Artificial Intelligence Patents and Economic Growth: A Growth Framework for OECD Countries

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https://doi.org/10.62345/jads.2025.14.4.4

Abstract

Artificial Intelligence has entered the mainstream, yet its contribution to the GDP of OECD countries remains largely unknown. This work focuses on the relationship between AI Innovation and GDP Growth, particularly AI Patents. In this work, three econometric techniques were employed: Fixed Effects (FE) models, FGLS-Parks regressions, and PCSC regressions. AI Patents positively correlate with growth for all models. Unemployment and government spending showed negative effects. The highly reanalysed conclusion records technological advancements of AI that were integrated into the economy. The unemployed and government spending positively correlate. Pegged to the artificial intelligence industry, the workforce offers great potential for the digital economy, growing in value to the (digitally) inclusive and sustainable (economy) of the (customer). The unemployed receive government support to promote and stimulate AI.

Keywords: GDP Growth, AI Patents, Government Expenditure, Unemployment.

Introduction

Today, machine learning (ML) and artificial intelligence (AI) dominate digital technologies. In turn, they affect crucial industries like healthcare (Gul et al., 2026), finance, and transportation (Yang et al., 2021). These technologies become increasingly influential, raising pertinent questions about how they affect the economy. Several theories of economic growth, including the endogenous and neoclassical theories, posit a positive relationship between productivity and economic growth, driven by technological innovation. The growth rate of computing and artificial intelligence is unprecedented, thereby drawing the attention of policymakers and researchers.

Over the last 60 years, the production process has shifted from traditional inputs to ICTs and labor-flexible methods. Since the 1990s, the production of goods and services has improved due to technological innovations. The Internet and the advancement of computers have changed traditional manufacturing. New innovations have transformed industries by refining production processes and efficiency, and by advancing automation and precision. Zeira (1998) formulated a model of economic growth that shows the increasing demand for capital and decreasing demand for labor as a result of technological advancement. Several authors have provided empirical evidence to support this claim and identified ICTs and AI as major contributors to economies of

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scale (Nchake & Shuaibu, 2022; Wang et al., 2011; Nightingale, 2000). The innovations are expected to further accelerate productivity, thereby enhancing GDP growth.

In the blink of an eye, the last 10 years have seen the impact of artificial intelligence (AI) adoption take center stage due to the rapid shift of applied AI in the workplace. The CFM-CEPR report, released in May 2023, cast a prospective lens on the impact of AI on the economies and labor markets of developed countries over the next decade, specifically on global economic growth and unemployment dynamics. Most reviewers expect AI's impact to lead to global economic growth of 4 to 6 percent, exceeding the predicted average global growth of 3.5 percent. However, concerning the economic impact of AI on the unemployment levels in developed economies, the majority of reviewers expect it to be minimal. Most others were split on the expected trend in unemployment levels. Most reviewers were cautious in this regard, perhaps due to the early stage of AI development and the highly uncertain future it represents.

The surpassing development AI has experienced over the past years, going from a mere concept that belonged to the fantasy world, to something that has become a crucial part of one's daily living, has been groundbreaking. As Mihir Shukla, a tech entrepreneur, noted during the World Economic Forum 2023, "AI is not on its way; it is already here," highlighting its ubiquity. ChatGPT, one of the generative AI products developed by OpenAI, has over a billion users, a testament to that shift, as it provides assistance in writing and coding, among other functions. The rate of AI adoption, in this case, is historic: ChatGPT reached 100 million users in just 60 days, a feat Instagram took 2 years to achieve. A report by Stanford University (HAI 2023) further demonstrates this phenomenon by revealing that from 2015 to 2021, there was a grant of AI-related patents that was t

rip the amount. AI now performs a myriad of tasks, from logistics to legal writing to disease diagnosis, as machine learning (ML) continues to optimize efficiency and accuracy. The purpose of this research is two-fold: first, to analyze the impact of AI on the economic development of OECD countries; second, to assess its impact on the structure of modern economic growth within these countries.

Economic growth is heavily reliant on technological progress, predominantly in science and innovation. Other studies have analyzed such linkages using indicators such as patenting, scientific publications, and computer and internet ownership. These works in turn lay the groundwork for understanding the impact of AI innovations on economic growth in OECD countries.

Literature Review

The endogenous growth model is often employed to explore the relationship between technology and economic growth. Arrow (1962) posited that technological advancement is an underlying good generated by the accumulation of knowledge through the process of learning by doing. Under this hypothesis, a constant pattern of behaviour and experience translates into production, which underpins steady, long-term growth in GDP. Arrow also noted that the new net physical capital, which is technologically advanced as a result of acquired knowledge and skills, improves the system's production and efficiency.

