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The Role of Artificial Intelligence in Economic Growth: System GMM Evidence from 42 Countries

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ABSTRACT

This study examines the relationship between artificial intelligence (AI) and economic growth, focusing specifically on the channels through which AI-driven innovation may affect GDP growth. AI innovation is proxies by the number of granted AI-related patents, which also reveals the strength and robustness of patent activity in this field. The econometric approach, OLS, FE, Difference and System GMM, is used to investigate the significant macroeconomic determinants, including inflation, population growth, unemployment, government expenditure, and gross fixed capital formation (GFCF). The study findings show that AI patents are negatively associated with GDP growth in this model. It suggests that, at the national level, AI-related innovations are yet to be transformed into measurable economic gains. A plausible explanation is that AI technologies remain in an initial stage of adoption and diffusion, and their implementation requires skilled labor,

complementary infrastructure, and substantial upfront costs, factors that delay their productivity-enhancing effects. Besides, GFCF, government expenditure, and population growth show a significant positive effect on GDP growth across the countries. It shows the continued importance of old drivers of economic expansion, mainly inflation, demographic dynamics, public spending, and physical investment. However, mergers are a barrier to economic growth. Therefore, unemployment does not appear to exert a statistically significant impact on the model employed. The results suggest that AI's future growth is unclear and needs more study, particularly regarding how AI advances can lead to wider economic gains. For now, the data confirms that economic progress hinges on macroeconomic stability and investment; AI's potential for growth will probably emerge over time with institutional readiness and supportive economic contexts.
Keywords: GDP growth, Gross fixed Capital formation, Artificial Intelligence, System GMM.

INTRODUCTION

Over the past few decades, computer science and digital technology, especially artificial intelligence (AI) and machine learning, have advanced rapidly, transforming key industries such as health care (Ahmad et a., 2025), finance, manufacturing, and transportation. While these technological transformations have revolutionized entire industries, their influence on economic aggregates and growth paths is a pressing matter that warrants inquiry. In particular, using AI and machine learning has shown great promise in streamlining processes, reducing costs, and increasing productivity. As a result, both are considered the driving forces behind today's economic models. Examples include applying AI-based algorithms to improve the accuracy of disease diagnoses in healthcare (Topol, 2019) and integrating machine learning models into the finance industry, revolutionizing risk management and fraud detection (Gupta et al., 2021). Likewise, AI-driven automation is refining manufacturing processes, enabling greater efficiency and economies of scale (Brynjolfsson & McAfee, 2014). Groundbreaking changes have also occurred in the transport sector, where AI has enabled the development of autonomous vehicles and intelligent traffic management systems that have the potential to reduce congestion while increasing safety (Litman, 2020). These milestones highlight the revolutionary role that AI and digital technologies are playing in driving innovation and economic output. However, alongside this rapid adoption comes the incompatibility of emerging technologies, threatening to disrupt labor markets, lead to skill mismatches, and exacerbate inequality, requiring policymakers to consider the socioeconomic implications of these technologies (Acemoglu & Restrepo, 2018).

Inspired by such technological changes, Zeira (1998) developed an economic growth model based on the diffusion of technological innovations that, although less labor-intensive, required greater capital inputs. This framework is consistent with the path currently being taken by modern economies, in which continuous technological advancements are likely to become increasingly capital-intensive, leading to changes in the structure of production processes. Empirically, too, the ability of these innovations to achieve economies of scale could be corroborated (Nightingale, 2000; Wang et al., 2011; Nchake & Shuaibu, 2022; and Shuaibu, 2012). This examines how improvements in marginal costs further boost productivity through competition, leading to the development of multiple industries.

Technological innovation is typically operationalized in empirical studies using proxies, such as patent and scientific publication volumes. Patents indicate market-oriented inventions, while publications indicate fundamental research advancements and the spread of new knowledge (Griliches, 1990). These metrics deliver important insights into how innovation shapes economic performance. For example, more patent- and research-dense economies are more likely to have strong growth paths driven by broader technological diffusion and productivity increases. Many such measures have been used repeatedly in extra-mixed studies, underscoring emphasizing their importance in accounting for the complex nature of technological innovation as the fundamental explanation of long-run financial growth and competitiveness.

