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## Artificial Intelligence Patents, Scientific Publications and Economic Growth: Evidence from G7 Countries

### Yapay Zekâ Patentleri, Bilimsel Yayınlar ve Ekonomik Büyüme: G7 Ülkelerinden Kanıtlar

#### ABSTRACT

Artificial intelligence technologies encompass innovative technologies that directly form the basis of inventions or are used as critical elements in the development of inventions. This study examines the relationship between artificial intelligence patents, scientific publications, and economic growth, specifically for G7 countries, using annual data for the period 1996-2022. The F-test and Hausman test were applied to determine the appropriate panel data model. The analyses revealed that the random effects model was applicable; within this framework, heteroscedasticity, autocorrelation, and inter-unit correlation issues were evaluated. Due to these issues, the random effects model was re-estimated using the Driscoll-Kraay robust error estimator. The findings show that artificial intelligence patents are positively affected by economic growth and the number of scientific publications.

**Keywords:** Artificial Intelligence, Economic Growth, Panel Data Analysis

#### ÖZET

Yapay zekâ teknolojileri, doğrudan buluşların temelini oluşturan ya da buluşların geliştirilmesinde kritik bir unsur olarak kullanılan yenilikçi teknolojileri kapsamaktadır. Bu çalışma, 1996-2022 dönemine ait yıllık verilerle G7 ülkeleri özelinde yapay zekâ patentleri, bilimsel yayınlar ve ekonomik büyüme arasındaki ilişkiyi incelemektedir. Uygun panel veri modelini belirlemek amacıyla F testi ve Hausman testi uygulanmıştır. Analizler sonucunda rassal etkiler modelinin kullanılabilir olduğu anlaşılmış; bu çerçevede değişen varyans, otokorelasyon ve birimler arası korelasyon sorunları değerlendirilmiştir. Söz konusu sorunların mevcut olması nedeniyle, rassal etkiler modeli Driscoll-Kraay sağlam hata tahmincisiyle yeniden tahmin edilmiştir. Elde edilen bulgular, yapay zekâ patentlerinin ekonomik büyümeden ve bilimsel yayın sayısından olumlu yönde etkilendiğini göstermektedir.

**Anahtar Kelimeler:** Yapay Zekâ, Ekonomik Büyüme, Panel Veri Analizi

#### 1. INTRODUCTION

The concept of artificial intelligence (AI) was officially introduced into the literature in 1956 as part of the Dartmouth Summer Research Project. This project aimed to establish a new research discipline focused on building machines that could mimic human intelligence and to bring together researchers from different scientific disciplines on a common ground (Haenlein & Kaplan, 2019). In academic literature, artificial intelligence (AI) is defined in various ways, depending on the perspectives of different disciplines. The Britannica Dictionary defines AI as the ability of a computer or computer-controlled robot to perform tasks unique to humans. While AI currently doesn't yet exhibit full human flexibility in tasks requiring extensive or complex knowledge, there are examples that can perform certain functions on a par with humans (Britannica, 2023). AI is the ability of computer systems to analyze, learn, and interpret in ways similar to human thinking (Nabiyev, 2005). AI is a collection of algorithms that self-improve over time by automating data-driven decision-making (Goodfellow et al., 2016). AI can also be defined as the process of equipping computing software with the ability to produce human-like solutions to complex problems and mimic human thought processes, and the application of these capabilities (DeCanio, 2016).

To accelerate the development of AI technologies, many countries are both strategically promoting and providing financial resources for research and development (R&D) activities in key areas such as the design of AI algorithms, strengthening the relevant hardware infrastructure, and disseminating AI-based applications. Such initiatives are considered an important indicator of global scientific and technological competitiveness. One notable example in this context is the "Next Generation Artificial Intelligence Development Plan," published by the People's Republic of China in 2017. This strategy document, prepared by the State Council of China, provides a comprehensive roadmap aimed at achieving global leadership in artificial intelligence by 2030 (State Council of the People's Republic of China). Patent information is an invaluable resource for identifying key players in a given technology field and assessing their capacity for innovation (Pejic-Bach et al., 2019). Relevant international patent classifications (IPC) are used to determine the technological focus and scope of an AI patent (Hu, 2020; Liu et al., 2022). The IPC system is organized as a multi-level hierarchy comprising sections, classes, subclasses, main groups, and subgroups. This structured framework enables the detailed and specific classification of patents, facilitating a more precise identification of technological content (Chen and Chang, 2012). Organizations utilize the IPC system to categorize their prototypes and research publications, allowing them to assess and compare their R&D performance across various technological domains. This process aids in pinpointing areas of strength and identifying where resources should be allocated (Jotisakulratana et al., 2013). AI patents mostly cover algorithmic structures, machine learning-based methods, and process-oriented systems where AI technology is functionally integrated. Such patents present innovative solutions that incorporate AI into technology not only theoretically but also at an applied level (Raghavender and Singh, 2023; Hole et al., 2015). The primary contributors to AI patent applications are businesses and universities; businesses play a significant role in technological innovation (Zhang et al., 2022).

