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Leveraging the potential of artificial intelligence (AI) in exploring the interplay among tax revenue, institutional quality, and economic growth in the G-7 countries

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Abstract

Due to G-7 countries' commitment to sustaining United Nations Sustainable Development Goal 8, which focuses on sustainable economic growth, there is a need to investigate the impact of tax revenue and institutional quality on economic growth, considering the role of artificial intelligence (AI) in the G-7 countries from 2012 to 2022. Cross-Sectional Augmented Autoregressive Distributed Lag (CS-ARDL) technique is used to analyze the data. The study's findings indicate a long-run equilibrium relationship among the variables under examination. The causality results can be categorized as bidirectional, unidirectional, or indicating no causality. Based on the CS-ARDL results, the study recommends that G-7 governments and policymakers prioritize and strengthen the integration of AI into their institutions to stimulate growth in both the short- and long-term. However, the study cautions against overlooking the interaction between AI and tax revenue, as it did not demonstrate support for economic growth. While the interaction between AI and institutional quality shows potential for contributing to growth, it is crucial to implement robust measures to mitigate any potential negative effects that may arise from AI's interaction with tax systems. Therefore, the study suggests the development of AI-friendly tax policies within the G-7 countries, considering the nascent nature of the AI sector/industry.

1 Introduction

The G-7 nations, namely Canada, France, Germany, Italy, Japan, United Kingdom, and United States, represent a diverse group of developed economies characterized by rapid technological advancements, varying levels of revenue mobilization capabilities and stable institutional development. The G-7 countries share commonalities such as advanced industrialization, political stability, high standards of living, and influence in global affairs. They often work together to address economic challenges, promote free trade, and collaborate on global issues like climate change, security, and development. As these nations strive for sustained economic growth and development, the interplay between artificial intelligence (AI), tax revenue, institutional quality, and their impact on economic growth becomes a topic of significant interest and importance. Understanding the dynamics between these variables in this context is essential for formulating effective policies and strategies to harness the benefits of AI-driven advancements in G-7 economies.

AI, with its rapid advancements in recent years, has the potential to transform industries, societies, and economies. AI encompasses a range of technologies and applications that simulate human intelligence and perform tasks autonomously. Its potential benefits in areas such

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as automation, data analysis, and decision-making make it a powerful tool for enhancing productivity, efficiency, and innovation (Makridakis 2017). Tax revenue is a vital component of a country's fiscal framework, enabling governments to finance public goods, infrastructure development, social programs, and other essential initiatives (Zimmermannova et al. 2016). The ability to effectively collect tax revenue depends on factors such as tax policies, administration systems, compliance rates, and enforcement mechanisms (Zimmermannova et al. 2016; Akitoby 2018). The level of tax revenue generated plays a crucial role in determining the government's capacity to invest in key sectors that drive economic growth (Vinnitskiy 2020). Institutional quality, encompassing elements such as rule of law, transparency, political stability, regulatory frameworks, etc., which sets the foundation for economic activities, investment, entrepreneurship, economic development, and governance within a country (Chhabra et al. 2023). They provide stability, predictability, and trust, attracting both domestic and foreign investments (Chhabra et al. 2023).

The G-7 countries have recognized the transformative potential of AI in sectors such as healthcare, agriculture, finance, and others, and they are actively involved in AI-related initiatives and development, investing in AI technologies, implementing policy initiatives, establishing research institutes, and supporting startups (Cyman et al. 2021; Dukhi et al. 2021). In the area of taxation for example, the rapid progress of technology, including Big Data, Analytics, AI, Machine Learning, the Internet of Things (IoT), Mobility, and Cloud Computing, is set to bring significant implications for tax administrations on a global scale. These dynamic technological advancements present straightforward yet intelligent tools that can enhance taxpayer satisfaction, empower tax agency personnel, streamline operations, and modernize services. This range of technological innovations acts as the primary catalyst for driving digital transformation in tax systems.

However, despite their efforts, these countries continue to face multitude of challenges in these sectors. Tax revenue plays a crucial role in the fiscal system of G-7 economies, constituting a substantial portion of government revenue (Cottarelli and Schaechter 2010). Each country within the G-7 group relies on diverse sources of tax revenue, including Income Tax, Value Added Tax (VAT)/Goods and Services Tax (GST), Payroll Taxes, Corporate Taxes, Property Taxes, Excise Taxes, Capital Gains Tax, Import/Customs Duties, among others. It is important to note that the specific tax revenues and their proportions vary among G-7 countries due to differences in tax policies, economic structures, and priorities.

On the one hand, the G-7 economies is faced with different institutional challenges which include legitimacy and global governance, accountability and transparency, effectiveness and implementation, representation and inclusivity, etc. (see for example Bayne 1995; Timmermann 2007; World Bank 2020, 2021; Transparency International 2022; Muhammad and Khan 2023; Fernández-Rodríguez et al. 2023, among others). On the other hand, the G-7 countries have witnessed diverse levels of economic growth in recent years, driven by factors such as their export-oriented manufacturing sector, infrastructure investments, services sector, government reforms, domestic consumption, etc. (International Monetary Fund (IMF) 2010; Liao and Beal 2022). However, some of the countries continue to face challenges including inflation, geopolitical factors, structural constraints, unemployment, and inequality, which influence their economic growth trajectory (IMF 2010; Liao and Beal 2022).

In this context, understanding the impact of the interaction between AI and tax revenue, and AI and institutional quality on growth for the G-7 economy is vital for policymakers and researchers seeking to harness the potential synergies and implications for economic growth. The integration of AI into taxation systems could have multifaceted effects. This is because AI can significantly enhance tax mobilization efforts by streamlining tasks, saving time, and improving access to information (Serrano Antón 2021). The integration of AI into tax practices and administration is gaining attention, as it presents opportunities to optimize processes that are currently manual and time-consuming (Serrano Antón 2021). For example, AI has the potential to significantly enhance tax mobilization efforts by handling large volumes of data much more efficiently than humans (Patrick et al. 2022).

In tax administration, this means faster processing of tax returns, quicker identification of errors, and more efficient handling of routine inquiries (Saragih et al. 2023). This efficiency can lead to increased compliance and reduced backlogs in tax offices (Saragih et al. 2023; Kuznetsova et al. 2023). AI algorithms assist in detecting patterns and anomalies that may suggest fraud or non-compliance by analyzing tax returns, financial statements, and relevant data (Faúndez-Ugalde et al. 2020; Kuznetsova et al. 2023). Automating routine tasks with AI can reduce administrative costs for tax authorities and this includes tasks like processing forms, answering basic taxpayer inquiries, and managing databases (Faúndez-Ugalde et al. 2020; Saragih et al. 2023; Kuznetsova et al. 2023).

AI can flag suspicious activities for further investigation by tax authorities, potentially leading to the recovery of lost revenues and a reduction in tax evasion (Faúndez-Ugalde et al. 2020). AI can offer personalized guidance to taxpayers, aiding their comprehension of complex tax laws and obligations (Kamil 2022). This can enhance taxpayer satisfaction and compliance. AI can bolster tax revenue mobilization by optimizing data processing, improving compliance, and
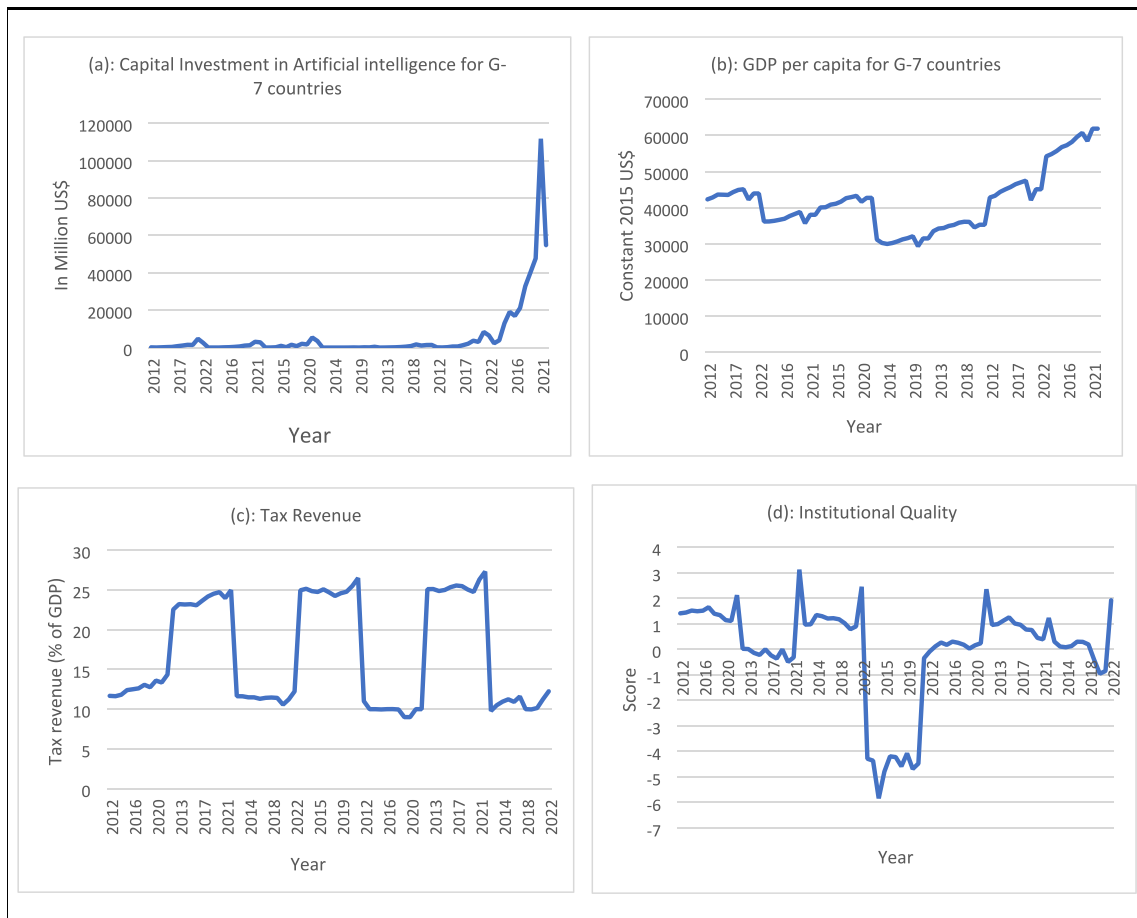
Fig. 1 **a** Capital investment in artificial intelligence for G-7 countries; **b**: GDP per capita for G-7 countries; **c** tax revenue for G-7 countries; and **d** institutional quality for G-7 countries (constructed using principal component analysis)