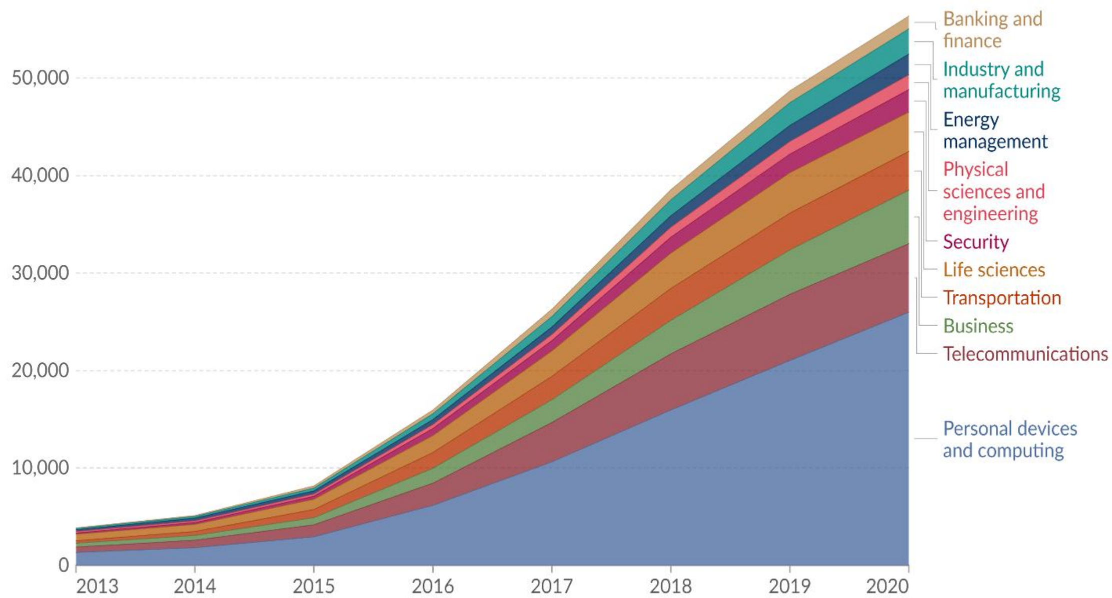

Figure 1: Annual granted patents related to artificial intelligence, by industry, World

LITERATURE REVIEW

Any new research on technology and economic growth must consider that the central role of innovation as a driver of productivity and development has been highlighted throughout the literature, with Solow (1956) as the seminal work, suggesting that technological advancement is a crucial exogenous factor in driving sustained economic growth. Solow's framework highlights that long-run growth comes not simply from higher levels of capital or labor but from technological improvements. Endogenous growth theories (see, for instance, Romer (1990) build on this by claiming that innovation, knowledge spillovers, and research and development (R&D) lead to technological adoption and capital accumulation, suggesting that technology is an essential component of the growth process.

Witnessing similar trends, empirical studies confirm the theoretical foundations by showing that technological innovation drive productivity growth and structural change. An example of this is seen in Zeira (1998), which examines how the adoption of new technologies precipitates capital-deepening processes that a) displace labor inputs in favor of capital-intensive methods of production and b) engender new economies of scale, likewise, more recent investigations (e.g., Wang et al. Innovation-driven technological change improves industrial efficiency and competitiveness, especially in developing economies, as illustrated by Pohl (2011) Zafar, S, et al. (2025) and Nchake and Shuaibu (2022). These results highlight the importance of technological innovation as a global economic engine for sustainable growth and development.

There is growing evidence that artificial intelligence is having a significant impact on the economy. (Furman & Seamans, 2018) Various indicators, such as robotics shipments, AI startups, and patent counts, have shown a substantial increase in AI-related activity in recent years. (Furman & Seamans, 2018) Artificial intelligence can boost productivity growth, green finance (safdar et al., 2026) but its effects on the labor market may be mixed, at least in the short run. (Furman & Seamans, 2018, khan et al., 2023)

Research suggests a 1% increase in artificial intelligence penetration can lead to a 14.2% increase in total factor productivity. The negative impact of AI on economic growth and the boost in productivity can be attributed to its value-added, skill-biased, and technology-upgrading effects (Gao & Feng, 2023). However, the magnitude of these effects may vary depending on factors such as property rights, industry concentration, and the structure of factor endowments within firms. (Gao & Feng, 2023)