Scientific publications and patents represent two fundamental outputs of knowledge creation and technological advancement, and they are inherently interrelated. Empirical studies suggest that scholarly research often lays the groundwork for subsequent patent filings, with many patents drawing heavily on existing scientific literature. As a result, enhancing scientific output is increasingly recognized as a key catalyst for stimulating patent activity (Azoulay et al., 2019).

A substantial relationship exists between the proliferation of AI patents and the trajectory of economic growth. AI technologies contribute significantly to growth dynamics by increasing productivity, triggering new product and process innovations, and strengthening the competitive advantage of enterprises. In this context, patents registered in the field of AI are considered a critical indicator not only of technological development but also of national innovation capacity and knowledge-based economic activities (Aghion et al., 2019).

The international economic upheavals of the 1970s increased the importance of economic and fiscal policy coordination among the major industrialized countries. The Bretton Woods fixed exchange rate system collapsed in 1971, and the 1973 oil crisis increased uncertainty in global markets. During this period, the finance ministers of key countries began to strengthen policy coordination, thus laying the foundations for the G7 (Hajnal, 2007). The G7 is a platform comprised of developed countries with a significant share in the global economy and is one of the key forces shaping the world economy. The G7 countries consist of the United States, Canada, the United Kingdom, Germany, France, Italy, and Japan. These countries, all advanced industrial economies, form an important platform for discussing issues such as global economic governance, financial stability, and international policy coordination. The G7 countries meet regularly to coordinate global economic policies and strive to develop common policies in addressing international economic problems (Britannica, 2024; Council on Foreign Relations, 2025).

Statistics on the global research and development ecosystem show that innovation investments are concentrated in certain advanced economies, with countries like the US, Japan, Germany, and the UK maintaining their dominance in this area. According to 2022 data, over 80% of total global R&D spending, exceeding the \$3 trillion mark, was financed solely by these leading economies, demonstrating a high degree of financial centralization in technological development and scientific activities (National Center for Science and Engineering Statistics, 2024).

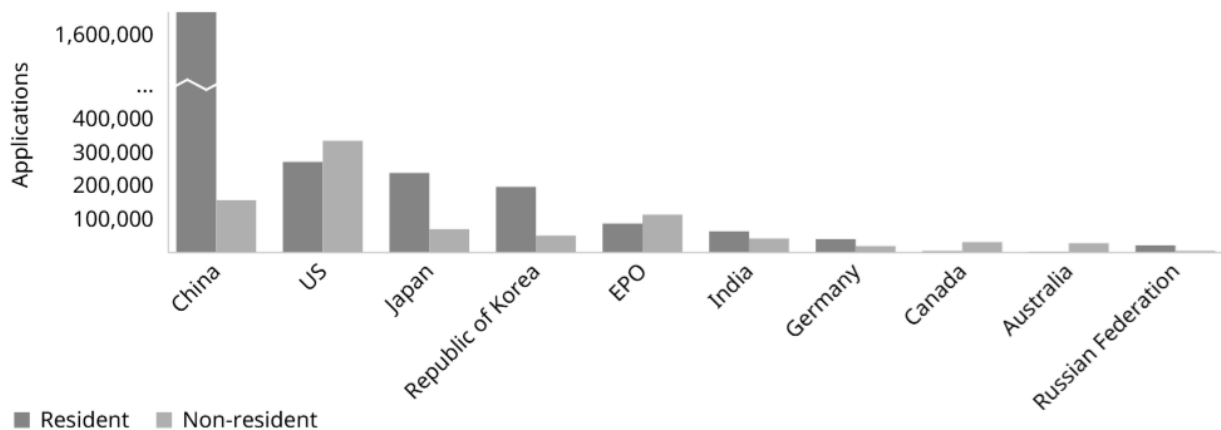
G7 countries have an investment intensity of approximately 2.6% in research and development (R&D), significantly above the global average. This high financial focus can be seen as a key indicator directly reflecting the advanced innovation infrastructures and competitive capacity of these economies in advanced technology production (The Global Economy, 2023).