detecting fraud, directly increasing government revenue (Saragih et al. 2023). Efficient tax collection, facilitated by AI, supports the equitable redistribution of resources, funds public services, reduce budget deficits, and creates an environment conducive to economic growth (Gorshkova et al. 2022). AI-driven/technology-driven insights into taxpayer behavior and economic trends aid in formulating effective tax policies, fostering a stable and growth-oriented fiscal environment (Gorshkova et al. 2022). These capabilities effectively bridge the gap between tax revenue collection and sustainable economic growth/development, positioning AI as a mediator in the tax revenue-economic growth relationship.

The integration of AI technologies can impact institutional quality by influencing factors such as transparency, accountability, efficiency, etc. (Ahn and Chen 2020). AI can contribute to more effective governance, automate administrative processes, improve service delivery, risk management and fraud detection, and data-driven policy formulation. However, challenges such as ethical considerations, lack of transparency, cybersecurity risks, and potential biases in

AI algorithms also need to be addressed to ensure that the integration of AI aligns with and strengthens institutional quality (Ahn and Chen 2020). Given Fernández-Rodríguez et al. (2023) emphasis on the substantial variations in institutional quality among G-7 and BRICS countries, where some nations exhibit more robust and effective governance systems than others, it is crucial to explore the interaction between AI and institutional quality, as well as AI and tax revenue in the G-7 context. Such exploration can offer valuable insights into how institutions and tax systems can harness AI technologies to enhance their effectiveness and foster economic growth.

Figure 1 presents a graphical representation of the time paths for our main variables of interest in this study, focusing on the G-7 countries. From the preliminary information conveyed by the visual graph, it is apparent that the four variables did not demonstrate a similar time path throughout the study period. This observation further underscores the importance of investigating the interrelationships between the variables depicted in Fig. 1. To the best of the authors' knowledge, there is a dearth of studies investigating the

interplay relationships between these variables in the context of G-7 countries. Therefore, the primary objective of this study is to address this research gap in the literature.

Furthermore, while AI, tax revenue and institutional quality individually have been recognized as significant factors that can influence economic outcomes (see for example Merrifield 2000; Castro and Camarillo 2014; Javed and 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), there is a need to understand the specific dynamics and implications of their interaction on economic growth in the G-7 context. Therefore, the research question that this study seeks to address are: (i) What are the causal relationships among the main variables of interest in the G-7 economy?; (ii) What are the short- and long-run impact of AI, tax revenue, institutional quality on economic growth in G-7 economy?; and (iii) What are the short- and long-run impact of tax revenue and institutional quality on economic growth conditioned on AI in G-7 economy?

These are the research questions that inspire the study's objectives and contributions. Therefore, the broad objective for this study seeks to explore how AI complements tax revenue and institutional quality to promote economic growth in a panel of G-7 economies over the period 2012–2022. While specifically, (i) the study investigate the causal relationships among AI, tax revenue, institutional quality, and economic growth; (ii) to investigate the short- and long-run impact of AI, tax revenue, institutional quality on economic growth; (iii) to investigate the short- and long-run impact of tax revenue and institutional quality on economic growth conditioned on AI. We used the principal component analysis approach to compute the institutional quality variable from six governance indicators and discussed policy implications arising from the study's results. The empirical results from this study inform evidence-based policy decisions regarding the adoption and implementation of AI technologies in tax systems and institutional frameworks to support economic growth in G-7 economies.

Our research on G-7 contributes to the existing literature in several ways compared to previous empirical studies. First, it investigates the causal relationships among AI, tax revenue, institutional quality, and economic growth. Second, it investigates the short- and long-run impact of AI, tax revenue, institutional quality on economic growth. Third, it examines the short- and long-run impact of tax revenue and institutional quality on economic growth, taking into account the potential influence of AI, and also discusses policy implications derived from the obtained results.

This study holds academic and policy significance in four ways. (i) The importance of the joint effect of AI and tax revenue in either promoting or retarding growth in G-7 economy; (ii) The vital role of the joint effect of AI and institutional quality in either promoting or retarding growth in G-7 economy; and (iii) Comprehending the interrelationship between AI, tax revenue and institutional quality may impact how G-7 countries approaches its AI, tax revenue and institution sector policies. The primary theoretical contribution of this study is that it briefly shows that modified Cobb–Douglas production function (Cobb and Douglas 1928) following previous empirical studies could be used to investigate this study's objectives.

The organization of this paper is as follows: Sect. 2 presents the literature review. Section 3 presents the methodology and data. Results from the empirical analysis are presented and discussed in Sect. 4, while policy implications and further discussion are found in Sect. 5. Finally, Sect. 6 concludes the study.

2 Literature review

The nexus between AI, tax revenue, quality of institutional, and economic growth is a multifaceted and evolving field of research. The primary objective of this literature review is to offer a comprehensive overview of the current body of literature that investigates the interconnectedness among these variables. Extensive theoretical and empirical research has been conducted to assess the influence of taxation on economic growth. The impact of tax policy instruments is found to differ in the context of endogenous and exogenous (neoclassical) growth theories. Scholars have utilized a wide range of tax components, rates, policies, and reforms to examine the proposed association between taxes and growth.

According to economic theory, taxes and various tax policies are believed to have distinct effects on economic growth. Some authors have posited that economic growth can also lead to an expansion in both total tax revenues and the tax-to-GDP ratio in an economy and vice versa. Diverse perspectives on the taxation-growth nexus have emerged from the empirical literature. For instance, Hamdi and Sbia (2013) discover a positive correlation between tax revenue and growth, while Fölster and Henrekson (2001) present contrasting findings. Specifically, according to Cashin (1995) and Kneller et al. (1999) studies, it was observed that distortionary tax adversely affects growth. In countries where the fiscal deficit is equal to or less than 1.5% of GDP, it acts as a catalyst for economic growth; however, once the fiscal deficit exceeds this threshold, it becomes an impediment to growth (Adam and Bevan 2005). In their analysis, Gill et al. (2006) integrate tax revenue as a fiscal policy variable to showcase the detrimental effect of tax revenue shocks on economic growth.

Conversely, Pula and Elshani (2018) establish a reciprocal causal relationship between tax revenue and growth in their study. Cerqueti and Coppier (2011) investigates

the tax-economic growth-corruption nexus. Their findings reveal that, across different country categories distinguished by varying levels of corruption ("low shame," "middle shame," and "high shame"), the growth rate initially experiences an upsurge with rising tax rates up to a certain threshold value. However, surpassing the threshold, further increases in the tax rate led to a decline in the growth rate. Importantly, for intermediate tax rates, the growth rate in "low shame" countries is lower compared to "uniform shame" countries, and the growth rate in "uniform shame" countries is lower than that in "high shame" countries. The study suggests that this divergence is due to the fact that countries with higher levels of honesty exhibit more significant variations in the growth rate in response to changes in the tax rate, as they are more responsive to such changes, compared to countries with higher levels of corruption.

Hatfield (2015) examines how the decentralization of tax can ultimately impact economic growth using endogenous growth model. The findings reveal that at the state of equilibrium, a decentralized government optimizes tax policies to maximize economic growth, whereas a centralized government does not prioritize this objective. In Jaimovich and Rebelo's (2017) study, the effects of taxation on growth exhibit a highly nonlinear pattern with low tax rates having a minimal influence on long-term growth rates. Thomas (2017) undertakes a macroeconomic empirical investigation of service taxation in India, with a specific emphasis on the period spanning from 1994 to 1995. The findings of the study unveil a noteworthy and statistically significant income elasticity of service tax revenue collection, despite India's comparatively low tax-to-GDP ratio and the modest contribution of service tax to the overall tax revenue collection.

Gurdal et al. (2021) examines the government expenditure-taxation-growth nexus for G-7 countries over the period from 1980 to 2016. The outcomes derived from the panel causality test conducted in the time domain provide evidence of bidirectional causality between tax revenue and growth, persisting in both the short- and long-run. Moreover, there is evidence of a long-run causal association between growth and government expenditure. In a similar investigation, Rahman and Siddiquee (2022) explore the government expenditure-taxation-growth nexus within the context of a developing country, specifically focusing on Bangladesh. The study employs the Autoregressive Distributed Lag (ARDL) bounds testing method. Results from the application of the Granger causality test indicate that direct tax exhibits bidirectional causal relationships with economic growth, while indirect tax and revenue expenditure demonstrate a unidirectional relationship with GDP in the short-run. Furthermore, in the long-run, it is observed that indirect tax exerts a negative impact on growth, while revenue expenditure and fiscal deficit have positive effects on economic growth.