While firm-level effects of AI on productivity are informative, understanding the broader implications for the aggregate economy is essential. Some studies have found that the impact of AI automation on the innovation process can have more dramatic, permanent effects on productivity growth than changes in final goods production. Patents are considered one of their most important metrics of technological development, as they reflect the commercialization of innovations and the ability to generate them. Patents are good for the economy, particularly in well-developed innovation systems, as several empirical studies show. For example, He (2019) and Fan and Liu (2021) show that patent activities in high-income countries promote industrial innovation and boost competitiveness. Yang (2022) similarly identifies patents as the engine of the following technology frontiers and of sustaining growth strategies. However, as Nguyen and Doytch (2022) and Ullah et al. (2025) elaborate, the influence of patents can be short-lived, particularly in areas where innovation is stagnant or primarily reliant on foreign technological imports.

By comparison, scientific publications, which result from knowledge accumulation and disseminate research, showed an ambiguous empirical association with a country's economic growth. Although these frameworks are said to be highly significant in regions with integrated innovation landscapes, the literature offers contradictory evidence regarding a close relationship between the degree of development of innovation systems and the models' theoretical significance, arguing for an indirect or contextual nature of the processes they describe. For instance, Sweet and Eterovic (2019) studied that scientific publications play a more important role in economies with strong institutional frameworks and robust research infrastructure. Similarly, Blind et al. (2022); Jamal, F., et al. (2024) show the importance of spillover effects from academic research in promoting technological development and productivity. However, these become more complicated while the economy mediates them at large.