Nguyen and Doytch (2022) and Qiu et al. (2021) established a correlation between patents and GDP growth. They observed that in economically advanced countries, patents positively and directly influence the GDP growth rate. In less developed economies, this influence is mitigated as the countries are less able to leverage the impacts of technology. In addition, ICT patents are shown to have a positive influence on advanced economies, but this effect is insignificant in the long run. These findings vary in the extent to which economic conditions influence the level of technological growth attained.

Lu (2021) developed a three-sector endogenous growth model to analyse how artificial intelligence (AI) affects household utility and economic growth. Although this model examines the optimistic and potentially positive impacts of utility improvements, we recognize that the advancements we develop in AI do positively affect household utility and increase economic growth in the short run. However, the model shows that, from a household perspective, the short-run growth impacts of utility and AI are intertwined in complicated ways. Additionally, there is a consistent trend toward companies replacing human labour with AI. It is this trend and the findings that provide an answer to how the phenomena stemming from utility-improving AI impact a household. These findings provide a more sophisticated understanding of how the roots of utility-enhancing AI impact wellbeing and economic growth.

Bandari (2019) outlines the impact of AI on small business revenue (391 firms) in the developing world. Based on this report, AI does not improve the operations of small businesses but does increase revenue growth at a high rate. Likewise, Demioli et al. (2021) investigated the link between AI and productivity using data from a worldwide sample of 5,257 firms with records of AI patents. It was found that labour productivity is affected in small and medium enterprises (SMEs) and the service sector (Hemous & Olsen, 2022). Their model efficiently incorporates these dynamics into its structure. In the same vein, Yang et al. found that, in Taiwan's electronics sector, non-AI and non-AI patents at the single-firm level enhanced productivity. Positive impacts on employment and output were found for both patents.

He (2019) employed provincial sample data to assess the effect of AI on GDP growth across China's provinces. He used a proxy for AI as a fixed resource outlay in information and communication technology (ICT) as a percent of GDP, which differs from other studies, which usually use AI-specific patents or publications. The role of AI in advancing the economically sustainable growth of China's various regions was further elaborated by Fan and Liu (2021). The two studies corroborated the theoretical potential for AI growth. More broadly, Solarin and Yen (2016) examined the relationship between economic development and academic publications using a cross-country panel dataset. Their findings, irrespective of the focus, whether on rich or developing countries, showed a significant positive effect.

A plethora of research has used different proxies for artificial intelligence, such as publications, patents, fixed asset investments, and ICT (the most common). AI patents and some of the particular variables for these expected economies (OECD countries) have been overlooked. Previous economic research shows that other forms of technological innovation, particularly artificial intelligence (AI), contribute most to a country's overall GDP growth, but the effects differ across countries, depending on each country's economic factors. More recent economic research has focused on the automation of activities (AI innovations) and AI patents that positively affect labour productivity and economic growth across sectors (vertical and horizontal), and the efficiency of firms within advanced countries. Arrow (1962) spoke of the economy of learning-by-doing and the productivity-enhancing effects of technical change. But the outcomes of different patent systems of economies differ quite a lot. Some argue that there are patents with no long-term consequences, while others report that consequences vary across countries and industries. These results carry a lot of knowledge: AI patents and factors in these particular economies (OECD) are not much of a concern in some countries, but many studies are required with a strong focus to aid economically driven research on the impact of AI on economic growth.

Research Methodology

Source of data: Panel data variables for OECD nations from 2013–2022 were utilized in this study. The available data for each variable determines which time spin is used.