**Table 1.** R&D Expenditure as a Percentage of GDP in G7 Countries

Country	R&D Expenditure (% of GDP)
United States	3.46
Japan	3.3
Germany	3.14
United Kingdom	2.91
France	2.22
Canada	1.7
Italy	1.45

**Source:** The Global Economy (2023), based on OECD and World Bank data.

The global distribution of intellectual property rights in the field of artificial intelligence exhibits an asymmetrical structure, with technological innovation concentrated in certain advanced economies. In particular, G7 countries such as the US, Japan, Germany, the UK, and France play a dominant role in AI patent applications and registrations, acting as innovation hubs that determine the developmental direction and standards of this strategic technology (OECD, 2025). As of 2022, China, the United States, and the European Union (EU) account for the majority of global artificial intelligence (AI) patent applications. China leads in AI patents, followed by the US and the EU with a significant number of applications each. These countries play a decisive role in the global AI ecosystem through their patent strategies and policies (Spegele et al., 2025). In 2024, the United States Patent and Trademark Office (USPTO) received approximately 333,000 patent applications from foreign applicants, a figure that exceeds twice the number of applications filed in China. Among the five largest patent offices, four reported an increase in the volume of applications during the same period: China (9%), Japan (2.2%), South Korea (1.2%), and the United States (0.8%) (WIPO, 2025).

**Graph 1.** Patent applications at the top 10 offices, 2024

**Source:** (WIPO, 2025)

Given this context, the primary aim of this study is to explore the relationship between the number of AI patents, the volume of scientific publications, and economic growth. Given the limited empirical evidence on this specific relationship, this study endeavors to make a significant contribution to the existing academic literature. The analysis focuses on the G7 countries—Canada, France, Germany, Italy, Japan, the United Kingdom, and the United States—owing to their status as advanced economies with consistent and reliable statistical data. Moreover, these nations are recognized as global leaders in scientific and technological innovation, making them particularly relevant for this investigation. The subsequent sections of the paper comprise a review of the literature, a description of the dataset and methodology, presentation of the empirical findings, and a conclusion summarizing the main results.

## 2. LITERATURE REVIEW

Patents and academic publications are important analytical tools for monitoring and evaluating technological advances, as they provide measurable indicators and reflect the structural characteristics of innovative activities. Hullmann and Meyer (2003) analyzed publication and patent data in the field of nanotechnology to compare the development of Europe and the United States. The findings indicate a rapid increase in both regions. Similarly, Heinze (2004) examined nanoscience and nanotechnology activities in Europe through publications and patent applications, providing a comparative perspective with the United States. This study revealed that while Europe is strong in publications, it lags behind in some technological

areas. Frietsch and Wang (2007) examined the relationship between intellectual property rights and innovation in China. Findings from patent and publication data clearly demonstrate the growth in China's innovation capacity. Thomas et al. (2011) used patent and publication data to measure the R&D productivity of US states and found significant performance differences among states. Ali and Sinha (2014) examined the opportunities and challenges facing nanotechnology innovation in India. The study indicated that while the country has great potential, structural shortcomings are slowing down the process. Wong et al. (2014) examined innovation patterns in low-carbon technologies in emerging Asian economies. Analyses based on patent and publication data revealed significant differences in innovation levels across countries. Kim and Lee (2015) examines the effects of scientific and technological knowledge on economic growth using panel data analysis across countries. The findings indicate that what is critical for economic growth is not scientific knowledge, such as academic papers, but technological knowledge generated through patents. Furthermore, it was found that the production of scientific knowledge does not automatically translate into technological knowledge; rather, technological knowledge is primarily shaped by institutional R&D activities. These efforts were found to be more intensive in East Asian countries and more limited in Latin America. Ntuli et al. (2015), covering the period 1981-2011, examines the causal relationship between research output (number of published articles) and economic growth in OECD countries. Bootstrap panel causality analysis was used, taking into account inter-country dependencies and heterogeneity. The findings reveal a unidirectional causality from research output to economic growth in the USA, Finland, Hungary, and Mexico; and a causality from economic growth to research output in Canada, France, Italy, New Zealand, the United Kingdom, Austria, Israel, and Poland. No significant causality was found for other countries. Singh et al. (2015) analyzed the contribution of universities in China and East Asia to national innovation systems. This study, which evaluated publication and patent outputs, highlighted the central role of universities in the innovation system. Dalton et al. (2016) quantitatively assessed technological innovations in knee arthroplasty through patent and scientific publication data. The study found that innovation trends in this field are concentrated in specific subfields. Shapira and Kwon (2018) analyzed the research and innovation profile in synthetic biology using publication and patent data. The results emphasized the rapid growth and strategic importance of this field. Dağlı (2022) examined the factors influencing AI technologies using panel data analysis. This study revealed that education level, R&D investments, and digital infrastructure significantly impact AI development in G7 countries. Gonzales (2023) evaluates the role of artificial intelligence patents on economic growth using a country-based panel dataset covering the period 1970-2019. AI patents were separated from other types of innovation using a text-based filtering method in public databases. Econometric analyses using the fixed effects and generalized moments (GMM) method show that the contribution of AI patents to economic growth is more significant and stronger than the effect measured through total patents. Finally, Kalai et al. (2024) examine the impact of artificial intelligence on economic growth in 30 European countries during the period 2000-2021. Both symmetric (PMG-ARDL) and asymmetric (PMG-NARDL) models were used for analysis. The findings indicate that increases in artificial intelligence positively impact economic growth in the long term. Specifically, it was found that positive shocks boost economic growth, while negative shocks have a decreasing effect.

