Journal of Social and Economic Development
https://doi.org/10.1007/s40847-024-00401-0

RESEARCH PAPER

Artificial intelligence's (AI's) role in enhancing tax revenue, institutional quality, and economic growth in selected BRICS-plus countries

Charles Shaaba Saba[1] · **Nara Monkam**[2]

Accepted: 27 November 2024

Abstract

The BRICS countries, comprising Brazil, Russia, India, China, and South Africa, aim to achieve United Nations Sustainable Development Goal 8, which emphasizes sustainable economic growth. This study adds to the empirical literature by examining the impact of tax revenue and institutional quality on economic growth, incorporating the role of artificial intelligence (AI) in selected BRICS-Plus countries (the above-mentioned five countries) from 2012 to 2022. Utilizing the innovative Cross-Sectional Augmented Autoregressive Distributed Lag estimation technique, the analysis reveals a long-run equilibrium relationship among the variables. The study employs a modified Cobb–Douglas production function for its theoretical framework. The results indicate bidirectional causality between tax revenue and AI, economic growth and institutional quality, as well as institutional quality and tax revenue. Based on these findings, the study recommends that BRICS governments and policymakers enhance the integration of AI into tax systems to promote growth in both the short and long terms. However, it also advises caution regarding the interaction between AI and institutional quality, which did not support economic growth. While the AI and tax revenue interaction shows promise for fostering growth, robust measures are necessary to mitigate potential negative effects from AI's interaction with institutional quality. Consequently, the study advocates for the development of AI-friendly institutional policies in BRICS countries, considering the dynamic and rapidly evolving AI sector.

Keywords Artificial intelligence (AI) · Tax revenue · Institutional quality · Economic growth · BRICS countries

JEL Classification H2 · O33 · O43

✉ Charles Shaaba Saba
sabacharlesshaaba@yahoo.com

Nara Monkam
fn.monkam@up.ac.za; nmonkam@gmail.com

[1] School of Economics, College of Business and Economics, University of Johannesburg, Auckland Park Kingsway Campus, PO Box 524, Auckland Park, Johannesburg, South Africa

[2] Department of Economics, Faculty of Economic and Management Sciences (EMS), University of Pretoria, Private Bag X 20, Hatfield Pretoria 0028, South Africa

Published online: 13 January 2025

Introduction

In August 2023, during the 15th BRICS Summit, South African President Cyril Ramaphosa revealed that six emerging market nations—Argentina, Egypt, Ethiopia, Iran, Saudi Arabia, and the United Arab Emirates—were invited to join the bloc. However, by December 29, 2023, Argentina formally withdrew its application, and while Saudi Arabia has not officially joined, it actively participates in the organization's activities as a guest. Consequently, this study concentrates on selected BRICS-Plus countries, due to their long-established bilateral relations characterized by principles of non-interference, equality, and mutual benefit. The BRICS countries—Brazil, Russia, India, China, and South Africa—comprise a diverse group of emerging economies notable for their rapid technological advancements, varying capacities for revenue generation, and differing levels of institutional development. These countries have become significant global economic players, characterized by large populations, abundant resources, and increasing influence. As they seek sustainable economic growth, understanding the artificial intelligence (AI)–tax revenue–institutional quality nexus becomes crucial. This study investigates how these factors interact to influence growth in the selected BRICS-Plus countries, driven by four key considerations: (1) AI's potential to revolutionize various societal aspects, including taxation and institutions; (2) the challenge for BRICS to achieve the United Nations Sustainable Development Goal (SDG) 8, which focuses on sustainable economic growth; (3) the critical role of tax revenue and institutional quality in promoting or hindering economic growth; and (4) the research gaps in empirical literature on economic growth that need thorough exploration.

In recent years, domestic resource mobilization (DRM) has gained prominence in the economic development discourse in developing countries. DRM refers to generating savings from domestic resources and allocating them to socially productive investments, including private savings channeled through the financial sector and public savings through borrowing and taxation (African Economic Outlook 2010). In Africa, DRM, especially through taxation, is crucial for achieving the African Union's Agenda 2063, Agenda 2030, and the SDGs. It serves as the primary financing source for development on the continent. This explains why African countries strive to enhance their fiscal capacity, aiming to increase tax revenue from around 20% of GDP to levels seen in some Organization for Economic Cooperation and Development (OECD) countries, which approach 40% (Boly et al. 2020).

Tax revenue plays a crucial role in a nation's fiscal strategy, funding public services, infrastructure, and social programs. Its effectiveness hinges on factors like tax policies, administrative systems, compliance, and enforcement (Zimmermannova et al. 2016; Akitoby 2018). The level of tax revenue collected is vital for government investment in sectors essential to economic growth (Vinnitskiy 2020). Meanwhile, institutional quality, encompassing rule of law, transparency, political stability, and regulatory frameworks, is foundational for economic activity, investment, entrepreneurship, and governance (Chhabra et al. 2023; Shi et al. 2023; Kashif et al. 2024). Strong institutions attract both domestic and international investment by providing stability, predictability, and trust (Chhabra et al. 2023). Additionally, with rapid advancements, AI holds the potential to revolutionize industries, societies, and economies by simulating human intelligence to autonomously enhance productivity, efficiency, innovation in automation, data analysis, and decision-making (Makridakis 2017).

The BRICS countries recognize AI's transformative potential in sectors such as healthcare, agriculture, and finance and are actively investing in AI technologies, implementing policy initiatives, establishing research institutes, and supporting startups (Cyman et al. 2021; Dukhi et al. 2021). In taxation, technological advancements like Big Data, Analytics, AI, Machine Learning, the Internet of Things (IoT), Mobility, and Cloud Computing are poised to significantly impact tax administrations globally. These technologies offer intelligent tools to improve taxpayer satisfaction, empower tax agency personnel, streamline operations, and modernize services, driving digital transformation in tax systems.

Despite these efforts, BRICS countries still encounter challenges in these sectors. Tax revenue remains vital to the fiscal systems of BRICS economies, representing a significant share of government income (Neog and Gaur 2021). Each BRICS nation depends on various tax revenue sources, such as oil and gas taxes, goods and services taxes, and corporate taxes. Consequently, each country's unique tax policies and challenges shape the overall landscape of tax revenue in the BRICS group. Additionally, BRICS countries face institutional challenges such as corruption, limited political freedoms, weak rule of law, bureaucratic inefficiencies, and inadequate service delivery (see, for example, World Bank 2020, 2021a; Slipowitz 2021; Transparency International 2022; Freedom House 2022). These challenges affect the economic growth trajectory of these countries, influenced by factors such as export-oriented manufacturing, infrastructure investments, the services sector, government reforms, domestic consumption, dependence on natural resources, international sanctions, geopolitical influences, structural constraints, unemployment, and inequality (World Bank 2021b; International Monetary Fund 2021).

Understanding the impact of AI on tax revenue and institutional quality in the BRICS context is crucial for policymakers and researchers aiming to leverage AI's potential benefits for economic growth. AI can enhance tax administration, improve compliance, and reduce tax evasion through sophisticated monitoring and data analysis, potentially increasing tax revenue and socially productive investments. However, AI adoption in taxation may also pose challenges related to privacy, security, and fairness, which could impact public confidence in tax administration and have broader implications for economic growth. AI's integration into institutional quality can influence transparency, accountability, and efficiency, contributing to more effective governance, improved service delivery, and data-driven policy formulation. However, ethical considerations, lack of transparency, cybersecurity risks, and potential biases in AI algorithms need to be addressed to ensure AI strengthens institutional quality (Ahn and Chen 2020).

Given the significant differences in institutional and governance quality among BRICS countries (Singh 2022), it is crucial to explore how AI interacts with both institutional quality and tax revenue within the BRICS context. This exploration can provide valuable insights into how institutions and tax systems can harness AI technologies to enhance their effectiveness and foster economic growth. Figure 1 is a graphical representation of the time paths for the main variables of interest in this study, focusing on the BRICS countries. The preliminary information conveyed by the graphs indicates that the four variables did not follow a similar time path throughout the study period, underscoring the importance of investigating the interrelationships between these variables. To the best of the authors' knowledge, few studies have examined these relationships within the BRICS context. Therefore, the primary objective of this study is to address this research gap. While AI, tax revenue, and institutional quality have individually been recognized as significant factors influencing economic outcomes, there is a need to understand the specific dynamics and implications of their interactions on economic growth within the BRICS context (see, for example, Merrifield 2000; Castro

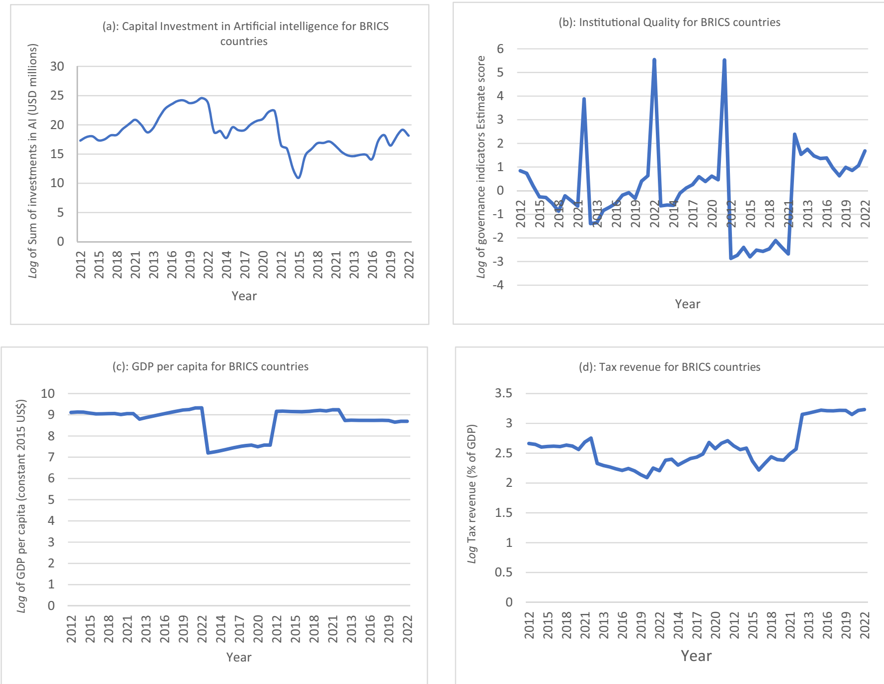

Fig. 1 **a** Capital investment in artificial intelligence for BRICS countries; **b** institutional quality for BRICS countries; **c** GDP per capita for BRICS countries; **d** tax revenue for BRICS countries. *Source*: Authors' Visualization

and Camarillo 2014; Javed, 2016; Alonso et al. 2020; Radhakrishnan and Chattopadhyay 2020; Ghahramani and Pilla 2021; Minh Ha et al. 2022; Jabeur et al. 2022, among others).

Hence, the research questions this study seeks to address are: (1) What are the causal relationships among the main variables of interest in the BRICS economies? (2) What are the short- and long-run impacts of AI, tax revenue, and institutional quality on economic growth in the BRICS economies? (3) What are the short- and long-run mediating effects of AI on the impact of tax revenue on economic growth in the BRICS economies? (4) What are the short- and long-run mediating effects of AI on the impact of institutional quality on economic growth in the BRICS economies? (5) What policy implications can be derived from the findings regarding the relationships between the key variables of interest?

This study specifically explores how AI complements tax revenue and institutional quality in both the short and long terms to promote economic growth in a panel of five BRICS economies over the period 2012–2022. It also examines the causal relationships between these variables in the BRICS countries over this period, using principal component analysis to compute the institutional quality variable from six governance indicators. In summary, the BRICS economies, marked by technological progress, revenue generation disparities, and institutional variations, lack comprehensive insights into the combined effects of AI, tax revenue, and institutional quality on economic growth. This study aims to fill this gap by examining how the interactions between AI and tax revenue, and AI and institutional quality, influence economic growth in BRICS countries.