Figure 1: Flowchart

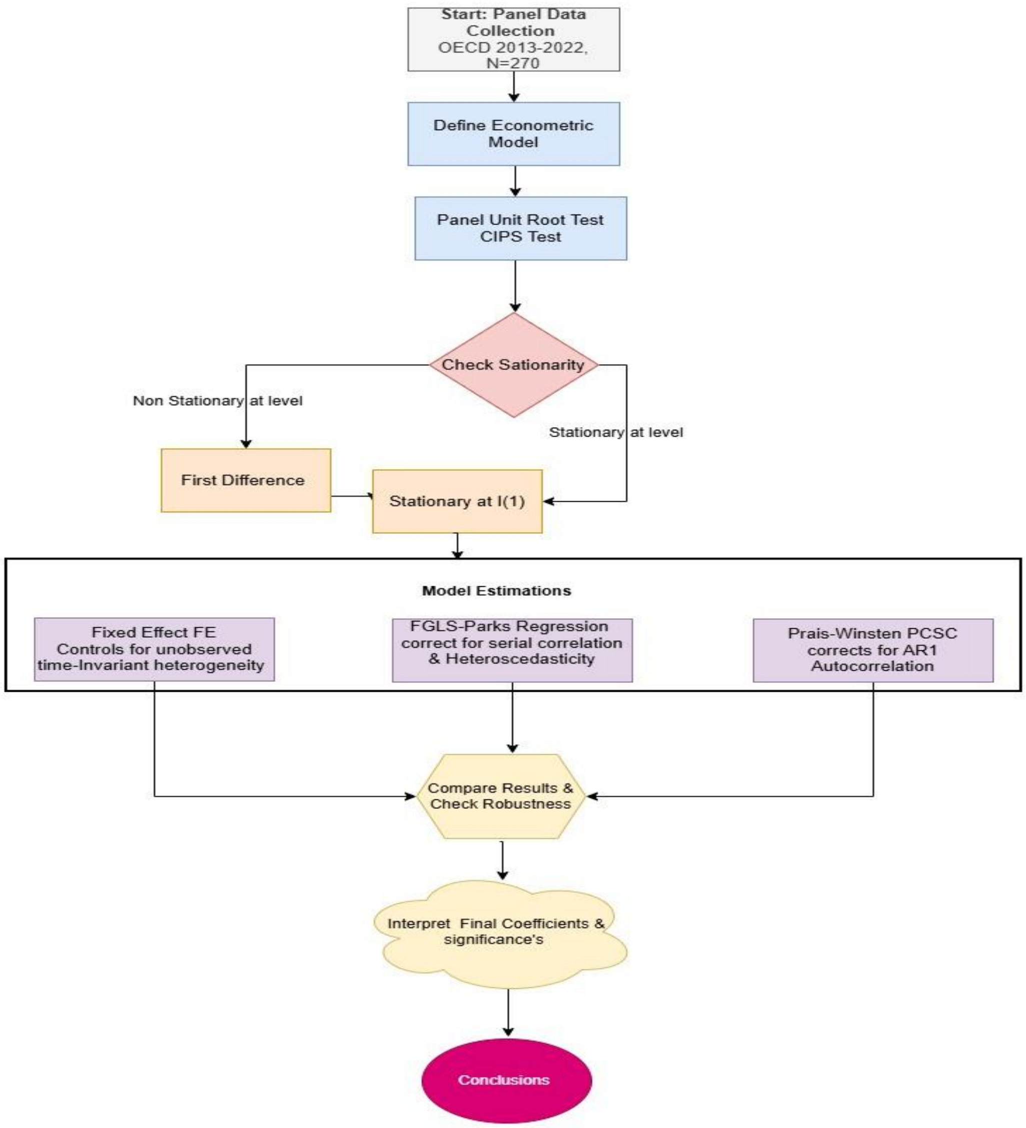
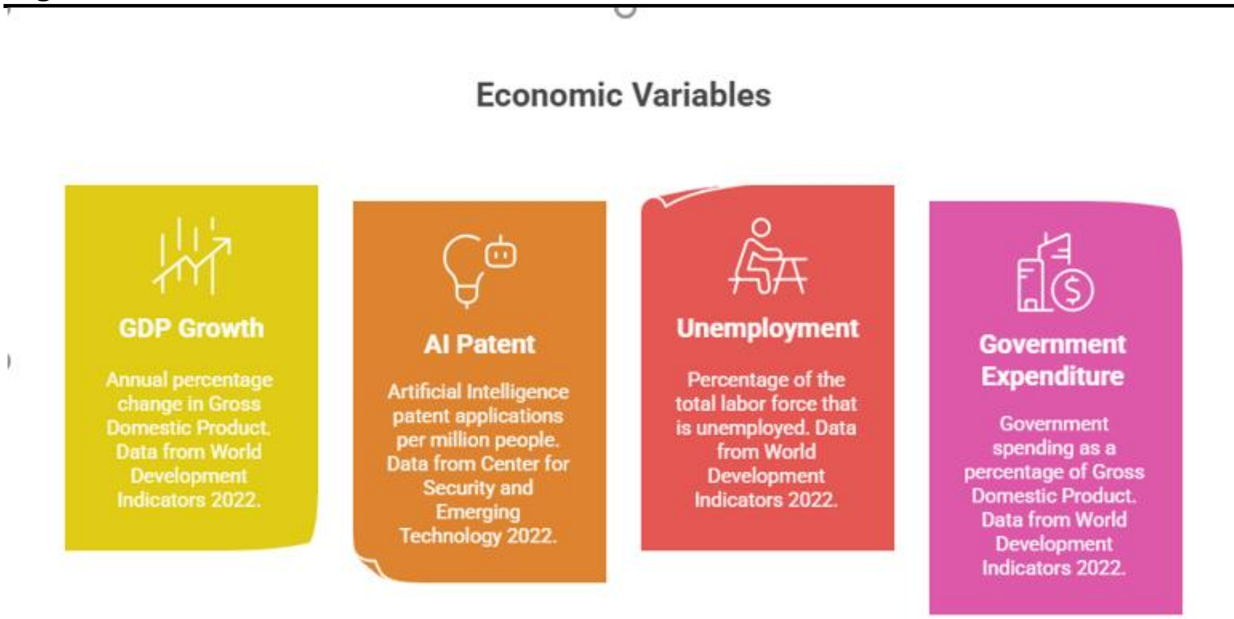