By employing the pooled-mean group (PMG) estimator approach, Ojede and Yamarik (2012) investigates the tax policy-economic growth nexus for 48 US states for the 1967–2008 period. Their study reveals that property and sales tax rates exhibit negative effects on long-run income growth, while income tax rates do not have a significant impact. Gnangnon (2022) examines the growth-tax transition reform nexus using a two-step system-GMM econometric model. The study encompasses a sample of 101 developing countries spanning from 1980 to 2019. The empirical analysis reveals that tax transition reforms have a positive impact on growth, even in countries where non-resource tax revenue represents a substantial share of the overall public revenue. Using the dynamic panel data modelling, Pradhan et al.'s (2022) study examines the financial market development-taxation propensity-growth nexus for OECD and non-OECD countries spanning 1961 to 2019. The findings of the study reveal that long-term economic growth is positively influenced by both the development of financial markets and the propensity for taxation.

Adefolake and Omodero (2022) examines tax revenue-economic growth nexus for the case of Nigeria between 2000 and 2021 by utilizing the VECM econometric model. The findings indicate that various sources of tax revenue, such as Petroleum Profit Tax (PPT) and Value Added Tax (VAT), have a positive and statistically significant effect on growth. In contrast, the study reveals that Company Income Tax (CIT) has a negative and statistically significant impact on growth. Khujamkulov and Abizadeh (2023) explores the total tax revenues-economic growth nexus for transitional economies using the fixed-effect and difference and system GMM panel regression approaches. The findings of the study reveal that increased growth is associated with a rise in the total tax revenue-to-GDP ratio. Gechert and Heimberger (2022) employs a meta-regression method to analyze the growth effect of tax cut from a comprehensive dataset comprising 441 estimates derived from 42 primary studies. Their analysis reveals potential publication bias favoring the reporting of growth-enhancing effects of corporate tax cuts. After accounting for the bias, they found no significant evidence to reject the hypothesis of a zero effect of corporate taxes on growth.

Using FEM and the GLS econometric approaches, Ho et al.'s (2023) study examines the economic growth effect of tax revenue contingent on the role of trade openness for 29 developing countries between 2000 and 2020. Overall, the outcomes indicate a growth positive effect of tax revenue, and this effect was further amplified by trade openness. Applying the SEM and ML econometric estimation techniques, Amoh et al.'s (2023) study explores how institutional quality moderate the tax evasion-corruption-economic development nexus in Ghana for the period 1996–2020. Overall, the study reveals GDP per capita positive effect

of tax evasion which was further moderated by quality of institution.

Over the years, extensive research has examined various factors that contribute to short- and long-term economic growth and development at different levels, including country-specific, regional, economic blocs, and global levels. These studies have identified factors such as trade openness, technology, government size, and income distribution as significant determinants of growth (see, for example, the pioneering work by Barro (1991), and the study conducted by Levine and Renelt 1992, among others). Furthermore, emerging growth theories have put forth the idea that quality of institutional may also play a critical role in understanding the variations in economic performance across countries and regions (Butkiewicz and Yanikkaya 2006; Nawaz et al. 2014; Salman et al. 2019). For example, Hashim Osman et al. (2011) examines economic performance effect of institutions in 27 SSA countries for the period between 1984 and 2003. The findings of the study reveal that institutional variables play a crucial role in the process of economic performance, while the control variables used in the study exhibit a minimal impact.

Sathyamoorthy and Tang (2018) examines institutional quality-export-led growth for a panel of 119 countries over the period 1990 to 2010. The finding reveals that quality of institutional quality mediates the export-led growth relationship in general, and for middle-income group of countries. Sabir and Qamar (2019) examines the fiscal policy-institutional quality-inclusive growth nexus for developing Asian countries spanning 1996–2017 using the SGMM approach. The empirical results reveal inclusive growth positive effects of fiscal policy and institutions. Fernández-Rodríguez et al. (2023) conduct a comprehensive analysis of the relationship between the corporate effective tax rate (ETR) and institutional factors in both the G-7 and BRIC countries. The study employs a panel data methodology and includes a sample of 25,878 listed firms spanning the period from 2010 to 2018. The research findings demonstrate that all the variables examined, namely statutory tax rate, government effectiveness, regulatory quality, rule of law, and open markets, exert an influence on the ETR.

AI, represented by industrial robots or investment in AI, has emerged as a transformative resource and technology, propelled by groundbreaking advancements (Zhao et al. 2022). With the advent of deep learning, AI has swiftly found applications across various economic and societal domains, expanding its reach and impact. This pervasive integration of AI has enhanced its capacity to permeate society, leverage resources, and foster continuous growth (Zhao et al. 2022). Significantly, AI has emerged as a pivotal catalyst for technological progress, presenting novel opportunities for growth and societal advancement. The roots of AI can be traced back to the Dartmouth Conference held in 1956, during which it was formally introduced as the discipline focused on the development of intelligent machines and computer programs (Zhao et al. 2022). This landmark event marked the inception of extensive research efforts in the field, setting the stage for subsequent advancements (Moor 2006).

The existing body of literature on AI predominantly centers around topics such as economic growth and development, employment, total factor productivity (TFP), technical innovation, income distribution, industrial integration model (Goos et al. 2009; Hémous and Olsen 2022; Zhao et al. 2022; Aghion et al. 2018; Arntz et al. 2016; Kromann et al. 2020; Brynjolfsson et al. 2019; Iain et al. 2019; Purdy et al. 2017). Recently, a growing number of studies have begun to investigate the impact of AI on growth. Notably, Graetz and Michaels (2018) identified TFP as a significant transmission channel through which AI affects growth. Additionally, Acemoglu and Restrepo (2018a, b) posited that AI has the potential to effectively address the challenges posed by aging populations and enhance economic growth by augmenting TFP. Qiu et al. (2021) presented a novel growth model that integrated technological progress and GDP. The findings of the study indicate that countries along the "Belt and Road" initiative have the potential to experience substantial improvements in their GDP through technological advancements.

The recent study of Lu (2021) developed the three-sector endogenous growth model to examines the growth and welfare effect of AI. The 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. Bandari (2019) examines the revenue growth effects of AI for 391 small businesses in developing countries. The study's findings underscored the significance of AI in small businesses and indicated that leveraging AI applications can yield favorable outcomes in terms of revenue growth.

Despite empirical literature on various tax structures, institutional quality and growth, to the best of our knowledge, no studies have examined how AI can distinctively complement tax revenue and institutional quality to promote growth in G-7 countries using the novel CS-ARDL approach. It is on this basis that we embark on this study for the purpose of recommending policies that will help G-7 countries achieve the SDG 8, which focuses on sustainable economic growth. We also consider the issues of homogeneity and cross-sectional dependence (CD) in the series under the unit root and cointegration techniques. Most panel series in the literature assume that the

residual terms are unrelated, which ignores the issues of CD between countries. Accounting for the issues of CD in the series is essential as G-7 countries possess varying levels of economic tiles. We applied the Dumitrescu–Hurlin (2012) panel causality technique that considers heterogeneity among countries.

Additionally, to the best of our knowledge, this is the first study to simultaneously employ the novel Cross-Sectional Autoregressive-Distributed Lag (hereafter, CS-ARDL) technique proposed by Chudik and Pesaran (2015). We primarily relied on the CS-ARDL approach, given its advantages over the others. The CS-ARDL method has several advantages over other panel data estimators. It yields robust results in the presence of cross-sectional dependence and can be applied to series with different orders of integration, including $I(0)$, $I(1)$, or both. Additionally, it produces accurate results in cases of endogeneity, weak exogeneity and allows for both pooled, mean group, and pooled-mean group estimates based on the homogeneity or heterogeneity of slope coefficients. Furthermore, to ensure the robustness of our analysis, we employ one additional econometric method, namely the Augmented Mean Group (AMG) estimator (Eberhardt and Bond 2009; Eberhardt and Teal 2010) which also demonstrates a high level of robustness, effectively addressing concerns related to cross-sectional dependence and slope heterogeneity.

3 Methodology and data

3.1 Empirical strategy

The preliminary empirical strategy used in this study include principal components approach/analysis (PCA), descriptive analysis, scatter plot (graph), panel unit root test (first-and second-generation), slope homogeneity test, cross-sectional dependence (CD) test, CIPS panel unit root tests, panel cointegration test (first- and second-generation), fully modified ordinary least square (FMOLS) and the dynamic OLS (DOLS) and Dumitrescu and Hurlin (2012) panel causality estimation techniques. We did not provide all the estimated equations for the aforementioned econometric techniques because they are readily available in other empirical literatures. However, we focused our attention on the CS-ARDL econometric model which is our main estimation technique. Furthermore, to ensure the robustness of our analysis, we employ one additional econometric method, namely the Augmented Mean Group (AMG) estimator (Eberhardt and Bond 2009; Eberhardt and Teal 2010). Figure 2 provides a visual representation
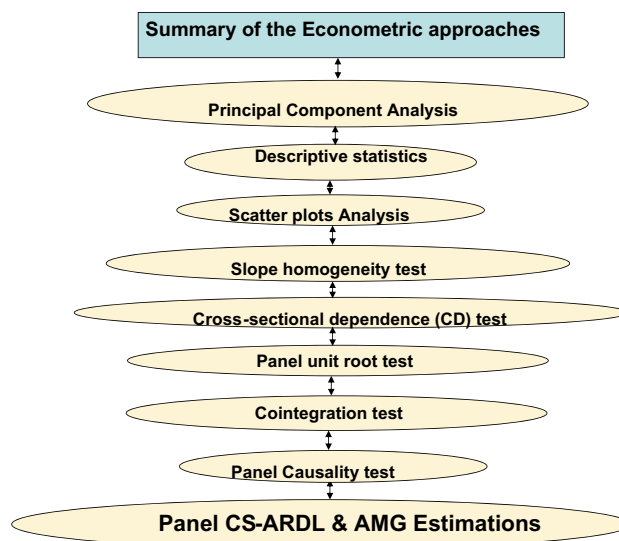

Fig. 2 Summary of the econometric approaches

of the methodological approach used in this study for ease of reference.