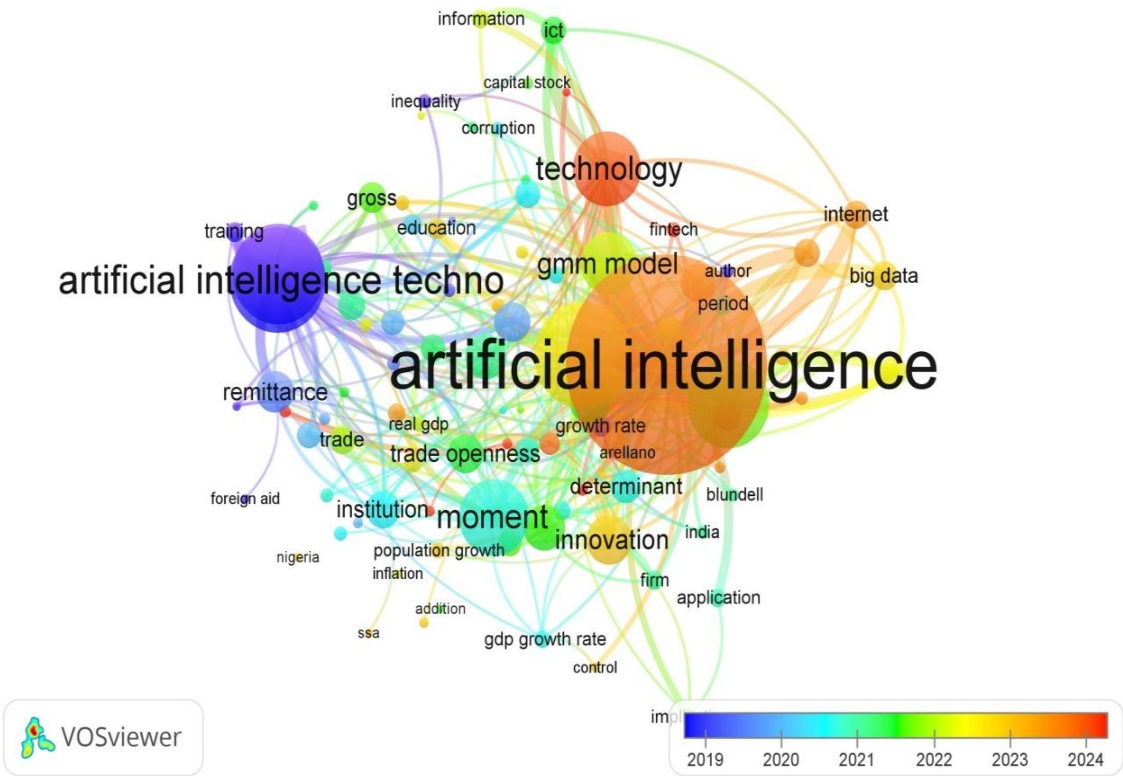

Figure 2: studies from 2000 to 2025

There is hardly any empirical evidence on the impact of artificial intelligence (AI) on economic growth because comprehensive data on such AI is still not widely available. There are broad, but mostly theoretical, expectations that AIs can improve productivity and drive long-term economic growth, but the impact remains tentative. Early findings suggest that the impact of AI innovation on economic performance is positive and may exceed that of previous waves of innovation in terms of productivity gains. However, empirical evidence remains inconclusive, and multiple studies note the challenge of measuring AI's actual effects due to uncertainty about adoption rates and the evolving nature of AI technologies.

While comparisons with previous technologies, notably the Industrial Revolution, can add context, they also highlight the challenges of quantifying the transformative effects AI is bringing about. The evidence is promising, but understanding the impact of AI on the world's economies and industries is far from solved. These shifts especially favor developed nations, while sectors increasingly entrenched in global value chains will probably be the most affected. However, we remain cautious about long-run prospects for AI-enabled productivity as the empirical literature is currently scarce. A deeper dive is needed to understand AI's relationship with economic growth relative to previous technologies.

METHODOLOGY

Data

The dataset used in this analysis covers the period of 2013 to 2022 and information from 42 randomly selected available countries Domestic Product growth (GDPG), which is taken as the percent change in GDP in a year, received from World Development Indicators (WDI) The dataset also includes indicators like AI patent (AIPATENT) (i.e., the number of AI-related patent applications granted per million people) by the Center for Security and Emerging Technologies (2024). Other variables are patent applications (PATENT), gross fixed capital formation (GFCF), government expenditure (GOVEXP), inflation (INFLA), unemployment rate (UNEMP), and population growth (POPGRO) from WDI. These variables give a macro picture of economic performance, technology innovation, and demographic shifts, allowing us to perform a high-level overview of the elements influencing economic growth, i.e., past, between 1990 and 2020, and compare the trends between countries.

Variable Description

Variable	Indicator	Description	Source
GDP growth	GDPG	GDP annual growth % of GDP	WDI
Artificial intelligence	AIPATENT	Artificial Intelligence Patent applications granted per 1 million people - Field: All	Center for Security and Emerging Technology (2024)
Patents Applications	PATENT	Patent applications per 1 million people - Field: All	WDI
Unemployment	UNEMP	Unemployment, total (% of total labor force) (national estimate)	WDI
Government expenditure	GOVEXP	General government final consumption expenditure (% of GDP)	WDI
Gross fixed capital formation	GFCF	Gross fixed capital formation (% of GDP)	WDI

Population Growth	POPGRO	Population growth (annual %)	WDI
Inflation	INFLA	Consumer price index	WDI

Econometric model

The econometric model to be estimated to analyze the factors that explain GDP growth (GDPG) of 42 countries in the period from 2013 to 2022 will be: The model is Pooled OLS is given by:

$$GDPGit = \beta 0 + \beta 1 \quad L.GDPGit + \beta 2 \quad AIPATENTit + \beta 3 \quad UNEMPit + \beta 4 \quad GOVEXPit + \beta 5 \quad GFCFit + \beta 6 \quad POPGROit + \beta 7 \quad INFLAit + \varepsilon it \ldots (1)$$

The dependent variable is GDPGit (GDP growth for country ii in year tt). Further, the core independent variable is GDPGit (Lagged dependent variable). Therefore, the primary variables of interest are AIPATENTit or PATENTit. The control variables are UNEMPit, GOVEXPit , GFCFit, POPGROit, and INFLAit.

Now, check the country-specific effect to assess the fixed effect.

Fixed effect:

$$GDPGit = \alpha i \quad + \beta 1 \quad L.GDPGit + \beta 2 \quad AIPATENTit + \beta 3 \quad UNEMPit + \beta 4 \quad GOVEXPit + \beta 5 \quad GFCFit + \beta 6 \quad POPGROit + \beta 7 \quad INFLAit + \mu it \ldots (2)$$

Where αi represents the country-specific fixed effect.