While AI, tax revenue, and institutional quality have been acknowledged as influential factors, a critical gap exists in understanding the intricate interplay and consequences of their interactions within the BRICS context.

By addressing this research objective, the study aims to shed light on unexplored dimensions of economic dynamics within these countries. The findings could provide valuable insights into the nuanced relationships between cutting-edge technology, fiscal policies, and institutional frameworks, ultimately contributing to a deeper understanding of how these factors collectively influence economic growth. Such insights hold significance not only for academic discourse but also for policymakers, economists, and business leaders invested in the growth and development of these dynamic economies.

Our research on BRICS countries contributes to existing literature in several ways. Firstly, it investigates the causal relationships between AI, tax revenue, institutional quality, and economic growth. Secondly, it examines the short- and long-term impacts of AI, tax revenue, and institutional quality on economic growth. Thirdly, it explores the interaction between AI and tax revenue on economic growth. Fourthly, it investigates the interaction between AI and institutional quality on economic growth. Lastly, it discusses policy implications derived from the results obtained. We also consider issues of homogeneity and cross-sectional dependence (CD) in the series under unit root and cointegration techniques. Most panel series in the literature assume unrelated residual terms, ignoring CD issues between countries. Accounting for CD issues is essential as BRICS countries possess varying economic characteristics. We applied the panel causality technique proposed by Dumitrescu and Hurlin (2012), which considers heterogeneity among countries.

Additionally, to the best of our knowledge, this is the first study to employ the novel Cross-Sectional Autoregressive Distributed Lag (CS-ARDL) technique proposed by Chudik and Pesaran (2015). We primarily relied on the CS-ARDL approach due to its advantages: (1) CS-ARDL is suitable for dynamic panel data analysis, capturing both short- and long-term dynamics; (2) it accommodates cross-sectional heterogeneity, acknowledging unique characteristics of each BRICS country; (3) it addresses endogeneity issues by including lagged dependent variables and instrumental variables; (4) it offers a more efficient way to deal with endogeneity and omitted variable bias compared to traditional pooled OLS models; and (5) it yields robust results in the presence of cross-sectional dependence and can be applied to series with different orders of integration (Chudik and Pesaran 2015).

Despite these justifications, the CS-ARDL model has limitations: (1) it is complex to implement, requiring a thorough understanding of econometric techniques; (2) it assumes linear relationships and may experience estimation challenges with structural breaks; (3) results can be sensitive to model specifications, such as lag orders; and (4) it has demanding computational requirements, leading to longer processing times and increased resource needs. This study holds academic and policy significance in several ways: (1) it highlights the joint effect of AI and tax revenue on growth in BRICS countries; (2) it underscores the importance of the joint effect of AI and institutional quality on growth in BRICS countries; and (3) it enhances understanding of how the interrelationship between AI, tax revenue, and institutional quality can impact BRICS countries' approach to AI, tax revenue, and institutional sector policies. The primary theoretical contribution of this study is the use of a modified Cobb–Douglas production function (Cobb 1928), following previous empirical studies, to investigate the study's objectives.

The paper is structured as follows: Sect. 2 covers the literature review and development of hypotheses. Section 3 outlines the methodology and data. Section 4 discusses the results of the empirical analysis, followed by policy implications and additional discussions in Sect. 5. The study concludes in Sect. 6.

Literature review and hypotheses development

This literature review explores the evolving relationship between AI, tax revenue, institutional quality, and economic growth (Maruta et al. 2020; Ashraf et al. 2022; Kibria and Toufique 2023). It provides a comprehensive analysis of studies on how taxation impacts growth, noting that effects vary depending on whether tax policies are viewed through endogenous or exogenous (neoclassical) growth theories. Researchers have examined this by analyzing different tax components, rates, policies, and reforms.

Economic theory suggests that taxes variably impact economic growth. Some scholars find that growth boosts tax revenues and the tax-to-GDP ratio, while others report conflicting outcomes. For example, Hamdi and Sbia (2013) link tax revenue positively to growth, yet Fölster and Henrekson (2001) find the opposite. Distortionary taxes generally hinder growth (Cashin 1995; Kneller et al. 1999). Fiscal deficits up to 1.5% of GDP support growth, but beyond that, they impede it (Adam and Bevan 2005). Gill et al. (2006) included tax revenue as a fiscal policy variable to demonstrate the negative impact of tax revenue shocks on growth. In contrast, studies also show bidirectional causality between tax revenue and growth (Pula and Elshani 2018) and examine tax rate impacts on growth, noting that high integrity countries respond more positively to tax changes than corrupt ones (Cerqueti and Coppier 2011).

Hatfield (2015) assessed the impact of tax decentralization on growth using an endogenous growth model, finding that decentralized governments optimize tax policies to enhance growth, unlike centralized ones. Jaimovich and Rebelo (2017) identified a nonlinear link between low tax rates and minimal impact on growth. Thomas (2017) analyzed India's service taxation (1994–1995), revealing significant income elasticity despite low tax-to-GDP. Gurdal et al. (2021) studied G-7 nations (1980–2016) and found bidirectional causality between tax revenue, growth, and government spending. In Bangladesh, Rahman and Siddiquee (2022) used the ARDL method, noting bidirectional causality between direct tax and growth, and a negative long-run effect of indirect tax on growth.

Ojede and Yamarik (2012) analyzed the impact of tax policy on income growth across 48 US states (1967–2008), finding that property and sales taxes hinder long-term growth, while income taxes have no significant effect. Gnangnon (2024) expanded this focus by examining tax transition reforms in 101 developing countries (1980–2019), reporting positive growth impacts even in nations with high non-resource tax revenues. Pradhan et al. (2022) further analyzed financial market development's role in OECD and non-OECD countries, linking both financial growth and taxation propensity to positive long-term growth. In Nigeria, Adefolake and Omodero (2022) found that petroleum profit tax and VAT boost growth, while company income tax hampers it. Khujamkulov and Abizadeh (2023) observed that higher tax revenue-to-GDP ratios drive growth in transitional economies. However, Gechert and Heimberger (2022) revealed a publication bias favoring corporate tax cuts' growth-enhancing effects, finding no significant growth effect upon adjustment. Ho et al. (2023) reported that tax revenue supports growth in 29 developing countries, with trade openness amplifying this effect. Amoh et al. (2023) found that institutional quality moderates tax evasion's impact on GDP per capita in

Ghana, while Shi et al. (2022) observed that China's 2004 VAT reform improved firms' productivity and industrial upgrading.

These studies examine the intricate relationships between taxation, economic growth, institutional quality, and trade openness. Hatfield (2015), Gurdal et al. (2021), and Rahman and Siddiquee (2022) emphasize the complex dynamics between tax policy and economic outcomes, while Jaimovich and Rebelo (2017) and Gechert and Heimberger (2022) address the nuanced effects and limitations of tax rates and tax cuts. Ojede and Yamarik (2012) and Adefolake and Omodero (2022) show that tax types, such as property, sales, income, and VAT, impact growth differently across diverse economies. Pradhan et al. (2022) and Ho et al. (2023) highlight the roles of financial markets and trade openness in shaping these tax-growth dynamics. Based on these theoretical and empirical insights, a hypothesis is proposed to further investigate these relationships.

H_1: Tax revenue positively influences economic growth in both the short and long run in selected BRICS-Plus countries.

Research has extensively explored the determinants of economic growth across national and global contexts, highlighting trade openness, technological progress, government size, and income distribution as influential factors (Barro 1991; Levine and Renelt 1992). Recently, the focus has shifted toward institutional quality as a key factor explaining economic differences across regions (Ashraf et al. 2022; Kibria and Toufique 2023). Hashim et al. (2011), for example, found that institutional quality had a significant impact on economic performance in 27 Sub-Saharan African countries from 1984 to 2003, while other control variables showed limited effects.

Sathyamoorthy and Tang (2018) examined how institutional quality influences the export-growth relationship across 119 countries (1990–2010), finding that institutional quality significantly mediates this nexus, particularly in middle-income countries. Ashraf et al. (2022) extended this by addressing spatial factors in Belt and Road Initiative (BRI) economies, using spatial econometrics on data from 86 countries (1995–2019). Their findings reveal spatial dependencies in economic growth, with neighboring countries' institutional quality and openness providing positive spillovers. Kibria and Toufique (2023) further highlighted governance's role in socio-economic outcomes, applying both linear and nonlinear ARDL models to demonstrate governance's impact on quality of life over time. These studies, while distinct in methodology, underscore the vital role of institutional quality in economic performance. Ashraf et al. emphasize external spatial influences, while Kibria and Toufique focus on internal governance dynamics, together showing that strong institutions foster economic growth and regional benefits. This convergence supports the hypothesis that institutional quality positively impacts growth. Consequently, we put forward the following hypothesis:

H_2: Institutional quality has a positive effect on economic growth in both the short and long run in selected BRICS-Plus countries.

AI research largely focuses on its effects on economic indicators like growth, productivity, and technical innovation, among others (Hémous and Olsen 2022; Aghion et al. 2018; Brynjolfsson et al. 2019). Graetz and Michaels (2018) found total factor productivity as a main channel for AI-driven growth. Acemoglu and Restrepo (2018a, 2018b) showed that AI could address aging population challenges by increasing productivity. Qiu et al. (2021) developed a model associating technological progress with GDP growth under the "Belt and Road" initiative. Lu (2021) observed short-term growth and utility gains from AI's role in production, while Bandari (2019) highlighted AI's impact on revenue growth in small businesses in developing countries.

Kopka and Fornahl (2024) examine how latecomer firms adopt AI to develop new technological paths. They find that smaller firms operating at the productivity frontier experience productivity gains from AI, whereas larger firms see greater benefits in innovation, which challenges the leapfrogging hypothesis. Lundvall and Rikap (2022) explore China's rise in AI, emphasizing the simultaneous evolution of Corporate and National Innovation Systems, inspired by Freeman's study of Japan. Their findings highlight China's strengths in AI adoption and output driven by government investment, which benefits firms like Baidu and Tencent. However, they also note challenges in attracting top talent, setting standards, and advancing semiconductor technology. Additionally, Sabir and Qamar (2019) and Fernández-Rodríguez et al. (2023) underscore the influence of fiscal and institutional dynamics on economic outcomes, with focuses on growth and tax rates, respectively. Across these studies, Zhao et al. (2022), through Kopka and Fornahl (2024), agree on AI's transformative potential but vary in their assessments of its economic impacts and sustainability, especially regarding labor and innovation across firm sizes. Lundvall and Rikap's (2022) study uniquely incorporates China's geographical and strategic position in the global AI landscape, balancing strengths and challenges. Therefore, based on discussion of the above empirical studies, we formulate the following hypothesis:

H*$_3$*: AI has a positive effect on economic growth in both the short and long run in selected BRICS-Plus countries.

There is extensive research on diverse tax structures, institutional quality, and economic growth. However, to our knowledge, there are few studies that specifically explore the unique contributions of AI to enhancing tax revenue and institutional quality, to foster growth in BRICS countries through the innovative CS-ARDL method. Consequently, we put forward the following hypotheses:

H*$_4$*: AI is positively associated with the relationship between tax revenue quality and economic growth in both the short and long run in selected BRICS-Plus countries.

H*$_5$*: AI is positively associated with the relationship between institutional quality and economic growth in both the short and long run in selected BRICS-Plus countries.

This study is undertaken with the goal of proposing policies that will assist BRICS countries in achieving Sustainable Development Goal 8, which is centered on sustainable economic growth.