3.2 Theoretical framework and empirical model specification

Theoretically, this paper utilizes the Cobb–Douglas (Cobb and Douglas 1928) and Solow–Swan (Solow 1956a, b; Swan 1956) production functions with necessary modification for the purpose of investigating the relationship between artificial intelligence (AI), tax revenue, institutional quality, and economic growth within the context of G-7 economies. The aggregate growth function can be illustrated using a typical Cobb–Douglas production function with a constant rate of returns which is as follows:

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

$$Y_{i,t} = A K_{i,t}^{\mathcal{B}} L_{i,t}^{1-\mathcal{B}}, \tag{2}$$

where $Y, k, L,$ and A is GPD per capita (GDPPC), capital, effective labor, and technical progress/efficiency, respectively. The Solow–Swan growth approach suggests that technological progress is a key driver of output. AI, as a transformative technology, can contribute to productivity gains and innovation, leading to increased output. This theory posits that AI's ability to automate tasks, optimize processes, and make predictions can enhance overall efficiency and productivity in various industries (Aghion et al. 2018; Furman and Seamans 2019). AI can also act as a catalyst for creating new ideas and technologies, fostering long-term economic growth (Brynjolfsson and McAfee 2014).

Moreover, rapid economic expansion is associated with a wide range of factors, including tax revenue and institutional quality, among others, during the production process. Given that variable *A* encompasses various policy-oriented variables that are not directly captured in the equation, we augment our model to include tax revenue and institutional quality through the technical progress parameter to determine the empirical impact of these factors on output (Bassanini and Scarpetta 2002; Saba 2020a, b, c, d). Therefore, the augmented output function can be expressed as:

$$LGDPPC_{i,t} = f(X_{i,t}), \tag{3}$$

$$LGDPPC_{i,t} = \beta_0 + \beth_0 X_{i,t}, \tag{4}$$

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

where *LGDPPC* and *X* represents *log* of GDPPC (proxy for economic growth) and regressors,[1] respectively. The basic econometric models which were later transformed to CS-ARDL model and estimated can be found below:

Model 1:

$$\begin{aligned} LGDPPC_{i,t} = &\beta_1 + \beth_1 LAI_{i,t} + \beth_2 LGFCF_{i,t} + \beth_3 LTAXR_{i,t} \\ &+ \beth_4 LLHUM_{i,t} + \beth_6 INSQTY_{i,t} + \varepsilon_{1i,t}, \end{aligned} \tag{6}$$

where $\beta_1, \beth_1, \ldots, \beth_4$, and ε_{it} represents the constants, coefficient and the error term, respectively. Model 1 excludes the interaction terms between LAI and LTAXR, LAI and INSQTY, while the rest of the models (that is, model 7–8) does in a systemic manner one after the other.

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

$$\begin{aligned} LGDPPC_{i,t} = &\beta_1 + \beth_1 LAI_{i,t} + \beth_2 LGFCF_{i,t} + \beth_3 LTAXR_{i,t} + \beth_4 LHUM_{i,t} \\ &+ \beth_5 INSQTY_{i,t} + \beth_6 LAI_{i,t} * TAXR_{i,t} + \varepsilon_{1i,t} \end{aligned} \tag{7}$$

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

$$\begin{aligned} LGDPPC_{i,t} = &\beta_1 + \beth_1 LAI_{i,t} + \beth_2 LGFCF_{i,t} + \beth_3 LTAXR_{i,t} + \beth_4 LLHUM_{i,t} \\ &+ \beth_5 INSQTY_{i,t} + \beth_6 LAI_{i,t} * INSQTY_{i,t} + \varepsilon_{1i,t} \end{aligned} \tag{8}$$

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

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

where $\Delta LGDPPC$, $X_{i,t}$, $\overline{LGDPPC}_{t-1}$ & $\overline{X}_{t-1}$, $\Delta LGDPPC_{i,t-j}$ & $\Delta X_{i,t-j}$, $\Delta\overline{LGDPPC}_t$ & $\Delta\overline{X}_t$, 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}, Γ_{ij}, $\emptyset_{1i}$ and $\emptyset_{2i}$ 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 can be found in Table 1. The justification for including the regressors in the model is explained briefly below:

(a) *Artificial intelligence* (*AI*): AI influences economic growth through various ways. First, AI can: (i) enable automation, which leads to increased productivity and efficiency in production processes (Bessen 2018; Acemoglu et al. 2020); (ii) facilitate innovation by enabling new products, services, and business models (Brynjolfsson and McAfee 2017); (iii) improve decision-making through advanced data analytics, enabling better resource allocation and strategic planning (Manyika et al. 2017; Balliester and Elsheikhi 2018). These factors collectively and ultimately can contribute to economic growth by enhancing overall productivity, competitiveness, and economic output.

(b) *Gross fixed capital formation* (*GFCF*): It refers to the total investment in fixed assets such as machinery, equipment, buildings, and infrastructure. It plays a crucial role in economic growth by increasing the quantity and quality of capital stock, and it enables businesses to produce more goods and services, leading to higher output levels/it can lead to increased productivity by providing businesses with new and more efficient capital goods (Ali 2015). This can lead to businesses producing more output with the same amount of input, which can boost economic growth.

(c) *Tax revenue* (*TAXR*): It provides governments with the necessary funds to invest in infrastructure projects

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[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 1 Variable description and data sources

Variables	Description	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

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, b, c, d, 2023), Saba (2021a, 2023a; b, b; , ; , 2020a, b, c), Saba et al. (2023) and Saba and Biyase (2022)

such as transportation networks, schools, healthcare facilities, etc. These investments stimulate economic activity, create jobs, and improve productivity, ultimately contributing to long-term economic output (Besley and Persson 2013; Hatfield 2015).

(d) *Human capital* (*HUM*): The relationship between human capital and economic growth are well-established in the empirical literature. Human capital, which encompasses individuals' knowledge, skills, and health, plays a crucial role in driving growth (Asteriou and Agiomirgianakis 2001; Ljungberg and Nilsson 2009). Investments in education, training, and healthcare improve the quality and productivity of the workforce, foster innovation, and enhance labor market outcomes (Barro and Lee 2013). A highly skilled and healthy workforce contributes to increased productivity, technological advancement, and adaptability to changing economic conditions, all of which are key drivers of long-term economic growth (Barro and Lee 2013; World Bank 2018).

(e) *Institutional quality* (*INSQTY*): It simply refers to the effectiveness and efficiency of a country's institutions. Strong institutions provide a stable and transparent environment for economic activities, foster trust, protect property rights, enforce contracts, and ensure a level playing field (World Bank 2017). Good governance, rule of law, and control of corruption can promote business confidence, attract investments, and stimulate innovation and entrepreneurship (World Bank 2017; López-Calva et al. 2017). Sound institutions also have the capability to facilitate effective public policies and provide a conducive framework for economic growth and development. Empirical studies consistently highlight the importance of this variable to economic growth and development (see for example, Acemoglu et al. 2001; Butkiewicz and Yanikkaya 2006; Valeriani and Peluso 2011, among others).

3.3 Data and variables description

This research study employed annual panel data encompassing the G-7 countries, namely Canada, France, Germany, Italy, Japan, United Kingdom, and United States, for the period spanning from 2012 to 2022. The data sources included three primary databases, namely the Organization for Economic Cooperation and Development (OECD), the World Bank's World Development Indicators (WDI), and the World Governance Indicators (WGI). The

Table 2 Principal component and correlation matrix results for institutional quality. *Source*: Author's computation using WDI, WGI and ITU data

Institution quality variables							
Principal component results							
Compnnt	Eigenvalue	Difference	Proportion	Cumulative			
Compnnt 1	3.787	2.712	0.631	0.631			
Compnnt 2	1.074	0.492	0.179	0.810			
Compnnt 3	0.582	0.248	0.097	0.907			
Compnnt 4	0.333	0.142	0.056	0.963			
Compnnt 5	0.192	0.159	0.031	0.995			
Compnnt 6	0.032		0.005	1.000			
Principal components eigen-vectors results							
Variables	Compnnt 1	Compnnt 2	Compnnt 3	Compnnt 4	Compnnt 5	Compnnt 6	Unexplained
WGIc	0.458	−0.043	0.097	−0.582	0.664	0.010	0.203
WGIg	0.494	−0.062	0.102	−0.151	−0.482	−0.698	0.074
WGIp	0.108	0.888	0.413	0.159	0.062	−0.019	0.108
WGIreg	0.427	−0.267	0.108	0.777	0.354	−0.072	0.232
WGIr	0.489	−0.102	0.216	−0.066	−0.445	0.708	0.083
WGIv	0.336	0.352	−0.867	0.072	−0.020	0.078	0.439
Correlation matrix results	i	ii	iii	iv	v	vi	
(i) WGIc	1.000						
(ii) WGIg	0.833*** (0.000)	1.000					
(iii) WGIp	0.1473*** (0.010)	0.155*** (0.0069)	1.000				
(iv) WGIreg	0.651*** (0.000)	0.749*** (0.000)	−0.009*** (0.883)	1.000			
(v) WGIr	0.822*** (0.000)	0.962*** (0.000)	0.146*** (0.011)	0.782*** (0.000)	1.000		
(vi) WGIv	0.500*** (0.000)	0.549*** (0.000)	0.269*** (0.000)	0.407*** (0.000)	0.476*** (0.000)	1.000	

Where compnnt is component

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$, p value in parentheses

selection of the time frame and countries was based on data availability. The variable representing institutional 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.