### 3. DATA, METHOD AND FINDINGS

The study consists of an annual dataset covering the period 1996-2022. The largest available dataset for G7 countries was used. Data on the number of scientific publications, among the variables used in the study, were obtained starting from 1996. Data on artificial intelligence patents were available until 2022. Therefore, the research dataset was constructed to cover the common time period for both variables. Dummy variables were not included in the model for the 2008 global financial crisis and the COVID-19 pandemic, which occurred during the research period. The main reason for this is that the study aims to analyze the long-term dynamic relationship between artificial intelligence patents, scientific publications, and economic growth, rather than examining the effects of short-term cyclical shocks. Furthermore, the model structure used within the panel data framework is able to control the effects of periodic fluctuations to a certain extent through country and time dimensions. However, the exclusion of these global shocks from the model can be considered one of the potential limitations of the study.

A multiple regression model, designed in accordance with the panel data structure, was used to analyze the factors determining the number of artificial intelligence patents in the study. In this context, the logarithm of artificial intelligence patent applications was defined as the dependent variable; the logarithms of real gross domestic product per capita, representing economic growth, and the number of scientific publications were included in the model as independent variables. The model is expressed as follows:

$$\ln AI_{i,t} = \alpha + \beta_1 \ln GDP_{i,t} + \beta_2 \ln PUB_{i,t} + e_{i,t} \quad (1)$$

In this model,  $i$  denotes individual countries, while  $t$  refers to the time dimension. The constant term  $\alpha$  captures the intercept, and the coefficients  $\beta_1$  and  $\beta_2$  indicate the marginal impacts of economic size and scientific output on the number of AI-related patents, respectively. The term  $e_{i,t}$  represents the stochastic error component. Table 1 provides detailed definitions of the model variables along with their corresponding data sources. All statistical analyses were performed using the STATA software package.

**Table 2.** Dataset and Sources

Variables	Symbols	Sources
Artificial intelligence technology patents*	lnAI	OECD
GDP per capita (in US dollars at current prices)	lnGDP	World Bank
Number of scientific publications	lnPUB	World Bank

\* Number of patents in artificial intelligence technologies in the IP5 patent family

Table 3 summarizes the key statistics—mean, standard deviation, and range—for the variables used in the model.

**Table 3.** Descriptive Statistics on Variables

Variables	Minimum	Maximum	Mean	Standard Deviation
AI	63.7083	17986.47	3836.564	5030.437
GDP	20190	77860.91	38915.11	10103.26
PUB	32493.5	472448.4	121565.1	114854.6

This study examined the relationship between the number of patents, economic growth, and the number of scientific publications in G7 countries using panel data analysis.

Panel data analysis is a powerful econometric method that provides richer and more comprehensive information than traditional cross-section and time series analyses by considering the time dimension in estimating economic relationships. This method has the capacity to simultaneously examine differences between units (cross-section) and changes over time (time series). While cross-section data only reveals structural heterogeneity between different units, panel data analysis allows for the simultaneous analysis of both variation between units and evolution over time. This two-way analysis allows for a more holistic understanding of economic phenomena. Panel data methods also allow for the construction of more complex behavioral models and minimize estimation biases due to omitted variables, which can occur in analyses conducted with time series or cross-section data alone. This makes the resulting estimates more reliable and comprehensive. Furthermore, panel data analysis has the ability to incorporate the effects of factors that cannot be directly observed or quantitatively measured. In this respect, it offers a significant advantage, especially in the analysis of complex relationships in social and economic fields (Baltagi, 2001; Hsiao, 2003; Greene, 1993).

Panel data models offer richer analysis possibilities by combining unit and time dimensions. These models are fundamentally divided into three main approaches: pooled (classical) regression, fixed effects, and random effects. Pooled regression treats all observations as a single data set, ignoring inter-unit differences; therefore, it is limited by its failure to consider unit-specific fixed effects. The fixed effects model assumes that each unit has time-invariant, unobservable characteristics and incorporates these characteristics into the model as constant terms. This approach allows direct control for within-unit heterogeneity. The random effects model, on the other hand, assumes that unit effects are random and uncorrelated with the independent variables. However, violation of this uncorrelatedness assumption, i.e., the existence of a correlation between unit effects and the independent variables, leads to biased and inconsistent model estimates (Baltagi, 2005).