Empirical methodology and data

Empirical strategy

This study's empirical strategy includes principal components analysis (PCA), descriptive statistics, scatter plots, panel unit root tests, slope homogeneity tests, cross-sectional dependence (CD) tests, CIPS panel unit root tests, first- and second-generation panel cointegration tests, FMOLS, DOLS, Dumitrescu and Hurlin (2012) panel causality tests, and Augmented Mean Group (AMG) estimation. While not all estimated equations are shown, the CS-ARDL model is the primary approach. The panel AMG estimator (Eberhardt and Bond 2009; Eberhardt and Teal 2010) is also employed to ensure robustness against cross-sectional dependence and slope heterogeneity. Figure 2 provides a visual summary of the methodology (Table 1).

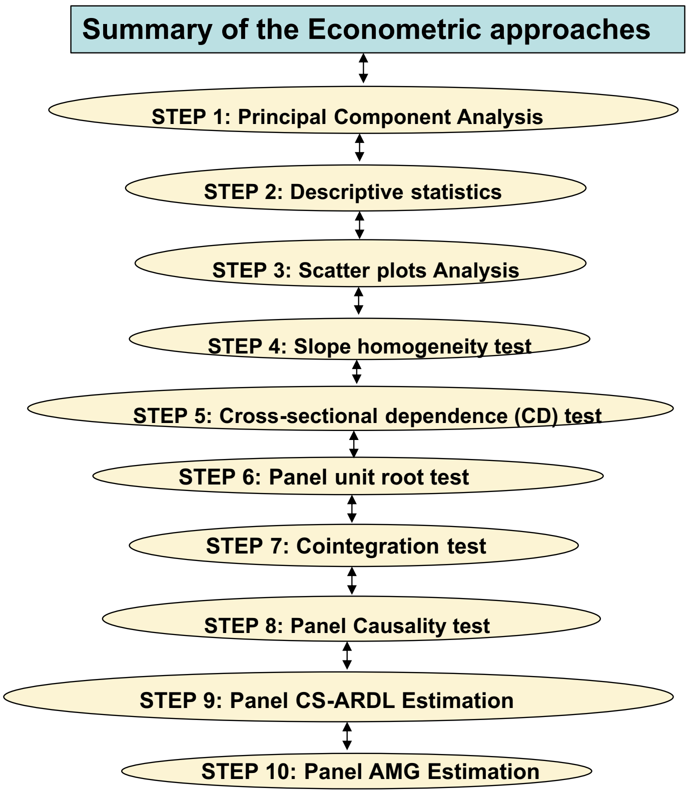

Fig. 2 Summary of econometric approaches. *Source*: Authors' Design

Table 1 Acronyms. *Source*: Authors' Design

AI	Artificial intelligence
BRICS	Brazil, Russia, India, China, and South Africa,
CS-ARDL	Cross-Sectional Augmented Autoregressive Distributed Lag
SDG	United Nations Sustainable Development Goal
DRM	Domestic resource mobilization
OECD	Organization for Economic Cooperation and Development countries
IoT	Internet of Things
CD	Cross-Sectional Dependence
OLS	Ordinary least squares
ARDL	Autoregressive Distributed Lag
VAT	Value-Added Tax
BRI	Belt and Road Initiative countries
SGMM	System Generalized Method of Moments
ETRs	Effective Tax Rates
FMOLS	Fully Modified Ordinary Least Squares
DOLS	Dynamic Ordinary Least Squares
AMG	Augmented Mean Group

Theoretical underpinning and empirical model specification

This paper is grounded in the Cobb–Douglas (1928) and Solow-Swan (1956) production functions, modified to examine AI, tax revenue, institutional quality, and economic growth within BRICS. AI technologies enhance productivity through automation and data analytics, leading to economic expansion and increased output (Schumpeter 1934). As AI adoption spreads, technological spillovers foster innovation across sectors, supporting a culture of competitiveness (Romer 1986; Lucas 1988). Higher profits from AI-driven productivity increase the taxable income base, potentially raising government revenue for public investment (Mill 1845 ; Czarnitzki et al. 2011). Tax incentives for AI R&D can further promote economic growth while shaping the technological landscape (Czarnitzki et al. 2011; Chand et al. 2020).

Institutional quality, particularly regulatory frameworks, is vital for AI adoption. Transparent policies reduce uncertainties and encourage AI innovation, while intellectual property protection boosts investment confidence (Hare 2001). Although AI may initially disrupt employment and industry structures, it ultimately leads to sustainable growth and economic transformation. Institutional adaptation is key to maximizing AI's benefits. Overall, the theoretical framework underscores AI's transformative impact on growth, supported by institutions that mediate short- and long-term outcomes. This dynamic is modeled by a Cobb–Douglas function with constant returns to scale:

$$Y_{i,t} = f\left(K_{i,t}, L_{i,t}\right) \tag{1}$$

$$Y_{i,t} = AK_{i,t}^{\beta} L_{i,t}^{1-\beta} \tag{2}$$

where Y, k, L and A denote GDP per capita (GDPPC), capital, effective labor, and technical progress/efficiency, respectively. According to the Solow-Swan growth model, technological progress is a crucial factor in driving output. AI, being a transformative technology, can enhance productivity and spur innovation, thereby increasing output. This model suggests that AI's capabilities in automating tasks, optimizing processes, and making predictions can significantly boost efficiency and productivity across various sectors (Aghion et al. 2018; Furman and Seamans 2019). Furthermore, AI can stimulate the generation of new ideas and technologies, promoting sustained economic growth (Brynjolfsson and McAfee 2014). Additionally, rapid economic growth during the production process is influenced by several factors, including tax revenue and institutional quality, among others. Since variable A includes various policy-related variables that are not explicitly represented in the equation, we expand our model to incorporate tax revenue and institutional quality through the technical progress parameter to empirically assess their impact on output (Bassanini and Scarpetta 2002; Saba 2020). Thus, the augmented output function can be formulated a

$$\mathrm{DPPC}_{i,t} = f\left(X_{i,t}\right) \tag{3}$$

$$\mathrm{LGDPPC}_{i,t} = \beta_0 + \beth_0 X_{i,t} \tag{4}$$

$$\mathrm{LGDPPC}_{i,t} = \beta_0 + \beth_0 X_{i,t} + \varepsilon_{it} \tag{5}$$

where LGDPPC and X denote the log of GDPPC (proxy for economic growth) and regressors,[1] respectively. The initial econometric models, which were subsequently transformed into the CS-ARDL model and estimated, are provided below:

Model 1:

$$\begin{aligned}\mathrm{LGDPPC}_{i,t} = \beta_1 + \beth_1\mathrm{LAI}_{it} + \beth_2\mathrm{LGFCF}_{it} + \beth_3\mathrm{LTAXR}_{it} \\ + \beth_4\mathrm{LLHUM}_{\mathrm{it}} + \beth_6\mathrm{INSQTY}_{it} + \varepsilon_{1it}\end{aligned} \tag{6}$$

where β, $\beth_1, \ldots, \beth_4$, and ϵ_{it} represent the constant term, coefficients, and the error term, respectively. In Model 1, the interaction terms between LAI and LTAXR, as well as LAI and INSQTY, are omitted. The subsequent models (Models 7–8) incorporate these interaction terms step by step.

Model 2: *Analyzing LAI and LTAXR interaction*

$$\begin{aligned}\mathrm{LGDPPC}_{i,t} = \beta_1 + \beth_1\mathrm{LAI}_{it} + \beth_2\mathrm{LGFCF}_{it} + \beth_3\mathrm{LTAXR}_{it} + \beth_4\mathrm{LHUM}_{it} \\ + \beth_5\mathrm{INSQTY}_{it} + \beth_6\mathrm{LAI}_{it} * \mathrm{LTAXR}_{it} + \varepsilon_{1it}\end{aligned} \tag{7}$$

Model 3: *Analyzing LAI and INSQTY interaction*

$$\begin{aligned}\mathrm{LGDPPC}_{i,t} = \beta_1 + \beth_1\mathrm{LAI}_{it} + \beth_2\mathrm{LGFCF}_{it} + \beth_3\mathrm{LTAXR}_{it} + \beth_4\mathrm{LLHUM}_{it} \\ + \beth_5\mathrm{INSQTY}_{it} + \beth_6\mathrm{LAI}_{it} * \mathrm{INSQTY}_{it} + \varepsilon_{1it}\end{aligned} \tag{8}$$

We outline the CS-ARDL model below, which is derived from the equations mentioned above.

$$\begin{aligned}\Delta\mathrm{LGDPPC}_{it} = \mathfrak{F}_i + \xi_i\Big(\mathrm{LGDPPC}_{i,t-1} - \beth_i X_{i,t-1} - \beta_{1i}\overline{\mathrm{LGDPPC}}_{t-1} - \beta_{2i}\bar{X}_{t-1}\Big) \\ + \sum_{j=0}^{p-1}\gamma_{ij}\Delta\mathrm{LGDPPC}_{i,t-j} \\ + \sum_{j=0}^{v-1}\Gamma_{ij}\Delta X_{i,t-j} + \emptyset_{1i}\Delta\overline{\mathrm{LGDPPC}}_t + \emptyset_{2i}\Delta\bar{X}_t + u_{it}\end{aligned} \tag{9}$$

where ΔLGDPPC, $X_{i,t}$, $\overline{\mathrm{LGDPPC}}_{t-1}$ & $\overline{X}_{t-1}$, $\Delta\mathrm{LGDPPC}_{i,t-j}\&\Delta X_{i,t-j}$, $\Delta\overline{\mathrm{LGDPPC}}_t\&\Delta\overline{X}_t$ and u_{it} represent the dependent variable, all independent variables in the long run, the long-run mean of the dependent and explanatory variables, the dependent and independent variables in the short run, the short-run mean of the dependent and independent variables, and the error term, respectively. Furthermore, j, t, $\beth_{1i}$, γ_{1i}, Γ_{ij}, $\varnothing_{1i}$ and $\varnothing_{2i}$ represent the cross-sectional dimension, time period, long-run coefficients of the independent variables, short-run coefficients of the dependent variable, short-run coefficients of the independent variables, short-run mean of the dependent variables, and short-run mean of the independent variables, respectively. The specifics of the dependent and independent variables are detailed in Table 2.

[1] Due to the governing rules, it is important for the reader to take note that we did not log variables with negative values.