4 Empirical results and discussion

4.1 Preliminary analysis

4.1.1 Principal component analysis

Table 2 presents the outcomes of the principal component analysis and correlation matrix for the institutional quality

(INSQTY) variable. Initially, we conducted tests to determine the extent of association among the indicators employed to construct the INSQTY index. The findings from Table 2 indicate a significant correlation between the indicators, thereby validating the prerequisite condition for performing the principal component analysis (PCA) (Saba and Ngepah 2022a, b, c). To establish a composite index for institutional quality, we selected the first principal component, as it accounts for the highest percentage of the overall variation, namely 3.79%. This decision was based on the eigenvalue criterion. Furthermore, Fig. 3, displaying the scree plots, provides additional support for our findings.

Fig. 3 Scree plot for institutional quality
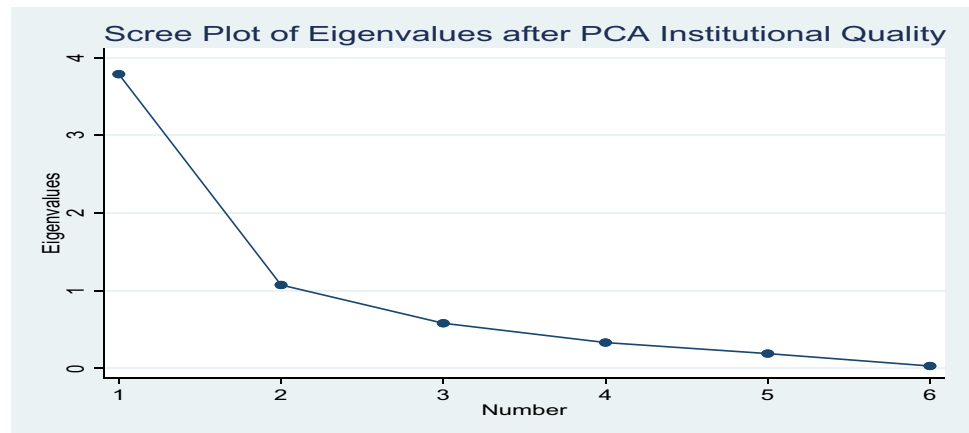
Table 3 Discriptive statistics results. *Source*: Author's computations

	LGDPPC	LAI	LTAXR	LGFCF	LHUM	INSQTY
Mean	10.620	6.270	2.747	27.318	4.657	7.89E−09
Median	10.643	6.625	2.530	27.051	4.629	0.300
Maximum	11.033	11.624	3.307	29.119	4.839	3.140
Minimum	10.287	−0.673	2.196	26.446	4.517	−5.868
Std. Dev.	0.192	2.520	0.404	0.787	0.075	1.946
Skewness	0.369	−0.287	0.213	1.186	0.951	−1.549
Kurtosis	2.567	2.924	1.208	3.314	3.011	4.601
Jarque–Bera	9.272	4.241	42.963	72.480	45.806	154.106
Probability	0.010	0.120	0.000	0.000	0.000	0.000
Observations	304	304	304	304	304	304

4.1.2 Summary statistics and scatter plot analysis

Table 3 presents the summary statistics for the variables under consideration. The series of LGDPPC, LAI, LTAXR, LGFCF, LHUM, and INSQTY exhibit mean (or median) values of approximately 10.620 (10.643), 6.270 (6.625), 2.747 (2.530), 27.318 (27.051), 4.657 (4.629), and 7.89E−09 (0.300), respectively. The variables' maximum and minimum values range approximately between 29.119 and −5.868, respectively. Skewness analysis reveals that variables with negative and positive skewness values are characterized by negatively and positively skewed distributions, respectively. Figure 4 presents scatter plots illustrating the relationship between economic growth and the explanatory variables. These plots visually depict a positive association between economic growth and AI, economic growth and institutional quality, while a negative association between economic growth and tax revenue. However, it is important to note that this preliminary relationship serves only as an indication of potential associations within the examined time periods for G-7 countries. It is crucial to highlight that the graphical approach employed in the scatter plots does not account for cross-sectional dependence issues, thereby limiting the validation of the negative/positive relationship between economic growth and the explanatory variables.

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

To begin our study, we conducted a slope homogeneity test suggested by Pesaran and Yamagata (2008), and the results of the test can be found in Table 4. Here both test statistics (delt and adjusted delta) and probability values seem to reject the assumption of homogenous slope coefficients at the 1% significance level. This would suggest the presence of strong country heterogeneity (in the long run) for the variables under consideration. To account for cross-sectional dependence, we tested for cross-sectional dependence in the data using Pesaran (2004) and Breusch and Pagan (1980) LM test techniques. The result of the two approaches in Table 5 shows that there is evidence of cross-sectional dependence in the series, with *p* values for the statistic being statistically significant at 1%. Therefore, the null hypothesis (cross-sectional independence) is rejected. This implies that levels of all the variables in one member of G-7 depend on the movements of these aspects in at least one other member within the G-7.
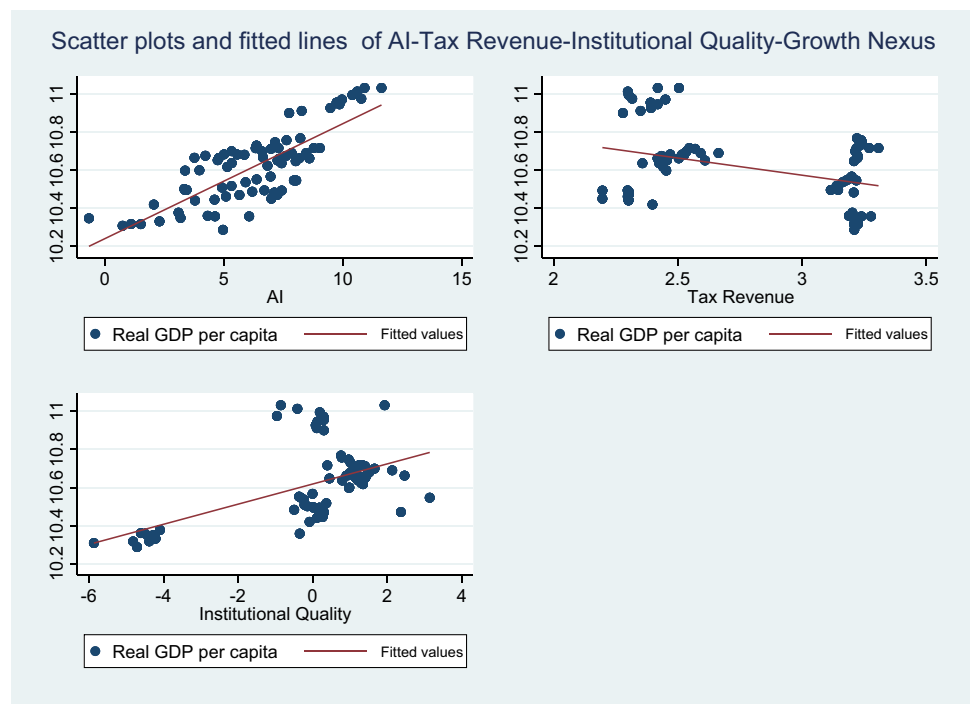
Fig. 4 Scatter plots graphical presentation

Scatter plots and fitted lines of AI-Tax Revenue-Institutional Quality-Growth Nexus

Table 4 Slope homogeneity results. *Source*: Author's computations

Test statistics (Delta)	Value	*p* value
Δ_{delt}	19.728***	0.000
$\Delta_{adjdelt}$	21.540***	0.000

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

Table 5 Cross-sectional dependence (CD) test results. *Source*: Author's computations

Variables	Pesaran test		Breusch–Pagan LM test	
	Statistic	*p* value	Statistic	*p* value
LGDPPC	23.83***	0.000	306.841***	0.000
LAI	28.17***	0.000	296.339***	0.000
LTAXR	9.82***	0.000	159.787***	0.000
LGFCF	15.03***	0.000	218.651***	0.000
LHUM	5.15***	0.000	174.954***	0.000
INSQTY	23.38***	0.000	302.860***	0.000

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

Although the asymptotic results of all first-generation panel unit root tests [that is, Levin-Lin-Chu (LLC) (Levin et al. 2002) and Im-Pesaran-Shin (IPS) (Im et al. 2003)] rely on the assumption of cross-sectional independence, we still tested the first-generation panel unit root. However, their reliability was less important. Table 6 shows the results at levels and first differences to determine whether the variables were integrated of order zero or one. The stationarity tests for the two techniques had a null hypothesis of a unit root. While some variables were not stationary at levels, a critical examination of the results in the last column of Table 6 shows that all variables had an integrated order of 1 at a significance level of at least 1%, indicating perfect stationarity at first differences (except for two variables).