Fixed effects and random effects models are widely employed techniques in panel data analysis. The random effects model operates under the assumption that the unobserved heterogeneity across cross-sectional units is random and incorporated into the composite error term (Greene, 1993). In panel data analysis, the F-test is an important statistical method used to test whether the fixed effects model provides a significant improvement over the classical (pooled) model. This test allows for the assessment of whether the inclusion of individual-specific fixed effects is necessary. The test compares the classical panel data model, which is a restricted model, with the unrestricted fixed effects model. If the fixed effects are found to be statistically significant, the classical model is considered inadequate, and the fixed effects model is preferred (Baltagi, 2005; Greene, 2012).

The Breusch-Pagan (1980) test is a Lagrange Multiplier (LM)-based test developed to test the presence of individual heterogeneity in regression models used in panel data analysis. This test is based on the residuals of a pooled least squares (OLS) regression model. The main purpose of the test is to determine whether the pooled OLS regression model or the random effects model is appropriate (Yerdelen Tatoglu, 2012). If the  $H_0$  hypothesis is rejected as a result of the test, this indicates that there is a non-negligible level of variance among the units, and the random effects model becomes more appropriate than the classical model (Hsiao, 2003; Wooldridge, 2010).

In panel data analysis, the Hausman test plays a crucial role in determining the appropriate model between fixed effects and random effects models. This test is used as a hypothesis test to assess the validity of the random effects model. The Hausman test is based on testing whether there is a systematic difference between the within-group estimators obtained from the fixed effects model and the generalized least squares (GLS) estimators obtained from the random effects model. The test statistic, calculated based on the difference in the variance-covariance matrices of the coefficient estimates in the two models, follows a chi-square ( $\chi^2$ ) distribution with  $k$  degrees of freedom. This statistic, usually denoted by the symbol  $H$ , tests whether the difference between the two estimators is zero (Yerdelen Tatoglu, 2012: 180).

The hypothesis of the Hausman test is expressed as follows:

$H_0$ : There is no correlation between the unit effect and the independent variables (Random effects).

$H_1$ : There is a correlation between the unit effect and the independent variables (Fixed effects).

An examination of Table 4 reveals that the diagnostic tests applied to determine the most suitable panel data model indicate deviations from the classical assumptions of linear regression. Consequently the use of the Ordinary Least Squares (OLS) model is deemed unsuitable for this context. To begin with, the F-test conducted to evaluate heterogeneity across individual units yielded a substantial test statistic of 97.01, with a corresponding p-value of 0.0000. This result is statistically significant at the 1% level, leading to the rejection of the null hypothesis ( $H_0$ ). As a result, the fixed effects model is preferred over the pooled OLS model. In addition, the Breusch-Pagan Lagrange Multiplier (LM) test, employed to assess the existence of a panel effect, produced a robust test statistic of 1298.24 ( $p = 0.0000$ ). This outcome confirms the relevance of the panel structure in the data and implies that classical OLS estimates may be biased and inconsistent. Finally, the Hausman test was applied to determine the most appropriate model between fixed effects and random effects, and the corresponding results were carefully examined. The test statistic was calculated as 0.69, and the corresponding p-value was found to be 0.6189. A high p-value indicates that there is no systematic difference between the fixed and random effects estimates. In this case, the random effects model was concluded to be the preferable approach because it provides both consistent and efficient estimates. As a result of these tests, hypothesis  $H_0$  was not rejected, and the random effects model was preferred.

**Table 4.** Model Identification Tests

Test	Test Statistics	Probability
F	97.01	0.000
Breusch-Pagan LM	1298.24	0.000
Hausman Test	0.96	0.6189

A number of tests are applied to select among estimators. Since the random effects model is preferred in this study, assumption tests will be relevant to this model. Tests such as Levene and Brown-Forsythe were developed to examine whether the error terms meet the assumption of homogeneity of variance. These tests stand out because they can provide reliable results even when the assumptions of classical analysis of variance are not met, that is, when the distribution is not normal. In these methods, which can also be adapted to panel data analysis, the absolute deviations of the observation units from the group central tendency measures (e.g., the mean, median, or trimmed mean) are calculated, and the F test is applied to these deviations to test for variance homogeneity (Un, 2018: 77). When the diagnostic tests in Table 4 are examined: When the Levene, Brown and Forsythe tests ( $W_0$ ,  $W_{50}$ ,  $W_{10}$ ) are compared with the Snedecor F-table with (6, 182) degrees of freedom, it is understood that the  $H_0$  hypothesis, which is established as "the variances of the units are equal", is rejected. Thus, it is seen that there is a heteroskedasticity problem.