Table 2 Variable description and data sources *Source*: Authors' Compilations

Variables	Description	Expected Sign	Sources
Dependent variable			
LGDPPC	*Log of* GDP per capita (constant 2015 US$) serves as proxy for economic growth		WDI database
Independent variables			
LAI	*Log* of venture capital investments in artificial intelligence (AI) serves as proxy for AI	+	OECD database
LGFCF	*Log* of Gross fixed capital formation (% of GDP)	+	WDI database
LTAXR	*Log* of Tax revenue (% of GDP) serves as proxy for tax revenue	+	WDI database
LHUM	*Log* of School enrollment, primary (% gross) serves as proxy for human capital	+	WDI database
LAI*LTAXR	Computed interaction between AI and tax revenue	±	Authors
LAI*INSQTY	Computed interaction between AI and institutional quality	±	Authors
Institutional quality (INSQTY) variable computed via PCA using the six governance indicators below		+	Authors
WGIc	Control of Corruption		WGI database
WGIp	Political stability and absence of violence/terrorism		WGI database
WGIg	Government effectiveness		WGI database
WGIreg	Regulatory quality		WGI database
WGIr	Rule of law		WGI database
WGIv	Voice and accountability		WGI database

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

Studies that have used these techniques include those of Saba and Ngepah (2022a, 2022b, 2022c, 2024), Saba and Monkam (2024), Saba et al. (2024a, 2024b), Saba and Pretorius (2024) and Saba (2022, 2023)

Table 3 Principal component and correlation matrix results for institutional quality. *Source*: Authors' Computations

Institution quality variables				
Compnnt	Eigenvalue	Difference	Proportion	Cumulative
Principal component results				
Compnnt 1	3.289	1.919	0.548	0.548
Compnnt 2	1.350	0.486	0.228	0.776
Compnnt 3	0.884	0.615	0.147	0.924
Compnnt 4	0.269	0.137	0.045	0.969
Compnnt 5	0.132	0.077	0.022	0.990
Compnnt 6	0.056		0.009	1.000

Institution quality variables							
Variables	Compnnt 1	Compnnt 2	Compnnt 3	Compnnt 4	Compnnt 5	Compnnt 6	Unexplained
Principal components eigenvectors results							
WGIc	0.510	−0.106	−0.038	0.586	−0.456	0.421	0.131
WGIg	0.381	−0.512	0.344	−0.099	0.630	0.261	0.163
WGIp	0.021	0.626	0.702	0.293	0.170	−0.027	0.462
WGIreg	0.477	0.170	0.236	−0.719	−0.411	0.042	0.211
WGIr	0.533	−0.009	−0.147	0.192	0.114	−0.803	0.067
WGIv	0.288	0.553	−0.557	−0.088	0.431	0.327	0.307
Correlation matrix results i		ii	iii	iv	v	vi	
(i) WGIc	1.000						
(ii) WGIg	0.654*** (0.000)	1.000					
(iii) WGIp	−0.044*** (0.514)	−0.193*** (0.004)	1.000				
(iv) WGIreg	0.681*** (0.000)	0.537*** (0.000)	0.259*** (0.000)	1.000			
(v) WGIr	0.903*** (0.000)	0.622*** (0.000)	−0.043*** (0.527)	0.759*** (0.000)	1.000		
(vi) WGIv	0.390*** (0.000)	−0.153*** (0.023)	0.151*** (0.026)	0.460*** (0.000)	0.558*** (0.000)	1.000	

Note: ***$p<0.01$; **$p<0.05$; *$p<0.1$ indicate levels of statistical significance, p value in parentheses. Here compnnt is component Source**:** Authors' computation using WDI, WGI and ITU data

Data and variables description

This study analyzes annual panel data from 2012 to 2022 for the BRICS countries—Brazil, China, India, Russia, and South Africa—chosen due to increased AI integration across sectors during this period (Cyman et al. 2021). The time frame provides current data, sourced from OECD, World Bank's WDI, and World Governance Indicators (WGI), enabling relevant policy analysis despite limitations in capturing long-term trends. Institutional quality, represented by six indicators detailed in Tables 2 and 3, was assessed using Principal

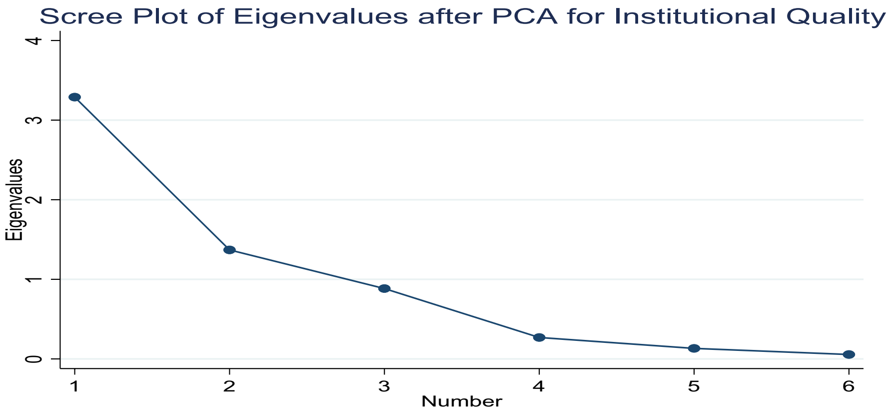

Fig. 3 Scree plot for institutional quality. *Source*: Authors' Visualization

Table 4 Descriptive statistics results. *Source*: Authors' computations

	LGDPPC	LAI	LTAXR	LGFCF	LHUM	INSQTY
Mean	8.699	18.624	2.600	3.168	4.628	0.000
Median	9.039	18.246	2.567	3.064	4.625	−0.115
Maximum	9.323	24.586	3.231	3.796	4.703	5.584
Minimum	7.199	11.002	2.091	2.572	4.562	−2.887
Std. Dev	0.660	3.093	0.340	0.369	0.038	1.814
Skewness	−1.276	0.082	0.726	0.394	0.295	0.818
Kurtosis	3.022	2.672	2.392	1.947	2.042	4.590
Jarque–Bera	59.726	1.233	22.740	15.85703	11.593	47.692
Probability	0.000	0.540	0.000	0.000	0.003	0.000
Observations	220	220	220	220	220	220

Component Analysis (PCA). Table 2 lists all study variables, offering insights into AI, tax revenue, institutional quality, and economic growth in BRICS countries.

Empirical results and discussion

Preliminary analysis

Principal component analysis

Table 3 summarizes the principal component analysis (PCA) used to create an institutional quality (INSQTY) index for BRICS countries by combining six governance indicators. The correlation matrix confirms strong correlations among the indicators, validating PCA's use (Saba and Ngepah 2022a, b, c). The first component, with an eigenvalue of 3.289, explains 54.8% of the total variance, making it the most informative. Governance indicators, particularly rule of law (WGIr), control of corruption

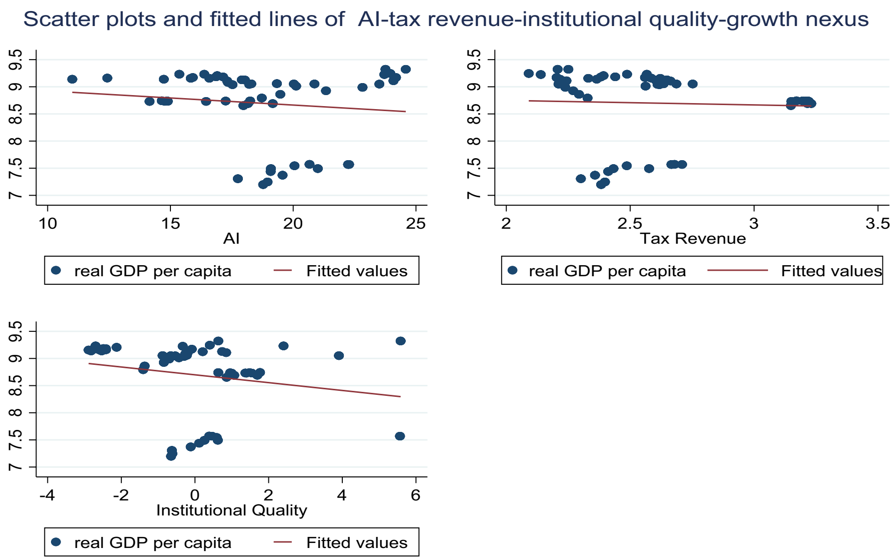

Fig. 4 Scatter plots graphical presentation. *Source*: Authors' Visualization

(WGIc), and regulatory quality (WGIreg), show high loadings, highlighting their influence on institutional quality. The scree plot in Fig. 3 supports focusing on this component as it best captures institutional quality across BRICS.

Summary statistics and scatter plot analysis

Table 4 presents statistical summaries of the study variables for BRICS countries. The mean and median for LGDPPC, LAI, LTAXR, LGFCF, LHUM, and INSQTY are 8.699 (9.039), 18.624 (18.246), 2.600 (2.567), 3.168 (3.064), 4.628 (4.625), and 0.000 (−0.115), respectively, indicating high economic growth, AI investments, stable tax revenue, gross fixed capital formation, and human capital, but diverse institutional quality. LGDPPC is negatively skewed, while LAI is near-normal. LTAXR, LGFCF, LHUM, and INSQTY show positive skewness, with Jarque–Bera tests confirming non-normality in most variables. Scatter plots suggest inverse relationships between LGDPPC and other explanatory variables (see Fig. 4).

Table 5 Slope homogeneity results. *Source*: Authors' computations

Test statistics (deLta)	Value	p value
Δ_{delt}	14.244***	0.000
$\Delta_{adjdelt}$	15.567***	0.000

***, ** and * denote significance at 1%, 5% and 10%, respectively

Table 6 Cross-sectional dependence (CD) test results. *Source*: Authors' computations

Variables	Pesaran test		Breusch–Pagan LM test	
	Statistic	*P* value	Statistic	*P* value
LGDPPC	−1.02***	0.000	139.890***	0.000
LAI	12.42***	0.000	67.825***	0.000
LTAXR	3.23***	0.000	56.706***	0.000
LGFCF	8.80***	0.000	57.796***	0.000
LHUM	−2.74***	0.000	114.674***	0.000
INSQTY	13.85***	0.000	215.232***	0.000

***$p < 0.01$, **$p < 0.05$, and *$p < 0.1$ are significance levels, respectively, that denote rejection of null hypothesis

Table 7 Panel unit root test results. *Source*: Authors' computations

Series	Model	Levels	First difference
LGDPPC	LLC	−1.523* (0.064)	−7.732*** (0.000)
	IPS	0.482 (0.685)	−9.015*** (0.000)
LAI	LLC	−0.970 (0.570)	−6.520*** (0.000)
	IPS	0.506 (0.694)	−7.720*** (0.000)
LTAXR	LLC	0.394 (0.653)	−6.296*** (0.000)
	IPS	0.036 (0.514)	−7.317*** (0.000)
LGFCF	LLC	−0.634 (0.263)	−6.188*** (0.000)
	IPS	−0.405 (0.343)	−7.354*** (0.000)
LHUM	LLC	0.866 (0.807)	−7.860*** (0.000)
	IPS	1.421 (0.922)	−7.387*** (0.000)
INSQTY	LLC	3.919 (1.000)	−9.217*** (0.000)
	IPS	2.756 (0.997)	−7.514*** (0.000)

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 levels, respectively

Table 8 CIPS panel unit root test results. *Source*: Authors' computations

Variables	Levels	1st Difference
LGDPPC	−1.223	−6.190***
LAI	−1.915	−6.188***
LTAXR	−1.569	−6.288***
LGFCF	−1.679	−6.181***
LHUM	−0.762	−6.187***
INSQTY	−1.380	−6.487***

*, ** 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

Table 9 Johansen–Fisher panel cointegration test results. *Source*: Authors' computations

H_0	H_1	Trace test			Maximum eigenvalue test		
		λ-trace statistic	*p* value	H_o	H_1	λ-max statistic	*p* value
$r=0$	$r \geq 1$	62.44***	0.000	$r=0$	$r \geq 1$	34.03***	0.000
$r \leq 1$	$r \geq 2$	107.0***	0.000	$r \leq 1$	$r \geq 2$	83.46***	0.000
$r \leq 2$	$r \geq 3$	245.7***	0.000	$r \leq 2$	$r \geq 3$	217.6***	0.000
$r=3$	$r \geq 4$	145.5***	0.000	$r=3$	$r \geq 4$	122.6***	0.000
$r \leq 4$	$r \geq 5$	59.51***	0.000	$r \leq 4$	$r \geq 5$	49.91***	0.000
$r \leq 5$	$r \geq 6$	28.07***	0.002	$r \leq 5$	$r \geq 6$	28.07***	0.002

*Rejection of the null hypothesis of no cointegration at least at the 10% level of significance. Probabilities are computed using asymptotic Chi-square distribution

Table 10 Westerlund panel cointegration tests. *Source*: Authors' computations

Statistic	Value	*Z* value	*P* value	Robust *P* value
G_t	− 1.386*	2.481	0.193	0.060
G_a	− 4.873*	2.359	0.191	0.070
P_t	− 2.411**	2.209	0.186	0.010
P_a	− 3.051*	1.845	0.167	0.090