Table 6 Panel unit root test results. *Source*: Author's computations

Series	Model	Levels	First difference
LGDPPC	LLC	−1.150 (0.125)	−3.243*** (0.001)
	IPS	−1.610* (0.054)	−8.783*** (0.000)
LAI	LLC	−2.452*** (0.007)	−8.945*** (0.000)
	IPS	0.254 (0.600)	−10.306*** (0.000)
LTAXR	LLC	1.454 (0.927)	−9.164*** (0.000)
	IPS	1.473 (0.930)	−9.064*** (0.000)
LGFCF	LLC	−1.771 (0.383)	−7.038*** (0.000)
	IPS	0.041 (0.516)	−9.708*** (0.000)
LHUM	LLC	−0.737 (0.230)	−8.704*** (0.000)
	IPS	−0.245 (0.403)	−9.920*** (0.000)
INSQTY	LLC	4.137 (1.000)	−10.696*** (0.000)
	IPS	1.673 (0.953)	−8.521*** (0.000)

Null: Unit root (assumes common unit root process): Levin, Lin and 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

Table 7 CIPS Panel unit root test results. *Source*: Author's computations

Variables	Levels	1st difference
LGDPPC	−1.375	−6.190***
LAI	−2.765***	−6.187***
LTAXR	−1.695	−6.181***
LGFCF	−1.456	−6.183***
LHUM	−1.176	−6.186***
INSQTY	−1.343	−6.183***

*, **, 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 Westerlund panel cointegration tests. *Source*: Author's computations

Statistic	Value	Z value	*p* value	Robust *p* value
G_t	−1.975**	1.863	0.169	0.037
G_a	−7.241***	2.482	0.094	0.003
P_t	−4.662*	1.496	0.133	0.086
P_a	−6.114*	1.651	0.151	0.066

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

Table 8 Johansen–Fisher panel cointegration test results. *Source*: Author's computations

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	1.000	$r = 0$	$r \geq 1$	0.000	1.000
$r \leq 1$	$r \geq 2$	267.6***	0.000	$r \leq 1$	$r \geq 2$	208.6***	0.000
$r \leq 2$	$r \geq 3$	344.0***	0.000	$r \leq 2$	$r \geq 3$	304.7***	0.000
$r = 3$	$r \geq 4$	197.5***	0.000	$r = 3$	$r \geq 4$	185.2***	0.000
$r \leq 4$	$r \geq 5$	116.0***	0.000	$r \leq 4$	$r \geq 5$	103.0***	0.000
$r \leq 5$	$r \geq 6$	61.54***	0.000	$r \leq 5$	$r \geq 6$	61.54***	0.000

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

Like the first-generation panel unit root results, the second-generation panel unit root (CIPS) results of Pesaran (2007) showed that the series were integrated of order 1 at least at a 1% significance level (see Table 7). This indicates that we can proceed to test the long-run equilibrium relationship between the series using the second-generation cointegration approach. More importantly, based on these estimates and the aforementioned unit root and cross-dependency tests, it does confirm the adequacy of the use of the panel CS-ARDL estimator to determine the existence of a possible relationship between all the variables used in this study.

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

Tables 8 and 9 present the results of the Johansen-Fisher and Westerlund (2007) panel cointegration tests, respectively, which were conducted to establish the existence of long-run equilibrium relationships between the dependent variable, economic growth, and the respective regressors. Before estimating the two approaches, we first determined the optimum lag length to be used for the estimations. The results in Table 10 indicate that the optimum lag length is

1, following the results of the three information criteria, namely SIC, and HQ. In Table 8, the Johansen-Fisher panel cointegration results reveal that there are ten cointegrating vectors, five from the trace statistic and five from the maximum eigenvalue statistic. This indicates the existence of a long-run equilibrium relationship between the variables used in this study.

We rejected the null hypothesis of no cointegration at a significance level of at least 1% for both the trace and maximum eigenvalue statistic values, thereby concluding that there is evidence of cointegration. For the purpose of robustness, we employed the Westerlund (2007) panel cointegration test to address the issue of cross-sectional dependence among countries. This test is considered more reliable than older ones (Khan et al. 2020). Results from the test in Table 9 indicate that all the four tests (that is the values of G_t, G_a, P_t, and P_a statistics) has a probability value smaller than 10%. However, the rejection of the null hypothesis of no cointegration for at least one test implies the existence of a long-run equilibrium relationship between the variables. This suggests that even with interconnections among countries, there is still a long-run relationship between the variables.

We used FMOLS and DOLS techniques proposed by Pedroni (2001, 2004) to estimate the long-run coefficients

Table 10 Optimum lag length selection results. *Source*: Author's computations

Lag	AIC	SIC	HQIC
0	5.464	5.545	5.496
1	− 22.095	− 21.526[a]	− 21.866[a]
2	− 21.840	− 20.784	− 21.416
3	− 21.592	− 20.046	− 20.971
4	− 21.353	− 19.321	− 20.536
5	− 22.865[a]	− 20.346	− 21.853

AIC Akaike information criterion, *SIC* Schwarz information criterion, *HQIC* Hannan–Quinn information criterion

[a]Indicates lag order selected by the criterion

of the explanatory variables, as these techniques address serial correlation and endogeneity issues better than OLS. The *R*-squared and Adjusted *R*-squared values, which were above 65% for both approaches, demonstrate that all our models were correctly specified. Therefore, we can proceed to interpret our estimated results. In Panel A of Table 11, in the long run, especially for the DOLS results, AI, tax revenue, and institutional quality significantly and positively impact economic growth. This implies that, in the long run, a 1% increase in AI, tax revenue, and institutional quality will contribute 0.017%, 0.030%, and 0.018%, respectively, to economic growth in the G-7 economy. In the long run, human capital and gross fixed capital formation significantly and positively impact economic growth. According to the neoclassical growth theory, alterations in tax policy are not expected to have a lasting impact on economic growth, but rather produce temporary effects (Ramsey 1928; Solow 1956a, b; Cass 1965).

In contrast, advocates of the endogenous growth theory argue that changes in tax rates can potentially yield long-term growth effects and stimulate economic activity (Romer 1986, 1990; Lucas 1988; Rebelo 1991; Pradhan et al. 2022). This indicates that our study aligns with the findings of previous research conducted by Romer, Lucas, Rebelo and Pradhan et al. even after considering the inclusion of AI and institutional quality in our model specification. Focusing on our main variable of interest in Panel B of Table 11, in the long-run, the interaction between AI and tax revenue significantly and negatively impacts economic growth. This implies that, in the long run, a 1% increase in interaction between AI and tax revenue will reduce economic growth by approximately -0.053% in the G-7 economy. While in Panel C of Table 11, in the long-run, the interaction between AI and institutional quality significantly and positively impacts

economic growth. This implies that, in the long-run, a 1% increase in interaction between AI and institutional quality will increase economic growth by 0.002%. This leads us to investigate the causality relationships that may exist between our variables of interest.

4.3 Panel causality and CS-ARDL estimation analysis

This section analyzed the causal relationship between the series under review. Table 12 presents the panel causality test results. In Table 12, two-way causality exists between: (i) economic growth and institutional quality; and (ii) AI and institutional quality. This implies that these variables depend on each other. Unidirectional causality runs from: (i) tax revenue to economic growth; and (ii) institutional quality to tax revenue. While no causality exist between AI and tax revenue. It implies that the presence or advancement of AI technology does not directly influence or impact the tax revenue. In other words, changes or developments in AI technology are not linked to changes in the tax revenue within a given context of G-7 economies. This also implies that the two variables are independent of each other in G-7 economy. Even if institutions exist to regulate AI industry, AI may not effectively contribute to resource mobilization.

This could be attributed to various factors such as lack of access (that is, limited access to AI technology, including infrastructure and connectivity, can hinder its widespread adoption and utilization for resource mobilization purposes), skill gaps (that is, insufficient knowledge and skills in AI among individuals and government tax organizations can hinder their ability to effectively leverage AI for resource mobilization efforts), data quality and availability, etc. We rejected/accepted the null hypothesis that there was no causation for each Chi-squared-value statistic since their p values were less/greater than the 10% significance level. The one-way causal relationship from tax revenue to growth aligns with the findings of Takumah and Iyke (2017), but contradicts the results of Pula and Elshani (2018) and Gurdal et al. (2021) studies. Figure 5 presents the visual summary of the Dumitrescu and Hurlin (2012) panel causality test results.

Table 13 presents the panel CS-ARDL results. Beginning with the estimates of the Error Correction Term (ECT) for all regression models, the values are − 1.001 (refer to Column 1), − 1.002 (refer to Column 2), and − 1.011 (refer to Column 3) which are 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 economic growth variable. Specifically, the negative ECT values indicate that any deviations from the long-run equilibrium will be corrected at a rate of approximately − 1.001, − 1.002,

Table 11 FMOLS and DOLS estimates. *Source*: Author's computations

Variables	FMOLS			DOLS		
	Coefficient	Std. error	Prob.	Coefficient	Std. error	Prob.
Panel A						
LAI	**0.015****	**0.006**	**0.021**	**0.017****	**0.008**	**0.022**
LTAX	**0.031****	**0.010**	**0.030**	**0.030****	**0.020**	**0.031**
LGFCF	0.189	0.016	0.000	0.186	0.018	0.000
LHUM	1.132	0.108	0.000	1.184	0.117	0.000
INSQTY	**0.018****	**0.008**	**0.029**	**0.018****	**0.008**	**0.035**
R-squared	0.712			0.871		
Adjusted *R*-squared	0.708			0.788		
Observations	280			280		
Panel B						
LAI	0.203	0.040	0.000	0.162	0.040	0.000
LTAX	0.466	0.096	0.000	0.300	0.099	0.003
LGFCF	1.079	0.097	0.000	1.215	0.097	0.000
LHUM	0.153	0.016	0.000	0.148	0.017	0.000
INSQTY	0.041	0.009	0.000	0.032	0.009	0.000
LAI* LTAXR	**− 0.067*****	**0.014**	**0.000**	**− 0.053*****	**0.014**	**0.000**
R-squared	0.763			0.910		
Adjusted *R*-squared	0.759			0.830		
Observations	296			280		
Panel C						
LAI	0.140	0.009	0.000	0.012	0.005	0.027
LTAX	0.027	0.000	0.000	− 0.151	0.038	0.000
LGFCF	1.103	0.0001	0.000	1.401	0.088	0.000
LHUM	0.193	5.28E−05	0.000	0.164	0.014	0.000
INSQTY	0.009	9.06E−05	0.000	0.002	0.008	0.762
LAI*INSQTY	**0.003*****	**8.19E−05**	**0.000**	**0.002*****	**0.002**	**0.001**
R-squared	0.660			0.988		
Adjusted *R*-squared	0.672			0.966		
Observations	296			272		

The bold results highlight the outcomes of variables of interest

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

and − 1.011 units per period, respectively, suggesting that the economic growth variable will adjust back towards its equilibrium level relatively quickly. Additionally, the *R*-squared values for all the models are above 80%, which implies that our models are correctly specified.