Table 1: variables, description, notation, and sources of data

Variables	Notation	Variable Description	Sources of Data
GDP Growth	GDPG	Annual % of GDP	WDI 2022
AI Patent	AIPATENT	AI patents applications per 1million	CSET 2022
Unemployment	UNEMP	% of total labour force	WDI 2022
Govt Expenditure	GOVEXP	(% of GDP)	WDI 2022

Figure 2: Economic variables



Econometric Model

$$GDPG_{it} = \beta_0 + \beta_1 AIPATENT_{it} + \beta_2 UNEMP_{it} + \beta_3 GOVEXP_{it} + \varepsilon_{it} \quad \ldots\ldots\ldots\ldots\ldots (1)$$

Where;

GDPG = Gross Domestic Product growth
AI PATENT = Artificial Intelligence Patent
UNEMP = Unemployment
GOVEXP = Government Expenditure
ε = error term"

The Econometric Method

The econometric techniques listed below are used with panel data.

Panel Unit Root

The panel unit root test is a method for determining whether a variable is stationary in a given panel data set (Khan et al., 2023). A variable in data is said to have stationary characteristics if its mean and variance, or its values and fluctuations, do not change over time (Khan et al., 2023; Gul et al., 2023). The focus of this research is to determine whether the variables are stationary at either level or in first differences using the CIPS test. The results indicate that the variables of government expenditure and GDP growth are stable after first differencing and are non-stationary at the level. Additionally, AI patents and unemployment have the same characteristics. The focus on stationarity is important for increasing the econometric model's robustness in identifying the variables of interest and reducing spurious regression results.

Fixed Effects (FE) Model

The method is appropriate for panel data with both temporal and cross-sectional components (e.g., countries or firms) when unobserved heterogeneity (i.e., differences within units) is assumed to be correlated with the explanatory variables. The fixed effects model controls for all time-invariant characteristics within each entity (Khan et al., 2023), thereby isolating the effects of variables assumed to change over time and removing substantial omitted-variable bias due to unobserved heterogeneity.

FGLS-Parks Regression

The FGLS-Parks regression methodology is adopted to account for serial correlation alongside heteroscedasticity in panel data. The approach corrects for autocorrelation and heteroscedasticity by estimating the error variance-covariance matrix. The approach accounts for cross-sectional dependence in temporally autocorrelated data and yields more consistent and efficient coefficient estimates. This is especially true for datasets with long panels. In totality, the FGLS-Parks regression improves model performance in empirical analysis by increasing the complexity of the error structure of the models in use.

Prais-Winsten (PCSC) Regression

The approaches are most beneficial when there is error-term autocorrelation, especially in panel data and when errors are serially correlated. The methodology incorporates the Cochrane-Orcutt correction for serial correlation and is warranted when the model's errors exhibit an AR(1) process.