*, **, 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 $4(\frac{T}{100})^{2/9} \approx 3$ recommended by Newey and West (1994); Barlett is used as the spectral estimation method

Table 11 Optimum lag length selection results. *Source*: Authors' computations

Lag	AIC	SIC	HQIC
0	6.321	6.421	6.361
1	− 16.354	− 15.649*	− 16.068*
2	− 16.042	− 14.733	− 15.512
3	− 15.767	− 13.854	− 14.992
4	− 15.599	− 13.082	− 14.580
5	− 16.908*	− 13.786	− 15.644

*Indicates lag order selected by the criterion. AIC is Akaike information criterion; SIC is Schwarz information criterion;

Hannan–Quinn information criterion

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

Table 5 reports the results of the slope homogeneity test, following Pesaran and Yamagata (2008). Both Δ (delta) and Δ_adj (adjusted delta) statistics are highly significant ($p = 0.000$), rejecting the null hypothesis of homogeneous slopes at the 1% level. This indicates significant heterogeneity in slope coefficients across BRICS countries,

Table 12 FMOLS and DOLS estimates. *Source*: Authors' computations

	FMOLS			DOLS		
Variables	Coefficient	Std. Error	Prob	Coefficient	Std. Error	Prob
PANEL A						
LAI	**0.064****	**0.026**	**0.015**	**0.004****	**0.002**	**0.044**
LTAX	**−0.071****	**0.037**	**0.053**	**0.185*****	**0.037**	**0.000**
LGFCF	0.106***	0.026	0.000	0.132***	0.046	0.005
LHUM	−0.556***	0.022	0.000	−0.371***	0.137	0.007
INSQTY	−0.007	0.035	0.845	−0.010***	0.002	0.000
R-squared	0.977			0.999		
Adjusted R-squared	0.976			0.998		
Observations	215	215	215	215	215	215
PANEL B						
LAI	0.246***	0.026	0.000	0.146***	0.037	0.000
LTAX	1.219***	0.037	0.000	0.856***	0.268	0.002
LGFCF	−0.104***	0.028	0.000	−0.005	0.103	0.960
LHUM	−0.175***	0.024	0.000	0.025	0.385	0.949
INSQTY	−0.021	0.035	0.547	0.022***	0.008	0.003
LAI* LTAXR	**−0.045****	**0.021**	**0.035**	**−0.048*****	**0.014**	**0.001**
R-squared	0.918			0.991		
Adjusted R-squared	0.914			0.989		
Observations	215	215	215	215	215	215
PANEL C						
LAI	−0.002	0.003	0.405	−0.002	0.003	0.483
LTAX	0.087**	0.045	0.055	0.137**	0.053	0.011
LGFCF	0.111***	0.045	0.015	0.101**	0.051	0.049
LHUM	−0.714***	0.164	0.000	−0.598***	0.182	0.001
INSQTY	0.045***	0.015	0.003	0.038**	0.018	0.039
LAI*INSQTY	**−0.003*****	**0.001**	**0.001**	**−0.002****	**0.001**	**0.011**
R-squared	0.999			0.999		
Adjusted R-squared	0.999			0.999		
Observations	215	215	215	215	215	215

***$p<0.01$; **$p<0.05$; *$p<0.1$. Probability values in bracket, while the dependent variable is real GDP per capita

meaning the relationship between variables differs by country, suggesting diverse relationships between variables. Table 6 presents cross-sectional dependence tests using Pesaran (2004) and Breusch–Pagan (1980) techniques. The results show significant dependence among variables, with 1% significance across tests, suggesting economic variables in one BRICS country influence others, emphasizing BRICS countries' economic interdependence. Table 7 shows panel unit root tests (LLC, IPS) revealing non-stationarity at levels for most variables, but stationarity at first differences (significant at 1%), indicating they are integrated of order one, I(1). Table 8's CIPS test corroborates this, confirming stationarity at first differences, validating the data for further econometric modeling with cointegration and dynamic panels.

Table 13 Dumitrescu and Hurlin (2012) panel causality test results. *Source*: Authors' computations

Model	Null hypothesis	W-statistic	Zbar-statistic	p value	Direction of relationship observed	Conclusion
1	LAI $\nrightarrow$ LGDPPC	6.653	0.733	0.224	LGDPPC $\rightarrow$ LAI	Unidirectional causality
	LGDPPC $\nrightarrow$ LAI	5.707***	0.186	0.000		
2	LTAXR $\nrightarrow$ LGDPPC	13.707***	4.808	0.000	LTAXR $\rightarrow$ LGDPPC	unidirectional causality
	LGDPPC $\nrightarrow$ LTAXR	6.421	0.599	0.549		
3	INSQTY $\nrightarrow$ LGDPPC	15.541***	5.868	0.000	LGDPPC $\leftrightarrow$ INSQTY	Bidirectional causality
	LGDPPC $\nrightarrow$ INSQTY	23.872***	10.680	0.000		
4	LTAXR $\nrightarrow$ LAI	10.992***	3.239	0.001	LTAXR $\leftrightarrow$ LAI	Bidirectional causality
	LAI $\nrightarrow$ LTAXR	15.258***	5.704	0.000		
5	INSQTY $\nrightarrow$ LAI	3.574	−1.046	0.296	INSQTY $\nrightarrow$ LAI	No causality
	LAI $\nrightarrow$ INSQTY	6.876	0.862	0.389		
6	INSQTY $\nrightarrow$ LTAXR	10.979***	3.232	0.001	INSQTY $\leftrightarrow$ LTAXR	Bidirectional causality
	LTAXR $\nrightarrow$ INSQTY	35.296***	17.281	0.000		

$\leftrightarrow$ and $\rightarrow$ denote bidirectional and unidirectional causality, respectively. $\nrightarrow$ denote does not homogeneously cause (i.e.,$\mathbf{H_0}$). ***$p < 0.01$, ** $p < 0.05$, *$p < 0.1$

The cointegration, fully modified least squares (FMOLS), and dynamic OLS (DOLS) long-run analysis

The cointegration analysis in Tables 9 and 10 confirms a long-run relationship between economic growth and explanatory variables in BRICS countries. Table 9's Johansen–Fisher panel cointegration test reveals twelve cointegrating vectors with *p* values below 1%,

Table 14 Panel CS-ARDL estimates. *Source*: Authors' computations

Variables	(1) CS-ARDL 1	(2) CS-ARDL 2	(3) CS-ARDL 3
Short-run est			
ΔINSQTY	**0.006*****	0.020***	0.307*
	(0.002)	(0.006)	(0.163)
ΔLAI	**0.004***	0.004	−0.009
	(0.002)	(0.012)	(0.010)
ΔLTAX	**−0.054*****	−0.099**	0.076**
	(0.015)	(0.041)	(0.034)
ΔLGFCF	0.030*	0.295***	0.480***
	(0.018)	(0.066)	(0.075)
ΔLHUM	0.084*	0.228	0.668
	(0.048)	(0.361)	(0.535)
ΔLAI* LTAXR		**0.004***	
		(0.002)	
ΔLAI*INSQTY			**−0.015***
			(0.008)
Adjust. Term			
ECT	−1.054***	−1.295***	−1.480***
	(0.015)	(0.066)	(0.075)
Long-run EST			
LR_INSQTY	**0.006*****	0.015***	0.189*
	(0.002)	(0.005)	(0.101)
LR_LAI	**0.004***	−0.004	−0.007
	(0.002)	(0.009)	(0.007)
LR_LTAX	**−0.002**	−0.080**	0.049**
	(0.012)	(0.032)	(0.020)
LR_LGFCF	0.028	0.017	0.022
	(0.017)	(0.121)	(0.081)
LR_LHUM	0.079*	0.158	0.444
	(0.044)	(0.032)	(0.347)
LR_LAI*LTAXR		**0.004***	
		(0.002)	
LR_LAI*INSQTY			**−0.009***
			(0.005)
Observation	210	210	210
R-squared	0.84	0.53	0.65

Standard errors in parentheses; *, **, and *** represent significance at the 1%, 5%, and 10% levels respectively.

Table 15 Robustness test results using AMG estimator. *Source*: Authors' computations

Variables	(1) AMG 1	(2) AMG 2	(3) AMG 3
INSQTY	**0.008****	0.004	0.223**
	(0.003)	(0.005)	(0.108)
LAI	**0.006*****	−0.121	−0.004
	(0.002)	(0.238)	(0.004)
LTAX	0.151	−0.544	0.178**
	(0.156)	(1.454)	(0.044)
LGFCF	0.778**	0.131*	0.057
	(0.339)	(0.075)	(0.101)
LHUM	−0.176	0.004**	0.734**
	(0.269)	(0.001)	(0.331)
ΔLAI* LTAXR		**0.943*****	
		(0.261)	
ΔLAI*INSQTY			**−0.010****
			(0.005)
Constant	8.878***	9.992**	7.107***
	(1.097)	(0.455)	(1.863)
Obs	220	220	220
Wald Chi^2	82.94***	3.75***	41.84***

Standard errors in parentheses; *, **, and *** represent significance at the 1%, 5%, and 10% levels respectively

indicating a stable equilibrium. Westerlund (2007) cointegration test results in Table 10, considering cross-sectional dependence, further validate this with significant G_t, G_a, P_t and P_a statistics ($p<10\%$), showing interconnections among BRICS economies (Khan et al. 2020). Table 11's lag selection based on SIC and HQ criteria recommends a lag length of 1, enhancing model accuracy by capturing dynamics without overfitting.

Table 12 applies FMOLS and DOLS techniques for robust estimation, highlighting positive effects of AI, tax revenue, and capital formation on growth (Pedroni 2001, 2004). Under DOLS, a 1% increase in AI, tax revenue, and capital formation boosts growth by 0.004%, 0.185%, and 0.132%, respectively (see Panel A). Conversely, human capital and institutional quality negatively impact growth, aligning with endogenous growth theory (Romer 1986; Pradhan et al. 2022). The interactions between AI and tax revenue and between AI and institutional quality yield negative impacts, indicating complexities introduced by AI within current frameworks (see Panel B and C of Table 12). High R-squared values confirm model fit, with findings resonating with the broader literature, including works by Romer (1986, 1990), Lucas (1988), Rebelo (1991) and Pradhan et al. (2022), which suggest that the impacts of technology and policy interventions can be nuanced and context-dependent. This leads us to investigate the causality relationships that may exist between our variables of interest.