Focusing on our variables of interest, for the first model which shows the results without the interaction term variables, in Column 1 of Table 13, the CS-ARDL results show that both in the short- and long-run, at a 10% level of significance, the impact of AI and institutional quality on economic growth is significant and positive. Specifically in the short run, a 1% increase in AI and institutional quality led to a 0.007% and 0.006% increase in economic growth, respectively. In the short run, tax revenue has a significant and negative impact on economic growth. This

is in line with the findings of Marsden (1984), Martin and Fardmanesh (1990), Widmalm (2001), Amiel et al. (2012), and Nkhalamo and Sheefeni (2017). A 1% increase in tax revenue leads to a − 0.137% decrease in economic growth, while in the long-run, the impact of tax revenue on economic growth is found to be negative and significant. This implies that both in the short- and long-run tax revenue does not promote economic growth in G-7 economy.

This is in contrast to expectations, as tax revenue is generally expected to play a crucial role in supporting economic growth. However, there are various factors and circumstances that can impede its positive impact which may be the case of G-7 economy. These include a high tax burden, distortions and disincentives, compliance costs, administrative inefficiencies, negative multiplier effects (in

Table 12 Dumitrescu and Hurlin (2012) panel causality test results. *Source*: Author's computations

Model	Null hypothesis	W-statistic	Zbar-statistic	p value	Direction of relationship observed	Conclusion
1	LAI ↛ LGDPPC	2.047	− 1.073	0.283	LGDPPC → LAI	Unidirectional causality
	LGDPPC ↛ LAI	0.736**	− 2.307	0.021		
2	LTAXR ↛ LGDPPC	1.085**	− 1.979	0.048	LTAXR → LGDPPC	Unidirectional causality
	LGDPPC ↛ LTAXR	3.280	0.087	0.931		
3	INSQTY ↛ LGDPPC	0.344**	− 2.673	0.008	LGDPPC ↔ INSQTY	Bidirectional causality
	LGDPPC ↛ INSQTY	0.401**	− 2.619	0.009		
4	LTAXR ↛ LAI	1.932	− 1.182	0.237	LTAXR ↛ LAI	No causality
	LAI ↛ LTAXR	3.281	0.088	0.930		
5	INSQTY ↛ LAI	0.351**	− 2.666	0.008	INSQTY ↔ LAI	Bidirectional causality
	LAI ↛ INSQTY	1.265*	− 1.808	0.071		
6	INSQTY ↛ LTAXR	0.978**	− 2.078	0.038	INSQTY → LTAXR	Unidirectional causality
	LTAXR ↛ INSQTY	1.822	− 1.286	0.199		

↔ and → denote bidirectional and unidirectional causality, respectively. ↛ denotes does not homogeneously cause (i.e., **H₀**)

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$
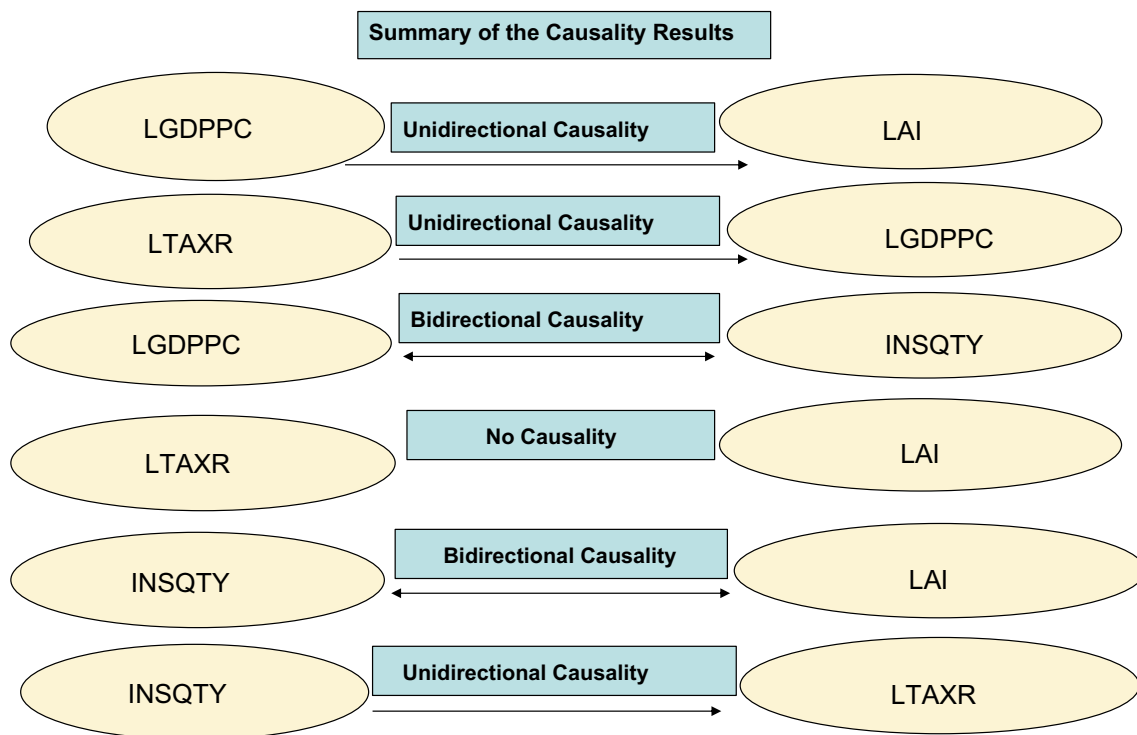
Fig. 5 Summary of the causality results

some cases, tax revenue may be used to fund inefficient or unproductive government spending, leading to a crowding-out effect), and international competitiveness concerns (Petruzzi and Buriak 2018; Danon and Chand 2019). Therefore, it is imperative for G-7 countries to collaborate and collectively address the challenges facing their tax systems.

For the second model in Column 2 of Table 13, which shows the impact of the interaction between AI and tax revenue on growth, the CS-ARDL results reveal that in both the short- and long-run the interaction between AI and tax revenue has a negative and significant impact on growth. This indicates that a 1% increase in the interaction between AI and tax revenue leads to − 0.023% and − 0.021% decrease in growth in the short- and long-run,

Table 13 Panel CS-ARDL estimates. *Source*: Author's computations

Variables	(1) CS-ARDL 1	(2) CS-ARDL 2	(3) CS-ARDL 3
Short run est.			
ΔINSQTY	**0.006****	0.006*	0.011**
	(0.003)	0.003	(0.005)
ΔLAI	**0.007***	0.067**	−0.001*
	(0.004)	(0.035)	(0.001)
ΔLTAX	**−0.137***	0.002	−0.197***
	(0.078)	(0.008)	(0.047)
ΔLGFCF	0.175*	0.240***	0.002
	(0.093)	(0.048)	(0.016)
ΔLHUM	0.383	−0.013	0.090**
	(0.273)	(0.024)	(0.040)
ΔLAI* LTAXR		**−0.023****	
		(0.011)	
ΔLAI*INSQTY			**0.002****
			(0.001)
Adjust. term			
ECT	**−1.001*****	**−1.002****	**−1.011*****
	(0.003)	**(0.002)**	**(0.005)**
Long run est.			
LR_INSQTY	**0.006****	0.006*	0.001
	(0.003)	(0.003)	(0.002)
LR_LAI	**0.007***	0.067**	−0.001*
	(0.004)	(0.034)	(0.001)
LR_LTAX	**−0.131***	0.002	−0.195***
	(0.078)	(0.008)	(0.047)
LR_LGFCF	0.175*	0.240***	0.002
	(0.093)	(0.048)	0.016
LR_LHUM	0.384	−0.012	0.089**
	(0.273)	(0.024)	(0.040)
LR_LAI*LTAXR		**−0.021****	
		(0.010)	
LR_LAI*INSQTY			**0.003****
			(0.001)
Observation	289	289	289
R-squared	0.99	0.99	0.96

Standard errors in parentheses

The bold results highlight the outcomes of variables of interest

*, **, and *** represent significance at the 1%, 5%, and 10% levels, respectively

Table 14 Robustness test results using AMG estimator. *Source*: Author's computation

Variables	(1) AMG 1	(3) AMG 2	(5) AMG 3
ΔINSQTY	**0.003*****	1.218***	0.039
	(0.001)	(0.140)	(0.023)
ΔLAI	**0.001***	0.011	0.002
	(0.001)	(0.189)	(0.002)
ΔLTAX	**−0.000***	−0.068	−0.045
	(0.000)	(0.488)	(0.037)
ΔLGFCF	0.205***	0.298**	0.238***
	(0.046)	(0.034)	(0.036)
ΔLHUM	1.225***	0.271**	0.052
	(0.172)	(0.139)	(0.169)
ΔLAI*LTAXR		**−0.000*****	
		(0.000)	
ΔLAI*INSQTY			**−0.003**
			(0.003)
Constant	4.381***	1.641	3.972***
	(1.465)	(2.119)	(1.381)
Obs	308	308	308
Wald Chi²	56.89***	418.25***	3931.35***

Standard errors in parentheses

The bold results highlight the outcomes of variables of interest

*, **, and *** represent significance at the 1%, 5%, and 10% levels, respectively

growth. This indicates that a 1% increase in the interaction between AI and institutional quality in the short- and long-run leads to 0.002% and 0.003% increase in growth, respectively. This implies that the interaction between the two variables promotes economic performance both in the short- and long-run in G-7 countries. The long-term result of CS-ARDL mode also align with the result of FMOLS and DOLS estimates. This is as expected for the G-7 economy, and it suggests that the integration of AI within the existing institutional framework does not pose challenges or unintended consequences for growth.