Results and Discussion

Table 2: Descriptive Statistics

Variables	Obs.	Mean	SD.	Min.	Max.
GDPG	270	2.15	3.091	-10.94	9.344
AIPATENT	270	3.468	7.501	-3.337	48.389
UNEMP	270	6.865	4.393	2.015	27.686
GOVEXP	270	5.232	1.125	3.078	8.494

Descriptive statistics provides the basic information about the data variables (Gul et al., 2023; Gul et al., 2023). The analysis of GDP growth across OECD countries during the period 2013-2022, covering 270 observations, sheds light on the variability of growth rates. Specifically, the mean GDP growth was 2.15%, rising above average growth during the period, while the standard deviation was 3.091. The growth rates increased with the mean with a minimum value of -10.94%, while the upper-end was considerably high given the 9.344% maximum. The mean of AI patents was at 3.468 with standard deviation of 7.501, indicating innovation of the countries, and was positively skewed. The unemployment rate has also shown positive skewness, with a mean value of 6.865% and standard deviation of 4.393% indicating a diverse unemployment rate and condition of the labor market. Government expenditure on average also has some moderate positive skewness on the data given that the mean was 5.232%, standard deviation of 1.125% indicating some differences on the fiscal spending across the observations.

Table 3: Matrix of correlations

Variables	GDPG	AIPATENT	UNEMP	GOVEXP
GDPG	1.000			
AIPATENT	-0.162	1.000		
UNEMP	-0.162	-0.168	1.000	
GOVEXP	-0.070	-0.080	-0.159	1.000

Table 3 shows the results of correlation matrix which as GDP growth has a weak negative correlation with AI patents (-0.162), unemployment (-0.162), and government expenditure (-0.070). AI patents also exhibit a weak negative correlation with unemployment (-0.168) and government expenditure (-0.080). Lastly, unemployment and government expenditure are weakly negatively correlated (-0.159).

Table 4: Unit Root Test Results

CIPS Test			
Variable	I(0)	I(1)**	Decision
GDPG	-2.255	-2.951	I(1)
AIPATENT	-2.432	-2.546	I(0)
UNEMP	-2.348	-2.896	I(0)
GOVEXP	-1.906	-2.537	I(1)

* & ** indicate the critical value of the I(0) and I(1) - 2.25 and -2.22 respectively.

The CIPS test results for unit roots in panel data are shown in Table 4. For each variable, the level and first difference statistics are compared against the critical values for I(0) (-2.25) and I(1) (-2.22). GDP growth is non-stationary at the level but becomes stationary after differencing, thus it is I(1). AI-Patent and Unemployment are stationary at the level with t-statistics lower than -2.25, so both are I(0). Government expenditure non-stationary at the level but becomes stationary after 1^{st} difference

Table 5: Estimation

Variable	Fixed effect	FGLS-Parks regression	PCSC
AIPATENT	.498 (0.006)***	.469 (0.000)***	.385 (0.000)***
UNEMP	-.241 (0.014) **	-.117 (0.01)**	-.148 (0.004)***
GOVEXP	-1.006 (0.04) **	-.348 (0.001)***	-.315 (0.013) **
Constant	9.411 (0.000) ***	5.056 (0.000)***	5.112 (0.000)***
N	270	270	270
$\rho_{u,i}$	.19471		-.1455434
"corr(u_i, xb)"	-0.4962	-0.1455	
χ2(4)"		26.10 (0.000)***	21.29 (0.000)***

*Note: *** p<.01, ** p<.05, * p<.10*

The given table shows the outcomes of the main estimations. Panel fixed effects, FGLS, and PCSC are the estimation methods employed. According to the estimation results, economic growth is positively and considerably impacted by AI innovation, as shown by AI patents, in all models. Parallel studies such as those by Yang (2022) and Lu (2021) align with the study's results. Government spending and unemployment have a major detrimental impact on economic expansion. Every constant is significant ($p < 0.01$) and positive. Wald chi-squared tests ($p < 0.01$) provide strong results for the models, which are based on 270 observations.

Conclusion

The focus of this study was on the relationship between the economic growth of AI within the OECD countries between 2013 and 2022. There are mixed ties between the economic growth of these countries and the integration of various AI patents. There is evidence that AI is on the rise, with the ability to enhance productivity and growth in advanced economies. There are also impacts on government expenditures and unemployment levels on GDP. There are also other aspects of GDP to consider beyond unemployment levels and government spending to maximize growth.
Similarly, other technological advances alongside artificial intelligence are driving the economy. The report includes several important policy recommendations. In other words, when there are necessary increases in unemployment rates, economic growth should come first to prevent further erosion of economic growth. There should be policies that focus on workforce upskilling and reskilling. Governments can reduce the adverse impacts of automation by supporting inclusive growth and training the AI workforce. Additionally, OECD governments should promote AI by allowing businesses to patent AI innovations. There are also a few other ways to do this, such as providing tax incentives to promote research and development, offering grants to support AI innovations, and encouraging partnerships between businesses and research institutions.

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