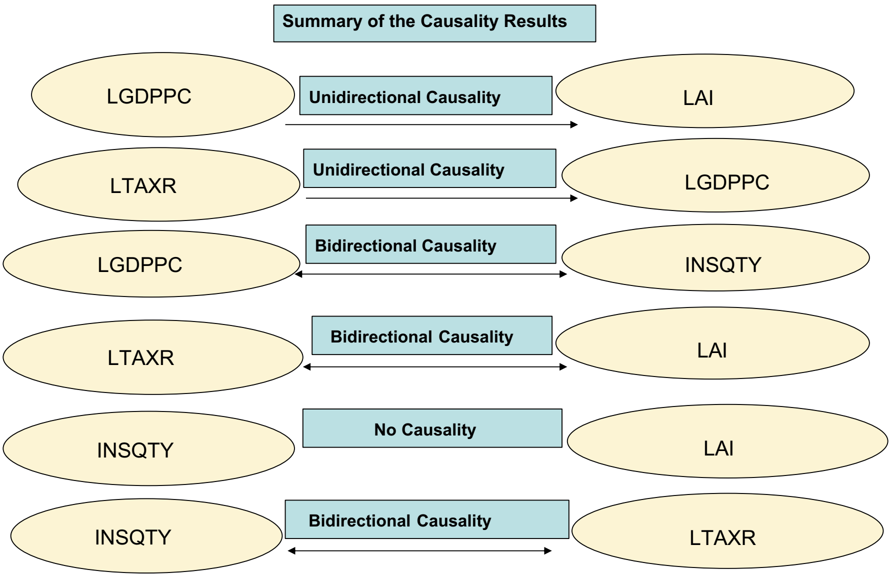

Fig. 5 Summary of the causality results. *Source*: Authors' Design

Panel causality, CS-ARDL, and robustness checks analysis

Table 13 presents the Dumitrescu and Hurlin (2012) panel causality test results, showing complex interdependencies among AI, tax revenue, institutional quality, and economic growth in BRICS countries. A two-way causality exists between economic growth (LGDPPC) and institutional quality (INSQTY), implying mutual reinforcement; better performing institutions boost growth, which, in turn, strengthens institutions. Similarly, a two-way causality between AI (LAI) and tax revenue (LTAXR) suggests that AI enhances tax collection efficiency, incentivizing further AI investments, aligning with studies showing AI-driven technologies or ICT potential to improve tax administration efficiency (Berdieva 2019; Gorshkova et al. 2022). The causality between tax revenue and institutional quality highlights how robust governance improves tax collection, enabling institutions to expand further, as shown by Syarifuddin and Damayanti (2015) and Ricciuti et al. (2019). Economic growth drives AI investments (unidirectional causality), indicating that economic expansion fuels AI advancement in BRICS countries. The causal link from tax revenue to growth supports Takumah and Iyke (2017) but challenges the argument by Pula and Elshani (2018) and Gurdal et al. (2021) that high taxes could deter growth. However, no causality between AI and institutional quality suggests that AI does not directly impact institutions, potentially due to regulatory adaptation lag or limited enforcement. Figure 5 provides a summary of the causality results.

Table 14 presents CS-ARDL estimates, revealing significant short-run and long-run relationships. The error correction term (ECT) in all models (-1.054, -1.295, and -1.480) indicates that economic growth quickly returns to equilibrium after short-run deviations. High R-squared values confirm the model's accuracy in predicting growth dynamics. Short-run estimates show a positive impact of institutional quality on growth, especially in Columns 1 and 2, aligning with Acemoglu et al. (2005), emphasizing institutions' role in stability. Long-run coefficients also confirm that strong institutions are vital for growth,

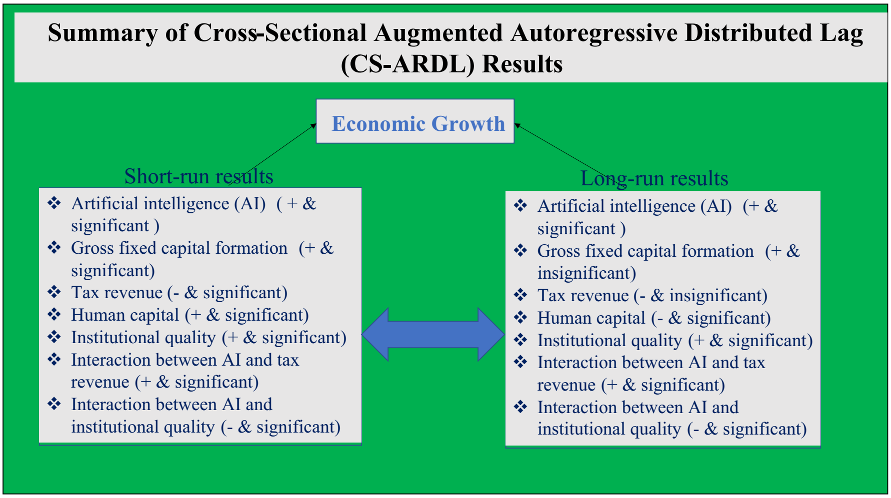

Fig. 6 Summary of Cross-Sectional Augmented Autoregressive Distributed Lag (CS-ARDL) Results. *Source*: Authors' Design

echoing Rodrik et al. (2004). Short-run impacts of AI on growth are mixed: positive but weakly significant in Column 1, while negative (insignificant) in Column 3, reflecting initial disruptions during AI integration, which is consistent with the Brynjolfsson and McAfee (2014) study. Long-run impacts of AI also vary; positive in Column 1, but negative in Columns 2 and 3, indicating that long-term growth benefits depend on AI adaptation levels in BRICS economies.

Tax revenue's influence on growth varies across models. In the short run, tax revenue negatively impacts growth in Columns 1 and 2, potentially due to investment disincentives (Barro 1990). Yet, positive effects in Column 3 suggest that efficient tax systems can foster growth, aligning with the studies of Marsden (1983), Martin and Fardmanesh (1990), Widmalm (2001), Amiel et al. (2012), and Nkhalamo and Sheefeni (2017). Long-run effects also vary: tax revenue enhances growth in Column 3, supporting efficient tax management's role in funding public goods and spurring growth (Myles 2009). Mixed short- and long-term effects reflect debates on taxation's role in growth which could be growth-enhancing or growth-inhibiting (Gemmell et al. 2011; Barro 1990).

In the short run, AI-tax revenue interaction positively affects growth (Column 2), indicating that effective tax policies amplify AI investments. Conversely, AI-institutional quality interaction negatively impacts growth (Column 3), reflecting possible challenges in aligning AI with current institutional frameworks. Long-run results are consistent; AI-tax revenue interaction (positive) implies that AI-driven tax improvements support growth, while AI-institutional quality interaction (negative) suggests potential hindrances due to institutional rigidity. These mixed impacts emphasize that while institutional quality fosters economic growth, aligning AI with existing institutions is challenging.

The findings reflect institutional economics, stressing governance's importance in economic outcomes (see for example, Nawaz et al. 2014; Hayat 2019; Abubakar 2020, among others). While AI shows growth potential, its benefits depend on institutional and economic contexts. The lack of growth support from AI-institutional quality interaction in BRICS countries may result from institutional challenges such as corruption, bureaucratic inefficiencies, and limited AI-specific frameworks. Established institutions may resist AI's disruptive nature, creating suboptimal growth impacts. Additionally, ethical concerns and inadequate regulatory frameworks could hinder AI adoption within institutions, stressing the need for targeted strategies to maximize AI's benefits within existing governance structures.

To confirm the CS-ARDL results' robustness, the study followed Sharif et al. (2022), using models addressing cross-sectional dependence in the long term. The AMG estimation applied, shown in Table 15, aligns closely with CS-ARDL short- and long-run results. Specifically, AI's interaction with tax revenue positively impacts BRICS countries' economic growth, while AI's interaction with institutional quality has a negative effect. Column 1 in Table 15 confirms similar impacts from institutional quality and AI on economic growth, consistent with Column 1 of Table 14. These findings affirm the reliability of CS-ARDL results for policy implications.

Policy implications

Given the significant negative impact of the interaction between artificial intelligence (AI) and institutional quality on economic growth in both the short and long terms, we recommend that BRICS governments conduct a thorough evaluation of their existing institutional frameworks and reforms. This evaluation should pinpoint areas for improvement, particularly in transparency, regulatory quality, accountability, rule of law, and government effectiveness, with a focus on AI investments. Policymakers should prioritize addressing institutional weaknesses that impede AI investment and its successful integration into the economy. Institutional policies must establish guidelines and regulations to support ethical and responsible AI development and deployment, addressing concerns such as bias, fairness, privacy, and accountability in AI algorithms and decision-making. Additionally, policies should promote investment in and the adoption of AI technologies that align with BRICS countries' values to foster economic growth.

The findings from Model 1 show that human capital has a positive effect on economic growth in both the short and long terms. However, this positive impact diminishes when AI interacts with tax revenue and institutional quality, rendering the effect of human capital on growth insignificant. This highlights the importance of implementing policies that invest in education and training programs to reduce the skill gap between AI technologies and institutional capacities. Enhancing education and training can improve public awareness of AI and its effects on institutional quality. We suggest stronger collaboration and dialogue among AI investors, institutional experts, and policymakers to close the gap between technology and governance in BRICS economies. Cross-sector partnerships and knowledge sharing are essential to align AI technologies with institutional frameworks and reforms in BRICS countries. Additionally, governments should encourage a culture of innovation and adaptability within institutions to effectively manage the challenges and opportunities presented by AI investments.

The results suggest that the integration of AI into tax systems has a significant positive effect on economic growth in BRICS countries, indicating substantial benefits. Therefore, BRICS governments should encourage AI adoption in their tax systems. However, several challenges exist: AI systems require large datasets, which could perpetuate biases in historical data and lead to discriminatory outcomes; there may be technological inequalities, as not all segments of the population have equal access to AI-driven tax systems; potential errors in tax calculations, and public resistance due to concerns about transparency, accountability, and misuse may arise (Suryani and Luthfiyyah 2023; Zhang and Tao 2020). To mitigate these challenges, it is crucial to prioritize ethical considerations, such as implementing robust data protection, using fair algorithms, ensuring inclusive access, providing education, and employing rigorous testing and monitoring to identify and address unintended consequences (Safdar et al. 2020; Ouchchy et al. 2020; Abdallah and Salah 2024). These steps will promote equitable and effective AI use in tax systems in the BRICS economies.

To drive economic growth, policies should encourage integrating AI technologies in tax administration and revenue collection. BRICS governments should invest in AI infrastructure, tools, and resources to boost the efficiency of tax operations, including AI-driven data analytics, automated tax compliance, and risk assessment algorithms. Simplifying and streamlining tax processes using AI can improve compliance for both taxpayers and authorities. Developing user-friendly AI platforms is essential for enhancing compliance at various levels, and these policies should be regularly evaluated and updated to keep pace with AI advancements. BRICS governments should also adopt AI to improve tax assessment accuracy and minimize errors in revenue collection. Implementing AI algorithms to detect tax evasion, fraud, and non-compliance can increase tax revenues and promote fair economic growth. Training and upskilling tax professionals in AI-related skills is crucial, enabling them to effectively manage AI technologies. A culture of continuous learning and adaptation is needed to maximize AI's benefits in tax systems. Additionally, fostering collaboration and knowledge sharing among tax authorities and AI experts within BRICS economies is vital. By exchanging best practices and lessons learned, these countries can support each other in advancing AI implementation, enhancing their tax systems, and driving economic progress.

Conclusion

This study analyzes how AI, tax revenue, and institutional quality influence economic growth in BRICS countries, aiming to support SDG 8 for sustainable growth. Covering 2012–2022, it utilizes the Cross-Sectional Augmented Autoregressive Distributed Lag (CS-ARDL) model to capture long-term relationships among the variables, including AI–tax revenue and AI–institutional quality interactions. Results show a stable, long-run equilibrium among these variables, with bidirectional causality identified between institutional quality and economic growth, as well as between tax revenue and AI. Additionally, the study finds unidirectional causality from economic growth to AI and from tax revenue to economic growth, while AI and institutional quality exhibit no causal relationship.

Using FMOLS and DOLS methods, the study reveals that AI, tax revenue, and capital formation positively affect economic growth, while the interactions of AI with tax revenue and institutional quality reduce growth. CS-ARDL findings in Model 1 show that AI and institutional quality enhance growth in both the short and long terms. However, tax revenue has a short-term negative effect and an insignificant long-term effect on growth. Model 2 highlights the positive impact of integrating AI with the tax system on growth, while Model 3 indicates that AI combined with institutional quality may hinder growth, underscoring the need for AI-compatible institutional policies (see Fig. 6).

The study emphasizes the importance of robust infrastructure, ethical frameworks, and public engagement in AI implementation for optimal tax revenue collection and institutional quality enhancement. It advocates for AI policies that ensure transparency, privacy, and compliance with societal values, particularly through regular audits and stakeholder collaboration in BRICS economies.

