness. *LSE Asia Research Centre Working Paper*, *63*.

Mombeuil, C., & Diunugala, H. P. (2021). UN sustainable development goals, good governance, and corruption: The paradox of the world's poorest economies. *Business and Society Review*, *126*(3), 311-338. https://doi.org/10.1111/basr.12241

Nam, H. J., & Ryu, D. (2023). FDI and human development: The role of governance, ODA, and national competitiveness. *Journal of International Financial Markets, Institutions and Money*, *85*, 101769. https://doi.org/10.1016/j.intfin.2023.101769

Neogi, C. (2020). Effect of ICT on the performance of Indian states in terms of human development indices. In *Digitalisation and Development: Issues for India and Beyond* (pp. 287-318). Springer, Singapore. https://doi.org/10.1007/978-981-13-9996-1_11

Newey, W. K., & West, K. D. (1994). Automatic lag selection in covariance matrix estimation. *The Review of Economic Studies*, 61(4), 631-653. https://doi.org/10.2307/2297912

Njoh, A. J. (2018). The relationship between modern information and communications technologies (ICTs) and development in Africa. *Utilities Policy*, *50*, 83-90. https://doi.org/10.1016/j.jup.2017.10.005

Nussbaum, M. (2011). *Creating capabilities: The human development approach*. Harvard University Press. https://doi.org/10.4159/harvard.9780674061200.c8

Park, G., & Dreamson, N. (2023). The heterogeneous effects of human development and good governance on mobile diffusion in the sub-Saharan region: Evidence from panel quantile regression. *Technological Forecasting and Social Change*, *189*, 122355. https://doi.org/10.1016/j.techfore.2023.122355

Pedroni, P. (2001). Purchasing power parity tests in cointegrated panels. *Review of Economics and statistics*, *83*(4), 727-731. https://doi.org/10.1162/003465301753237803

Pedroni, P. (2004). Panel cointegration: asymptotic and finite sample properties of pooled time series tests with an application to the PPP hypothesis. *Econometric Theory*, *20*(3), 597-625. https://doi.org/10.1017/S0266466604203073

Pesaran, M. H. (2007). A simple panel unit root test in the presence of cross-section dependence. *Journal of Applied Econometrics*, *22*(2), 265-312. https://doi.org/10.1002/jae.951

Pesaran, M. H. (2021). General diagnostic tests for cross-sectional dependence in panels. *Empirical economics*, 60(1), 13-50. https://doi.org/10.1007/s00181-020-01875-7

Pesaran, M. H., & Yamagata, T. (2008). Testing slope homogeneity in large panels. *Journal of Econometrics*, *142*(1), 50-93. https://doi.org/10.1016/j.jeconom.2007.05.010

Pradhan, R. P. (2011). Good governance and human development: Evidence form Indian States. *Journal of Social and Development Sciences*, *1*(1), 1-8. https://doi.org/10.22610/jsds.v1i1.622

Qin, Y., Xu, Z., Wang, X., & Skare, M. (2023). Artificial Intelligence and Economic Development: An Evolutionary Investigation and Systematic Review. *Journal of the Knowledge Economy*, 1-35. https://doi.org/10.1007/s13132-023-01183-2

Qureshi, M. A., Qureshi, J. A., Ahmed, A., Qaiser, S., Ali, R., & Sharif, A. (2020). The dynamic relationship between technology innovation and human development in technologically advanced countries: fresh insights from quantiles-on-quantile approach. *Social Indicators Research*, *152*, 555-580. https://doi.org/10.1007/s11205-020-02451-3

Rapley, J., (2013). *Understanding Development: theory and Practice in the Third World*. Routledge, London and New York. https://doi.org/10.4324/9780203769461

Robeyns, I. (2005). Selecting capabilities for quality of life measurement. *Social indicators research*, *74*, 191-215. https://doi.org/10.1007/s11205-005-6524-1

Rogers, D. S., Duraiappah, A. K., Antons, D. C., Munoz, P., Bai, X., Fragkias, M., & Gutscher, H. (2012). A vision for human well-being: transition to social sustainability. *Current Opinion in Environmental Sustainability*, *4*(1), 61-73. https://doi.org/10.1016/j.cosust.2012.01.013