The results of the Pesaran and Friedman tests indicate that the null hypothesis is rejected, as the p-values are below the 0.05 threshold ( $p < 0.05$ ), suggesting the presence of cross-sectional dependence among the units in the model. Additionally, the Frees Q test was employed to further assess cross-sectional dependence within the panel dataset. The resulting test statistic value (15.881) surpassed all corresponding critical values at the 90%, 95%, and 99% confidence levels (0.3583, 0.4923, and 0.7678, respectively). This outcome also leads to the rejection of the null hypothesis of no cross-sectional correlation. Consequently, it can be concluded that there is a statistically significant degree of interdependence among the units in the panel. Overall, the evidence from the Pesaran, Friedman, and Frees tests consistently confirms the existence of cross-sectional dependence in the dataset.

In the Bhargava, Franzini, and Narendranathan DW-d test and the Baltagi Wu local best invariant test, the primary hypothesis is  $H_0$ : There is no autocorrelation, while the alternative hypothesis is the presence of autocorrelation. These tests revealed that both test values were less than 2. Based on the results,  $H_0$  was rejected, and it was concluded that there was an autocorrelation problem.

**Table 5.** Diagnostic Test Statistics and Robust Estimator Results

Diagnostic Tests	Test Statistics
Levene, Brown and Forsythe Tests	
$W_0$	9.2901195 (df=6,182) p=0.00000001
$W_{50}$	4.6348819 (df=6,182) p=0.00020796
$W_{10}$	7.6962538 (df=6,182) p=0.00000022
Cross-Section Dependency Test Results	
Pesaran CD	41.058 (0.0000)
Friedman	139.270 (0.0000)
Frees	15.881
Critical values (Frees' Q)	alpha=0.10: 0.3583   alpha=0.05: 0.4923   alpha=0.01: 0.7678
Autocorrelation Test Results	
Modified Bhargava Durbin-Watson	0.15043765
Baltagi-Wu LBI	0.4379382
Variables	Coefficients   Robust Std. Error   z   P> z
lnGDP	0.3573326   0.1996812   1.79   0.074
lnPUB	1.079005   0.2254983   4.78   0.000
Constant	-8.679572   1.480567   5.86   0.000
Model Statistics	Wald $\chi^2=126.10$ (0.0000)   $R^2=0.69$

During the estimation process of panel data models, the presence of structural issues such as autocorrelation, heteroskedasticity, or cross-sectional dependence must be addressed appropriately. If any of these problems are detected, the analysis should proceed by correcting the standard errors—without altering the parameter estimates—through the use of robust standard errors. When such statistical irregularities are present, it is essential to apply correction techniques tailored to the specific issue in order to enhance the reliability and validity of the model (Yerdelen Tatoglu, 2012). Structural challenges encountered in panel data analysis can undermine the consistency and efficiency of the estimators. To mitigate these problems, various methodological approaches have been developed. Among them, Driscoll-Kraay standard errors stand out as a robust and widely accepted method in the academic literature for handling cross-sectional dependence and other related issues (Hoechle, 2007). The diagnostic test results reported in Table 5 indicate the presence of heteroskedasticity, cross-sectional dependence, and autocorrelation in the model. Therefore, Driscoll-Kraay robust standard errors were employed to obtain reliable and robust estimation results.

According to the random effects model, the effect of economic growth on AI patents is positive and statistically significant. A one-unit increase in economic growth will result in a 0.357 increase in the rate of AI patents. The effect of the number of scientific publications on AI patents is positive and significant. A one-unit increase in the number of scientific publications leads to a 1.079 increase in AI patents. The  $R^2$  value, which indicates the explanatory power of the independent variable on the dependent variable, is 0.69.

#### 4. RESULTS

The study examined the relationship between AI patents, scientific publications, and economic growth using annual data from 1996 to 2022 for the G7 countries. AI patents were used as the dependent variable in the model, while the number of scientific publications and GDP per capita were used as independent variables. The study, which used the panel data method, evaluated the results of the Driscoll-Kraay model, which yields robust estimation results. According to the results, a 1-unit increase in economic growth increases AI patents by approximately 0.357. Similarly, an increase in the number of scientific publications also positively affects the number of patents; a 1-unit increase in publications leads to an increase of approximately 1.079 units in AI patents.

Findings from the G7 countries indicate that encouraging research and development (R&D) activities plays a significant role in increasing technological output in AI. In this context, it is crucial for policymakers to focus on specific areas to accelerate progress in AI and encourage innovation. Financial incentives should be provided to researchers to promote the international dissemination of research in the field of artificial intelligence. Support programs that encourage interaction between universities and industry should be designed and expanded to accelerate the transfer of academic knowledge to industry. Such collaborations will contribute to the strengthening of knowledge-based innovation. Future research is recommended to expand the analysis of artificial intelligence (AI) patents by incorporating additional determinants such as R&D expenditures, education level, digital infrastructure, and human capital into models. Furthermore, examining AI patents by subcategorizing them, such as machine learning, natural language processing, etc., is believed to be beneficial for understanding which areas are most likely to experience growth and scientific production.