The findings, based on comprehensive BRICS data from sources like OECD and WDI, underscore potential limitations due to cross-country data inconsistencies and evolving AI technology. Future research could expand on these insights by analyzing specific BRICS economies or other regions, examining sector-specific AI impacts, or exploring additional variables like digital infrastructure and sustainability. This expanded focus would yield targeted policy insights for diverse economic contexts.

Acknowledgements We are grateful to the editor(s) and anonymous reviewer(s) for their valuable comments, which have significantly enhanced the quality of this study. The usual disclaimer applies.

Author's contributions CSS and NM conceptualized the study idea, drafted the paper, collected data, analyzed data, wrote the introduction section, organized the literature review, drafted the methodology section, interpreted the results and provided the discussions, concluded the study with policy implications, and organized the reference list. CSS and NM equally proofread, edited, and finalized the article.

Funding Open access funding provided by University of Johannesburg. The author(s) received no financial support for the research, authorship, and/or publication of this article.

Data availability All data generated or analyzed during this study are not included in this submission but can be made available upon reasonable request.

Declarations

Conflict of interest The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Ethical approval This article does not contain any studies with human participants or animals performed by the author.

Consent to participate Not applicable.

Consent for publication This manuscript is an original work produced by the author(s). CSS and NM are aware of its content and approves its submission. It is also important to mention that the manuscript has not been published elsewhere in part or in entirety and is not under consideration by another journal. The author(s) have given consent for this article to be submitted for publication in *Journal of Social and Economic Development*.

References

Abdallah M, Salah M (2024) Artificial Intelligence and Intellectual properties: legal and ethical considerations. Int J Intell Syst Appl Eng 12(1):368–376

Abubakar S (2020) Institutional quality and economic growth: evidence from Nigeria. Afr J Econ Rev 8(1):48–64

Acemoglu D, Restrepo P (2018a) Low-skill and high-skill automation. J Hum Cap 12(2):204–232
Acemoglu D, Restrepo P (2018b) The race between man and machine: implications of technology for growth, factor shares, and employment. Am Econ Rev 108(6):1488–1542
Acemoglu D, Johnson S, Robinson JA (2005) Institutions as a fundamental cause of long-run growth. Handb Econ Growth 1:385–472
Adam CS, Bevan DL (2005) Fiscal deficits and growth in developing countries. J Public Econ 89(4):571–597
Adefolake AO, Omodero CO (2022) Tax revenue and economic growth in Nigeria. Cogent Bus Manag 9(1):2115282
African Economic Outlook (2010) Economic outlook. 20th Feb 2024. file:///C:/Users/PC/Downloads/aeo2010_en.pdf
Aghion P, Jones BF, Jones CI (2018) Artificial intelligence and economic growth. In: The economics of artificial intelligence: an agenda. University of Chicago Press, pp 237–282. Accessed on 08th June 2023. https://www.nber.org/system/files/chapters/c14015/c14015.pdf
Ahn MJ, Chen YC (2020). Artificial intelligence in government: potentials, challenges, and the future. In: Proceedings of the 21st annual international conference on digital government research, pp 243–252
Akitoby B (2018) Five country cases illustrate how best to improve tax collection. Finance Dev 55(1):18–21
Alonso JA, Garcimartin C, Kvedaras V (2020) Determinants of institutional quality: an empirical exploration. J Econ Policy Reform 23(2):229–247
Amiel LN, Deller S, Stallmann JI (2012) Economic growth and tax and expenditure limitations. Rev Region Stud 42(3):185–206
Amoh JK, Ofori-Boateng K, Nsor-Ambala R, Anarfo EB (2023) Revisiting the tax evasion and corruption–economic development nexus in Ghana: fresh evidence from a SEM approach. J Econ Administ Sci. https://doi.org/10.1108/JEAS-01-2023-0020
Ashraf J, Luo L, Khan MA (2022) The spillover effects of institutional quality and economic openness on economic growth for the belt and road initiative (BRI) countries. Spat Stat 47:100566
Bandari V (2019) The impact of artificial intelligence on the revenue growth of small businesses in developing countries: an empirical study. Rev Contemp Bus Analyt 2(1):33–44
Barro RJ (1990) Government spending in a simple model of endogeneous growth. J Polit Econ 98(5):S103–S125
Barro RJ (1991) Economic growth in a cross section of countries. Q J Econ 106(2):407–443
Bassanini A, Scarpetta S (2002) The driving forces of economic growth: panel data evidence for the OECD countries. OECD Econ Stud 2001(2):9–56
Berdieva U (2019) Digital technologies as a factor of increasing the efficiency of tax administration. Int Finance Account 2019(2):8
Boly A, Nandelenga MW, Oduor J (2020) Mobilizing domestic resource in Africa for inclusive growth. Afr Econ Brief 11(3):1–6
Breusch TS, Pagan AR (1980) The Lagrange multiplier test and its applications to model specification in econometrics. Rev Econ Stud 47(1):239–253
Brynjolfsson E, McAfee A (2014) The second machine age: work, progress, and prosperity in a time of brilliant technologies. WW Norton & Company, New York
Brynjolfsson E, Rock D, Syverson C (2019) Artificial intelligence and the modern productivity paradox. Econ Artif Intell Agenda 23:23–57
Cashin P (1995) Government spending, taxes, and economic growth. Staff Pap 42(2):237–269
Castro GÁ, Camarillo DBR (2014) Determinants of tax revenue in OECD countries over the period 2001–2011. Contaduría y Administración 59(3):35–59
Cerqueti R, Coppier R (2011) Economic growth, corruption and tax evasion. Econ Model 28(1–2):489–500
Chand V, Kostic S, Reis A (2020) Taxing artificial intelligence and robots: critical assessment of potential policy solutions and recommendation for alternative approaches-sovereign measure: education taxes/global MEASURE: global education tax or planetary tax. World Tax J 12(4):711–761. https://doi.org/10.59403/2sjxe4d
Chhabra M, Giri AK, Kumar A (2023) Do trade openness and institutional quality contribute to carbon emission reduction? Evidence from BRICS countries. Environ Sci Pollut Res 30(17):50986–51002
Chudik A, Pesaran MH (2015) Common correlated effects estimation of heterogeneous dynamic panel data models with weakly exogenous regressors. J Econom 188(2):393–420
Cobb CW (1928) Douglas PH theory of production. Am Econ Rev Suppl 18(1):139–165
Cyman D, Gromova E, Juchnevicius E (2021) Regulation of artificial intelligence in BRICS and the European Union. Brics Law J 8(1):86–115

Czarnitzki D, Hanel P, Rosa JM (2011) Evaluating the impact of R&D tax credits on innovation: a microeconometric study on Canadian firms. Res Policy 40(2):217–229

Dukhi N, Sewpaul R, Sekgala MD, Awe OO (2021) Artificial intelligence approach for analyzing anaemia prevalence in children and adolescents in BRICS countries: a review. Curr Res Nutr Food Sci J 9(1):01–10

Dumitrescu EI, Hurlin C (2012) Testing for granger non-causality in heterogeneous panels. Econ Model 29(4):1450–1460

Eberhardt M, Bond S (2009) Cross-section dependence in nonstationary panel models: a novel estimator. MPRA Paper, No. 17692. Germany: University Library of Munich. https://www.mpra.ub.uni-muenchen.de/17692

Eberhardt M, Teal F (2010). Productivity analysis in global manufacturing production. Discussion paper, No. 515, Department of Economics. Oxford: University of Oxford. http://www.economics.ox.ac.uk/research/WP/pdf/paper515.pdf

Fernández-Rodríguez E, García-Fernández R, Martínez-Arias A (2023) Institutional determinants of the effective tax rate in G7 and BRIC countries. Econ Syst 47(2):101079

Fölster S, Henrekson M (2001) Growth effects of government expenditure and taxation in rich countries. Eur Econ Rev 45(8):1501–1520

Furman J, Seamans R (2019) AI and the Economy. Innov Policy Econ 19(1):161–191

Freedom House (2022) Freedom in the world 2022, The global expansion of authoritarian rule. Accessed on 13th June 2023. https://freedomhouse.org/sites/default/files/2022-02/FIW_2022_PDF_Booklet_Digital_Final_Web.pdf

Gechert S, Heimberger P (2022) Do corporate tax cuts boost economic growth? Eur Econ Rev 147:104157

Gemmell N, Kneller R, Sanz I (2011) The timing and persistence of fiscal policy impacts on growth: evidence from OECD countries. Econ J 121(550):F33–F58

Ghahramani M, Pilla F (2021) Leveraging artificial intelligence to analyze the COVID-19 distribution pattern based on socio-economic determinants. Sustain Cities Soc 69:102848

Gill A, Claus I, McLellan N, Lee B (2006) An empirical investigation of fiscal policy in New Zealand. https://ssrn.com/abstract=2005113 or https://doi.org/10.2139/ssrn.2005113

Gnangnon SK (2024) Tax transition reform and economic growth in developing countries. Int Trade J 38(6):523–546

Gorshkova NV, Ksenda VM, Grigorenko IV (2022) The impact of digital technologies of tax administration on increasing the inclusiveness and sustainability of economic development. In: Inshakova EI, Inshakova AO (eds) New technology for inclusive and sustainable growth: perception, challenges and opportunities, vol 287. Springer, Singapore, pp 223–234. https://doi.org/10.1007/978-981-16-9804-0_19

Graetz G, Michaels G (2018) Robots at work. Rev Econ Stat 100(5):753–768

Gurdal T, Aydin M, Inal V (2021) The relationship between tax revenue, government expenditure, and economic growth in G7 countries: new evidence from time and frequency domain approaches. Econ Chang Restruct 54:305–337

Hamdi H, Sbia R (2013) Dynamic relationships between oil revenues, government spending and economic growth in an oil-dependent economy. Econ Model 35:118–125

Hare PG (2001) Institutional change and economic performance in the transition economies. Econ Surv Europe, pp 77–92. Available at: https://unece.org/DAM/ead/sem/sem2001/papers/Hare.pdf

Hashim Osman R, Alexiou C, Tsaliki P (2011) The role of institutions in economic development: evidence from 27 Sub-Saharan African countries. Int J Soc Econ 39(1/2):142–160

Hatfield JW (2015) Federalism, taxation, and economic growth. J Urban Econ 87:114–125

Hayat A (2019) Foreign direct investments, institutional quality, and economic growth. J Int Trade Econ Dev 28(5):561–579

Hémous D, Olsen M (2022) The rise of the machines: automation, horizontal innovation, and income inequality. Am Econ J Macroecon 14(1):179–223

Ho TT, Tran XH, Nguyen QK (2023) Tax revenue-economic growth relationship and the role of trade openness in developing countries. Cogent Bus Manag 10(2):2213959

International Monetary Fund (IMF) (2021) World economic outlook recovery: during a pandemic health concerns, supply disruptions, and price pressures. Accessed on 13th June 2023. Available at: file:///C:/Users/PC/Downloads/text%20(1).pdf

Jabeur SB, Ballouk H, Mefteh-Wali S, Omri A (2022) Forecasting the macrolevel determinants of entrepreneurial opportunities using artificial intelligence models. Technol Forecast Soc Chang 175:121353

Jaimovich N, Rebelo S (2017) Nonlinear effects of taxation on growth. J Polit Econ 125(1):265–291