Saba, C. S. & Ngepah, N. (2022a). Convergence in renewable energy sources and the dynamics of their determinants: An insight from a club clustering algorithm. *Energy Reports,* 78, 116-125 *https://doi.org/10.1016/j.egyr.2022.01.190*

Saba, C. S. & Ngepah, N. (2022b). Convergence in renewable energy consumption and their influencing factors across regions: evidence from convergence algorithm approach. *Environmental Science and Pollution Research,* 29, 61412–61445. https://doi.org/10.1007/s11356-022-19731-9

Sarkodie, S. A., & Adams, S. (2020). Electricity access, human development index, governance and income inequality in Sub-Saharan Africa. *Energy Reports*, *6*, 455-466. https://doi.org/10.1016/j.egyr.2020.02.009

Sen, A. (1985). *Commodities and capabilities*. Oxford University Press.

Sen, A. (1999). *Development as Freedom*. Oxford University Press.

Sen, A. (2010). The mobile and the world. *Information Technologies & International Development*, *6*(SE), 1-4.

Sharma, G. D., Yadav, A., & Chopra, R. (2020). Artificial intelligence and effective governance: A review, critique and research agenda. *Sustainable Futures*, *2*, 100004. https://doi.org/10.1016/j.sftr.2019.100004

Smith, M., & Neupane, S. (2018). *Artificial intelligence and human development: toward a research agenda*. International Development Research Centre.

Soyyiğit, S. (2019). A comparative analysis of causality between institutional structure and economic performance for developed and developing countries. *Montenegrin Journal of Economics*, *15*(3). https://doi.org/10.14254/1800-5845/2019.15-3.3

Steinberger, J. K., & Roberts, J. T. (2010). From constraint to sufficiency: The decoupling of energy and carbon from human needs, 1975–2005. *Ecological Economics*, *70*(2), 425-433. https://doi.org/10.1016/j.ecolecon.2010.09.014

Topuz, S. G. (2022). The Relationship Between Income Inequality and Economic Growth: Are Transmission Channels Effective? *Social Indicators Research*, *162*(3), 1177-1231. https://doi.org/10.1007/s11205-022-02882-0

Tran, O. K. T., Le, H. D., & Nguyen, A. H. V. (2021). Role of institutional quality in economic development: A case study of Asian countries. *Problems and Perspectives in Management*, *19*(2), 357-369. http://dx.doi.org/10.21511/ppm.19(2).2021.29

Uddin, I., Ahmad, M., Ismailov, D., Balbaa, M. E., Akhmedov, A., Khasanov, S., & Haq, M. U. (2023). Enhancing Institutional Quality to Boost Economic Development in Developing Nations: New Insights from CS-ARDL Approach. *Research in Globalization*, 100137. https://doi.org/10.1016/j.resglo.2023.100137

Ulucak, R., Danish, & Li, N. (2020). The nexus between economic globalization and human development in Asian countries: an empirical investigation. *Environmental Science and Pollution Research*, *27*, 2622-2629. https://doi.org/10.1007/s11356-019-07224-1

United Nations Development Programme (2021). Human Development Index (HDI). In *Encyclopedia of Quality of Life and Well-Being Research*. United Nations Development Programme. https://doi.org/10.1007/978-94-007-0753-5_1342

Veenhoven, R. (2009). Well-being in nations and well-being of nations: Is there a conflict between individual and society? *Social Indicators Research*, *91*, 5-21. https://doi.org/10.1007/s11205-008-9323-7

Wang, Z., Rasool, Y., Asghar, M. M., & Wang, B. (2019). Dynamic linkages among CO2 emissions, human development, financial development, and globalization: empirical evidence based on PMG long-run panel estimation. *Environmental science and pollution research*, *26*, 36248-36263. https://doi.org/10.1007/s11356-019-06556-2

Westerlund, J. (2007). Testing for error correction in panel data. *Oxford Bulletin of Economics and statistics*, *69*(6), 709-748. https://doi.org/10.1111/j.1468-0084.2007.00477.x

Woodward, D. (2010). Democratizing global governance for sustainable human development. *Development*, *53*(1), 42-47. https://doi.org/10.1057/dev.2009.85

Zheng, J., & Wang, X. (2022). Impacts on human development index due to combinations of renewables and ICTs--new evidence from 26 countries. *Renewable Energy*, *191*, 330-344. https://doi.org/10.1016/j.renene.2022.04.033