#### REFERENCES

- Aghion, P., Jones, B. F., & Jones, C. I. (2019). Artificial intelligence and economic growth. In A. Agrawal, J. Gans, & A. Goldfarb (Eds.), *The economics of artificial intelligence: An agenda* (pp. 237-282). University of Chicago Press. <https://doi.org/10.7208/chicago/9780226613338.003.0012>.
- Ali, A., & Sinha, K. (2014). Exploring the opportunities and challenges in nanotechnology innovation in India. *J. Soc. Sci. Poli. Imp*, 2(2), 227-251.
- Azoulay, P., Graff Zivin, J. S., Sampat, B. N., & Wang, J. (2019). Public R&D investments and private-sector patenting: Evidence from NIH funding rules. *Journal of Political Economy*, 127(1), 93-143. <https://doi.org/10.1086/700092>
- Baltagi, B. H. (2001). *Econometric analysis of panel data*. John Wiley.
- Baltagi, B. H. (2005). *Econometric analysis of panel data* (3rd ed.). John Wiley & Sons Inc.
- Britannica. (2023). What is artificial intelligence. <https://www.britannica.com/question/What-is-artificial-intelligence>
- Britannica. (n.d.). *Group of seven (G7)*. <https://www.britannica.com/topic/Group-of-Seven>
- Chen, Y. L., & Chang, Y. C. (2012). A three-phase method for patent classification. *Information Processing & Management*, 48(6), 1017-1030.
- Council on Foreign Relations. (2025, July 8). What does the G7 do? <https://www.cfr.org/backgrounders/what-does-g7-do>
- Dağlı, İ. (2022). Yapay zekâ teknolojilerinde etkili faktörler üzerine bir model denemesi: En başarılı ülkelerle panel veri analizi. *Eskişehir Osmangazi Üniversitesi İktisadi ve İdari Bilimler Dergisi*, 17(2), 368-386. <https://izlik.org/JA36LF33FT>
- Dalton, D. M., Burke, T. P., Kelly, E. G., & Curtin, P. D. (2016). Quantitative analysis of technological innovation in knee arthroplasty: Using patent and publication metrics to identify developments and trends. *The Journal of Arthroplasty*, 31(6), 1366-1372. <https://doi.org/10.1016/j.arth.2015.12.031>
- DeCanio, S. J. (2016). Robots and humans—complements or substitutes? *Journal of Macroeconomics*, 49, 280-291.

- Frietsch, R., & Wang, J. (2007). Intellectual property rights and innovation activities in China: Evidence from patents and publications. *Fraunhofer ISI Discussion Papers-Innovation Systems and Policy Analysis*, No. 13.
- Gonzales, J. T. (2023). Implications of AI innovation on economic growth: A panel data study. *Journal of Economic Structures*, 12(1), 13. <https://doi.org/10.1186/s40008-023-00307-w>
- Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep learning*. MIT Press.
- Greene, H. W. (1993). *Econometric analysis*. McMillan.
- Greene, W. H. (2012). *Econometric analysis* (7th ed.). Pearson Education.
- Haenlein, M., & Kaplan, A. (2019). A brief history of artificial intelligence: On the past, present, and future of artificial intelligence. *California Management Review*, 61(4), 5-14. <https://doi.org/10.1177/0008125619864925>
- Hajnal, P. I. (2016). *The G8 system and the G20: evolution, role and documentation*. Routledge.
- Heinze, T. (2004). Nanoscience and nanotechnology in Europe: Analysis of publications and patent applications including comparisons with the United States. *Nanotech. L. & Bus.*, 1(4), 427-445.
- Hoechle, D. (2007). Robust standard errors for panel regressions with cross-sectional dependence. *The Stata Journal*, 7(3), 281-312. <https://doi.org/10.1177/1536867X0700700301>
- Hole, A., Bhandari, S., Birajdar, S., Surve, S., & Sarkate, A. (2025). Patenting artificial intelligence-based technologies in chemical and pharmaceutical sciences. In *Artificial intelligence for chemical sciences: Concepts, models, and applications* (pp. 73-97). Apple Academic Press.
- Hu, S. (2020, January). Comparative study on patent eligibility of artificial intelligence in the United States, China and Japan. In *2020 International Conference on Intelligent Transportation, Big Data & Smart City (ICITBS)* (pp. 965-968). IEEE.
- Hsiao, C. (2003). *Analysis of panel data* (2nd ed.). Cambridge University Press.
- Hullmann, A., & Meyer, M. (2003). Publications and patents in nanotechnology. *Scientometrics*, 58(3), 507-527.
- Jotisakulratana, M., Koomgun, N., Virojrid, R., & Udomsaph, B. (2013, July). Applying International Patent Classification (IPC) to strategic planning processes of an R&D organization: The case of NECTEC, Thailand. In *2013 Proceedings of PICMET'13: Technology Management in the IT-Driven Services* (pp. 1913-1918). IEEE.
- Kalai, M., Becha, H., & Helali, K. (2024). Effect of artificial intelligence on economic growth in European countries: A symmetric and asymmetric cointegration based on linear and non-linear ARDL approach. *Journal of Economic Structures*, 13(1), 22. <https://doi.org/10.1186/s40008-024-00345-y>
- Kim, Y. K., & Lee, K. (2015). Different impacts of scientific and technological knowledge on economic growth: Contrasting science and technology policy in East Asia and Latin America. *Asian Economic Policy Review*, 10(1), 43-66.
- Liu, H., Tai, Y., Lin, H., & Du, X. (2022, January). Analysis of technology hotspots in artificial intelligence field based on patent map. In *2022 International Seminar on Computer Science and Engineering Technology (SCSET)* (pp. 141-144). IEEE.
- Nabiyev, V. V. (2005). *Yapay zekâ: Problemler-yöntemler-algoritma* (2. Baskı). Seçkin Yayıncılık.
- National Center for Science and Engineering Statistics. (2024). *Global R&D and international comparisons*. National Science Foundation. <https://nces.nsf.gov/pubs/nsb20257/global-r-d-and-international-comparisons-2>