4.4 Robustness checks

As a means of testing the robustness of the CS-ARDL results, the study followed similar approaches adopted in recent literature (Wang and Zhang 2021; Sharif et al. 2023) using models that could account for cross-sectional dependence in the long-run. In doing so, the AMG estimation technique is employed for the variables under consideration. The results of the test are presented in Table 14. Upon examining the estimate presented in Table 14, we observed that the signs of all coefficients for the respective control variables in the AMG estimation were relatively consistent with those

respectively. This suggests that tax mobilization efforts supported by AI has not helped economic performance of G-7 countries both in the short- and long-run.

For the third model in Column 3 of Table 13, which shows the impact of the interaction between AI and institutional quality on growth, the CS-ARDL results highlight that in the short- and long-run, the interaction between AI and institutional quality has a positive and significant impact on

reported in the CS-ARDL estimations. The results of AMG for the first and second models are consistent with the long-run results of CS-ARDL.

5 Policy implications

Given that the interaction between artificial intelligence (AI) and institutional quality demonstrates a significant and positive impact on economic growth both in the short- and long -run. We recommend that G-7 governments further strengthen the existing institutional framework to support the AI industry for achieving faster growth in the long-term. Governments should focus on and strengthen institutional indicators related to transparency, regulatory quality, accountability, rule of law, and governance/government effectiveness, particularly in the context of AI investment. G-7 governments and policymakers should identify and prioritize specific institutional weaknesses that hinder investment in AI and the effective integration of AI technologies in the economy, and work towards addressing these weaknesses accordingly.

Formulated institutional policies should establish guidelines and regulations to support and ensure ethical and responsible AI investment/development and deployment, both in the short- and long-term. This should include addressing concerns related to bias, fairness, privacy, and accountability in AI development processes. Institutional policies should encourage investment, development and adoption of AI technologies that align with G-7 values for the purpose of promoting economic growth. The results in Model 1 indicate that human capital has a insignificant and positive impact on growth in both the short- and long-run. However, when AI is interacted with tax revenue and institutional quality, the impact of human capital on growth becomes significant only in the third model. This observation strongly suggests the need for policies that promote investment in education and training programs to bridge the skill gap between AI technologies and institutional capabilities. By providing education and training opportunities for the public, a better understanding of AI and its implications in relation to institutional quality can be developed.

We recommend stronger collaboration and dialogue between AI investors/developers, institutional experts/stakeholders, and policymakers to bridge the gap between technology and institutions in the G-7 economy. We recommend partnerships and knowledge sharing among G-7 countries to ensure that AI technologies align with the needs and values of the institutional framework in G-7 economies. Governments in G-7 should cultivate a culture of innovation and adaptability within institutions to effectively address the challenges and opportunities presented by investment in AI, which can potentially have adverse effects on economic performance.

Based on the results, the interaction between artificial intelligence (AI) and tax revenue demonstrates a significant and negative impact on economic growth, which implies that the integration of AI in tax systems has not yielded substantial benefits to the G-7 economy. Hence, it is imperative for G-7 governments to proactively take decisive actions to facilitate the adoption of AI in tax systems/administration, thereby promoting and supporting resource mobilization efforts within their respective countries. Policies should encourage the adoption and integration of AI technologies in tax administration and revenue collection processes for the purpose of promoting growth. The governments should aim at continuously promoting investment in AI infrastructure, tools, and resources to enhance the efficiency and effectiveness of tax operations. This should encompass policies that promote AI-powered data analytics, automated tax compliance systems, and intelligent risk assessment algorithms.

G-7 governments and policymakers should leverage AI to simplify and streamline tax processes for both taxpayers and tax authorities, aiming to promote growth. Policies that facilitate the advancement of user-friendly AI-driven platforms, which enhance taxpayer compliance with tax obligations at various levels, should be established, implemented, continuously evaluated, and periodically reviewed. This approach is essential considering the dynamic nature of AI as an emerging sector/industry. G-7 governments and policymakers should formulate and sustain policies that will help: leverage AI technologies to improve the accuracy of tax assessments and reduce errors in revenue collection; and implement AI-based algorithms to identify potential tax evasion, fraud, and non-compliance patterns. This can lead to increased tax revenues for the government and further increase growth in the economy, while ensuring a fair and level playing field for taxpayers.

G-7 government should provide training and upskilling opportunities for tax professionals in their economies to develop AI-related skills and equip tax authorities with the necessary knowledge to effectively utilize and manage AI technologies to foster economic growth. Policies that foster a culture of continuous learning and adaptation to embrace the opportunities presented by AI in tax systems should be continuously encouraged. Policies should actively encourage extensive collaboration and knowledge sharing between tax authorities and AI experts in the G-7 economy. The goal is to mitigate the adverse effects of the interaction between artificial intelligence (AI) and tax revenue on economic growth. Policies should promote the exchange of best practices, insights, and lessons learned in implementing AI in tax systems among G-7 countries. This exchange of knowledge is crucial to support countries that may be lagging behind, facilitating their progress and promoting

growth. By fostering collaboration and sharing experiences, G-7 countries can collectively benefit from each other's expertise in harnessing AI's potential for their tax systems and further drive economic advancement.

6 Conclusion

The G-7 nations, namely Canada, France, Germany, Italy, Japan, United Kingdom, and United States, are striving to maintain one of the United Nations Sustainable Development Goals (SDGs), specifically Goal 8, which focuses on promoting sustainable economic growth for nations. To attain this goal, it is crucial to leverage the explanatory variables identified in this study. This study examines the impact of tax revenue and institutional quality on economic growth contingent on AI for G-7 countries between 2012 and 2022. We applied the novel Cross-Sectional Augmented Autoregressive Distributed Lag (CS-ARDL) estimation and other novel econometric techniques. This research is unique compared to previous literature because it examines the causality relationship between AI, tax revenue, institutional quality, and economic growth. It further examines the impact of the interaction between AI and tax revenue, AI and institutional quality on economic growth. This is because globally, regionally and economic bloc wise, the investment in and the use of AI services/infrastructures is gradually permeating all sectors of the economy. Consequently, formulating integrated policies that are informed by the findings of this study has become critical in the G-7 context.

This study contributes to the literature by providing the following results. First, a long-run equilibrium relationship was established among the variables, while the causality results reveal that there is a two-way causality between institutional quality and economic growth, institutional quality and AI. Unidirectional causality runs from: economic growth to AI; tax revenue to economic growth; and institutional quality to tax revenue. While no causality exists between AI and tax revenue. Second, for the long-run coefficient estimates, the results from the FMOLS and the DOLS reveal that the interaction between AI and tax revenue significantly contribute to the reduction of economic growth, while the opposite holds for the interaction between AI and institutional quality.

Third, for Model 1, the CS-ARDL results reveal that both in the short- and long-run, AI and institutional quality has a significant and positive impact on economic growth. In both short- and long-run, tax revenue has a significant and negative impact on economic growth. This implies that in both the short- and long-run, tax revenue does not promote economic growth. However, on the one hand, in Model 2, the narrative seems to change when AI is interacted with tax revenue, as its impact becomes significant and negative both in the short- and long-run. This underscores the likely dangers that may be associated with integrating AI into the tax system. On the other hand, in Model 3, the narrative seems to also change when AI is interacted with institutional quality, as the impact of this interaction term becomes significant and positive both in the short- and long-run. This further suggests the need for institutional policies in G-7 to be more AI-friendly, considering that AI is an emerging sector/industry.

Our research is crucial for the strategic development of AI, tax systems, and institutional policies designed to promote economic performance in G-7 countries. This is because AI interaction with tax revenue, and institutional quality must be taken seriously to ensure sustainable economic growth. The successful implementation of AI for increased tax revenue collection would require robust data infrastructure, legal frameworks, stakeholder collaboration, and addressing privacy concerns. Responsible AI development, transparency in algorithms, data privacy, and regular system audits are crucial for aligning AI technologies with societal values. Public awareness and engagement are also essential for building trust in AI's role in tax administration. Furthermore, to maximise the mediating effects of AI on the impact of institutional quality on economic growth in G-7 economies, policymakers should prioritize context-specific implementation, ethical considerations, robust governance, integration with existing systems, capacity building, risk assessment, and public engagement.

Future research should examine whether the established conclusions in this study hold up to empirical inspection within country-specific or regional settings to further enhance our current understanding of the research topic. This will be particularly pertinent for deriving more country-specific or regional-level policy implications.

Declarations

Conflict of interest The author(s) declared no potential conflict of interest with respect to the research, authorship, and/or publication of this article.

Consent to participate Not applicable.

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