Javed O (2016) Determinants of institutional quality: a case study of IMF programme countries. In: The economic impact of international monetary fund programmes: institutional quality,

macroeconomic stabilization and economic growth. Springer, Cham, pp 7–35. https://doi.org/10.1007/978-3-319-29178-9_2
Kashif U, Shi J, Naseem S, Dou S, Zahid Z (2024) ICT service exports and CO_2 emissions in OECD countries: the moderating effect of regulatory quality. Econ Chang Restruct 57(3):94
Khan SAR, Yu Z, Belhadi A, Mardani A (2020) Investigating the effects of renewable energy on international trade and environmental quality. J Environ Manag 272:111089
Khujamkulov I, Abizadeh S (2023) Trends in tax revenues of transition economies: an empirical approach. Empir Econ 64(2):833–868
Kibria MG, Toufique MMK (2023) Institutional governance and quality of life: evidence from developing countries. SN Bus Econ 3(3):76
Kneller R, Bleaney MF, Gemmell N (1999) Fiscal policy and growth: evidence from OECD countries. J Public Econ 74(2):171–190
Kopka A, Fornahl D (2024) Artificial intelligence and firm growth—catch-up processes of SMEs through integrating AI into their knowledge bases. Small Bus Econ 62(1):63–85
Levine R, Renelt D (1992) A sensitivity analysis of cross-country growth regressions. Am Econ Rev 82(4):942–963
Lu CH (2021) The impact of artificial intelligence on economic growth and welfare. J Macroecon 69:103342
Lucas RE Jr (1988) On the mechanics of economic development. J Monet Econ 22(1):3–42
Lundvall BÅ, Rikap C (2022) China's catching-up in artificial intelligence seen as a co-evolution of corporate and national innovation systems. Res Policy 51(1):104395
Makridakis S (2017) The forthcoming Artificial Intelligence (AI) revolution: its impact on society and firms. Futures 90:46–60
Marsden K (1983) Links between taxes and economic growth: Some empirical evidence. Staff Working Papers. No. 605
Martin R, Fardmanesh M (1990) Fiscal variables and growth: a cross-sectional analysis. Public Choice 64(3):239–251
Maruta AA, Banerjee R, Cavoli T (2020) Foreign aid, institutional quality and economic growth: evidence from the developing world. Econ Model 89:444–463
Merrifield J (2000) State government expenditure determinants and tax revenue determinants revisited. Public Choice 102(1):25–48
Mill JS (1848) Principles of political economy with some of their applications to social philosophy. C.C.Little & Brown, Boston
Minh Ha N, Tan Minh P, Binh QMQ (2022) The determinants of tax revenue: a study of Southeast Asia. Cogent Econ Finance 10(1):2026660
Myles GD (2009) Economic growth and the role of taxation-disaggregate data. OECD economics department working papers no. 715, accessed on 24th August 2024. https://www.oecd-ilibrary.org/docserver/222775817802.pdf?expires=1724486036&id=id&accname=guest&checksum=B4DD0E0C25FFD1A738538FF55388C2CD
Nawaz S, Iqbal N, Khan MA (2014) The impact of institutional quality on economic growth: panel evidence. Pak Dev Rev 53(1):15–31
Neog Y, Gaur AK (2021) Shadow economy, corruption, and tax performance: a study of BRICS. J Public Aff 21(2):e2174
Newey WK, West KD (1994) Automatic lag selection in covariance matrix estimation. Rev Econ Stud 61(4):631–653
Nkhalamo JC, Sheefeni JP (2017) Tax and economic growth in Namibia. Eur J Bus Econ Account 5(2):52–61
Ojede A, Yamarik S (2012) Tax policy and state economic growth: the long-run and short-run of it. Econ Lett 116(2):161–165
Ouchchy L, Coin A, Dubljević V (2020) AI in the headlines: the portrayal of the ethical issues of artificial intelligence in the media. AI Soc 35:927–936
Pedroni P (2001) Purchasing power parity tests in cointegrated panels. Rev Econ Stat 83(4):727–731
Pedroni P (2004) Panel cointegration: asymptotic and finite sample properties of pooled time series tests with an application to the PPP hypothesis. Economet Theor 20(3):597–625
Pesaran MH (2004) General diagnostic tests for cross section dependence in panels. Economics 1240(1):1
Pesaran MH, Yamagata T (2008) Testing slope homogeneity in large panels. J Econom 142(1):50–93
Pradhan RP, Arvin MB, Nair MS, Hall JH (2022) The dynamics between financial market development, taxation propensity, and economic growth: a study of OECD and non-OECD countries. Qual Quant 56:1–32
Pula L, Elshani A (2018) The relationship between public expenditure and economic growth in Kosovo: findings from a Johansen co-integrated test and a Granger causality test. Ekonomika 97(1):47–62

Qiu W, Zhang J, Wu H, Irfan M, Ahmad M (2021) The role of innovation investment and institutional quality on green total factor productivity: evidence from 46 countries along the "Belt and Road". Environ Sci Pollut Res 29:16597–16611. https://doi.org/10.1007/s11356-021-16891-y
Radhakrishnan J, Chattopadhyay M (2020) Determinants and barriers of artificial intelligence adoption—a literature review. In: Re-imagining diffusion and adoption of information technology and systems: a continuing conversation: IFIP WG 8.6 international conference on transfer and diffusion of IT, TDIT 2020, Tiruchirappalli, India, December 18–19, 2020, proceedings, part I. Springer, pp 89–99
Rahman SH, Siddiquee MSH (2022) Short-and long-run growth effects of fiscal policy in Bangladesh. SN Bus Econ 2(9):148
Ricciuti R, Savoia A, Sen K (2019) How do political institutions affect fiscal capacity? Explaining taxation in developing economies. J Inst Econ 15(2):351–380
Rodrik D, Subramanian A, Trebbi F (2004) Institutions rule: the primacy of institutions over geography and integration in economic development. J Econ Growth 9:131–165
Romer PM (1986) Increasing returns and long-run growth. J Polit Econ 94(5):1002–1037
Romer PM (1990) Endogenous technological change. J Polit Econ 98(5):S71–S102
Saba CS (2020) Security as an outcome for promoting economic prosperity in the regional economic communities of Africa: evidence from a panel data analysis. Afr Secur Rev 29(4):376–400
Saba CS (2022) CO_2 emissions-energy consumption-militarisation-growth nexus in South Africa: evidence from novel dynamic ARDL simulations. Environ Sci Pollut Res. https://doi.org/10.1007/s11356-022-23069-7
Saba CS (2023) Nexus between CO_2 emissions, renewable energy consumption, militarisation, and economic growth in South Africa: evidence from using novel dynamic ARDL simulations. Renew Energy. https://doi.org/10.1016/j.renene.2023.01.070
Saba CS, Ngepah N (2022a) Convergence in renewable energy sources and the dynamics of their determinants: an insight from a club clustering algorithm. Energy Rep 8:3483–3506
Saba CS, Ngepah N (2022b) Convergence in renewable energy consumption and their influencing factors across regions: evidence from convergence algorithm approach. Environ Sci Pollut Res 29(40):61412–61445
Saba CS, Ngepah N (2022c) ICT diffusion, industrialisation and economic growth nexus: an international cross-country analysis. J Knowl Econ 13(3):2030–2069
Saba C, Pretorius M (2024) The mediating role of governance in creating a nexus between investment in artificial intelligence (AII) and human well-being in the BRICS countries. BRICS J Econ 5(2):5–44
Saba CS, Ngepah N (2024) The impact of artificial intelligence (AI) on employment and economic growth in BRICS: Does the moderating role of governance Matter? Res Global. https://doi.org/10.1016/j.resglo.2024.100213
Saba CS, Monkam N (2024) Leveraging the potential of artificial intelligence (AI) in exploring the interplay among tax revenue, institutional quality, and economic growth in the G-7 countries. AI Soc. https://doi.org/10.1007/s00146-024-01885-4
Saba CS, Asongu SA, Ngepah N, Ngoungou YE (2024a) Governance in the exploration of global and regional determinants of ICT development. Int J Innov Stud. https://doi.org/10.1016/j.ijis.2024.02.002
Saba CS, Djemo T, Ngepah N (2024b) The crucial roles of ICT, renewable energy sources, industrialization, and institutional quality in achieving environmental sustainability in BRICS. Environ Sci Pollut Res 31(24):35083–35114
Sabir S, Qamar M (2019) Fiscal policy, institutions and inclusive growth: evidence from the developing Asian countries. Int J Soc Econ 46(6):822–837
Safdar NM, Banja JD, Meltzer CC (2020) Ethical considerations in artificial intelligence. Eur J Radiol 122:108768
Sathyamoorthy V, Tang TC (2018) Institutional quality and export-led growth: an empirical study. J Econ Stud 45(1):193–208
Schumpeter JA (1934) The theory of economic development. Harvard University Press, Cambridge
Sharif A, Saqib N, Dong K, Khan SAR (2022) Nexus between green technology innovation, green financing, and CO_2 emissions in the G7 countries: the moderating role of social globalisation. Sustain Dev 30(6):1934–1946
Shi J, Yuan X, Sadowski BM, Kou K, Hu X, Li S, Dou S (2022) VAT reform, regional ownership structure, and industrial upgrading: evidence from firms in Northeast China. SAGE Open 12(2):21582440221095012
Shi J, Liu Y, Sadowski BM, Alemzero D, Dou S, Sun H, Naseem S (2023) The role of economic growth and governance on mineral rents in main critical minerals countries. Resour Policy 83:103718
Singh BP (2022) Does governance matter? Evidence from BRICS. Glob Bus Rev 23(2):408–425
Slipowitz A (2021) Freedom in the world 2021: democracy under siege. Freedom House, New York

Suryani W, Luthfiyyah A (2023) Artificial intelligence (AI) Opportunities and challenges of green marketing tourism. In: 5G, artificial intelligence, and next generation internet of things: digital innovation for green and sustainable economies, pp 178–188. https://doi.org/10.4018/978-1-6684-8634-4.ch008
Swan TW (1956) Economic growth and capital accumulation. Econ Rec 32(2):334–361
Syarifuddin S, Damayanti RA (2015) Good governance and fiscal capacity in regional expansion: a holistic analysis of qualitative perspective. J Econ Bus Account Ventura 18(1):15–28
Takumah W, Iyke BN (2017) The links between economic growth and tax revenue in Ghana: an empirical investigation. Int J Sustain Econ 9(1):34–55
Thomas MP (2017) Empirics of service taxation in India: a macroeconomic perspective. J Soc Econ Dev 19(1):143–160
Transparency International (2022) Corruption Perceptions Index 2022. Accessed on 12th June 2023. http://www.stopcorruption.moph.go.th/application/editors/userfiles/files/CPI%202022%20Report.pdf
Vinnitskiy DV (2020) Improving tax compliance in a globalized world: an approach of BRICS countries. Eur Asian Law Rev 3(2):99–114
Westerlund J (2007) Testing for error correction in panel data. Oxford Bull Econ Stat 69(6):709–748
Widmalm F (2001) Tax structure and growth: are some taxes better than others? Public Choice 107(3):199–219
World Bank (2020) Enhancing government effectiveness and transparency: the fight against corruption GLOBAL REPORT. Accessed on 12th June 2023. https://star.worldbank.org/sites/default/files/2021-01/Enhancing-Government-Effectiveness-and-Transparency-The-Fight-Against-Corruption%20%281%29.pdf
World Bank (2021a) CPIA Africa: assessing Africa's policies and institutions. World Bank
World Bank (2021b) Global economic prospects. Accessed on 14th June 2023. https://thedocs.worldbank.org/en/doc/600223300a3685fe68016a484ee867fb-0350012021/original/Global-Economic-Prospects-June-2021.pdf
Zhang J, Tao D (2020) Empowering things with intelligence: a survey of the progress, challenges, and opportunities in artificial intelligence of things. IEEE Internet Things J 8(10):7789–7817
Zhao P, Gao Y, Sun X (2022) How does artificial intelligence affect green economic growth?—Evidence from China. Sci Total Environ 834:155306
Zimmermannova J, Skalickova J, Siroky J (2016) What can tax revenues tell us about the economic activity of regions? Econ Sociol 9(1):114

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.