- Ntuli, H., Inglesi-Lotz, R., Chang, T., & Pouris, A. (2015). Does research output cause economic growth or vice versa? Evidence from 34 OECD countries. *Journal of the Association for Information Science and Technology*, 66(8), 1709-1716. <https://doi.org/10.1002/asi.23285>
- OECD. (2025). Identifying emerging AI technologies using patent data. *OECD Science, Technology and Industry Papers*.
- Raghavender, G. R., & Singh, G. (2023). Can artificial intelligence (AI) machine be granted inventorship in India? *Journal of Intellectual Property Rights*, 28(2), 123-131.
- Shapira, P., & Kwon, S. (2018). Synthetic biology research and innovation profile 2018. Publications and patents. *bioRxiv*. <https://doi.org/10.1101/485805>
- Singh, A., Wong, P. K., & Ho, Y. P. (2015). The role of universities in the national innovation systems of China and the East Asian NIEs: An exploratory analysis of publications and patenting data. *Asian Journal of Technology Innovation*, 23(2), 140-156.
- Spegele, B., Douglas, J., & Kubota, Y. (2025). China's Xi is building an economic fortress against US pressure. *The Wall Street Journal*, July 7.
- State Council of the People's Republic of China. (2017). New generation artificial intelligence development plan. [https://\\_ia.org/notice-state-council-issuing-newgeneration-artificial-intelligence-development-plan/](https://_ia.org/notice-state-council-issuing-newgeneration-artificial-intelligence-development-plan/)
- The Global Economy. (2023). Research and development expenditure (% of GDP) - G7 countries. [https://www.theglobaleconomy.com/rankings/research\\_and\\_development/G7/](https://www.theglobaleconomy.com/rankings/research_and_development/G7/)
- Thomas, V. J., Sharma, S., & Jain, S. K. (2011). Using patents and publications to assess R&D efficiency in the states of the USA. *World Patent Information*, 33(1), 4-10.
- Ün, Turgut (2018). Panel veri modellerinin varsayımlarının testi. (Editör: Selahattin Güriş). *Uygulamalı Panel Veri Ekonometrisi*, İstanbul: Der Yayınları.
- Wang, N., & Hagedoorn, J. (2014). The lag structure of the relationship between patenting and internal R&D revisited. *Research Policy*, 43(8), 1275-1285.
- Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data* (2nd ed.). MIT Press.
- Wong, C. Y., Mohamad, Z. F., Keng, Z. X., & Azizan, S. A. (2014). Examining the patterns of innovation in low carbon energy science and technology: Publications and patents of Asian emerging economies. *Energy Policy*, 73, 789-802.
- World Intellectual Property Organization. (2025). *World intellectual property indicators 2025*. <https://www.wipo.int/edocs/pubdocs/en/wipo-pub-941-17-2025-en-world-intellectual-property-indicators-2025.pdf>
- Yerdelen Tatoğlu, F. (2012). *Panel veri ekonometrisi* (1. Baskı). Beta Basım.
- Zhang, T., Chen, J., & Ouyang, Z. (2022). The technology development trends in the field of artificial intelligence-assisted drug discovery based on patent analysis. *Chinese Journal of New Drugs*, 31(4).