Now the Difference Generalized Method of Moments (Difference GMM):

$$GDPGit = \beta 1 \quad L.GDPGit + \beta 2 \quad AIPATENTit + \beta 3 \quad UNEMPit + \beta 4 \quad GOVEXPit + \beta 5 \quad GFCFit + \beta 6 \quad POPGROit + \beta 7 \quad INFLAit + \epsilon it \ldots (3)$$

This is the same structural form as Model 1, but estimated with the Difference GMM estimator, treating GDPG and GFCF as endogenous.
This model is presented in two columns in Table 4, each with a different key innovation variable.

Specification 1:

$$GDPGit = \beta 1 \quad L.GDPGit + \beta 2 \quad AIPATENTit + \beta 3 \quad UNEMPit + \beta 4 \quad GOVEXPit + \beta 5 \quad GFCFit + \beta 6 \quad POPGROit + \beta 7 \quad INFLAit + \epsilon it \ldots (4)$$

Specification 2:

$$GDPGit = \beta 1 \quad L.GDPGit + \beta 2 \quad PATENTit + \beta 3 \quad UNEMPit + \beta 4 \quad GOVEXPit + \beta 5 \quad GFCFit + \beta 6 \quad POPGROit + \beta 7 \quad INFLAit + \epsilon it \ldots (5)$$

AIPATENT, which measures the number of artificial intelligence patent applications per million people, is the primary independent variable, and GDPG (GDP growth) is the dependent variable in this model. The other control variables used in the models are UNEMP (unemployment rate), GOVEXP (government expenditure as a percentage of GDP), GFCF (gross fixed capital formation as a percentage of GDP), POPGRO (population growth rate), and INFLA (inflation rate measured by the consumer price index). These control variables are included to control for their potential influence on GDP growth and on our key variable of interest, artificial intelligence (AIPATENT). The error term, ϵti, accounts for unobservable factors that may influence GDP growth.

Estimation Technique

Panel studies mostly divided into two part panel time dimension and panel cross sectional dimension (Gul et al., 2023). When T>N, consider the panel time dimension and used time series approach such as CA-ARDL, Panel ARDL, FMOSL, DOLS etc. (Ullah,I 2023; and Khan et al., 2023). Besides, N>T, use cross sectional approaches such as GMM etc. Estimation in this analysis employs the Generalized Method of Moments (GMM) model, using the robust two-step system GMM estimator introduced by Roodman (2009) for Stata. This is a dynamic panel GMM estimator, suggested by Arellano & Bond (1991) and later improved by Blundell & Bond (1998). This is best for dynamic panel data models with a dependent variable that depends on the current explanatory variable and its lagged values. An important advantage of this method is that it addresses endogeneity issues (a common problem in panel data analysis). Endogeneity may be because of reverse causality or omitted-variable bias, and the system GMM estimator handles it more effectively than the difference GMM and fixed-effect models. When the model is endogenous, the system's internal GMM estimator yields more efficient and consistent estimates (Manasseh et al., 2022). System GMM addresses endogeneity bias, making it the GMM estimation method we now apply in this analysis.

RESULTS

Descriptive Statistics

The descriptive statistics provides the basic and initial information about the dataset (Gul et al., 2023; Khan et al., 2023). In this analysis shows the 430 observations. GDP growth has a mean of 2.23% and a high standard deviation of 3.86%, with values ranging from -28.76% to 13.36%. AI patent applications have a mean of 3.11 per million people and a large standard deviation of 8.06, ranging from -3.34 to 60.84. Patent applications average 188.03 per million people with a standard deviation of 334.62, spanning from 1.82 to 2128.24. Unemployment has an average of 7.57% and a standard deviation of 5.21%, with values ranging from 2.02% to 34.01%. Government expenditure averages 4.92% of GDP, and gross fixed capital formation averages 22.28%, with both showing considerable variation. Population growth has a mean of 0.49% and ranges from -14.32% to 3.31%, while inflation, with 420 observations, averages 3.24% and ranges from -1.74% to 72.31%. These statistics highlight substantial variation in economic and technological indicators across the countries, suggesting a diverse sample for analysis.

Table 1: Descriptive Statistics

Variable	Obs	Mean	Std. dev.	Min	Max

GDPG	430	2.225032	3.863268	-28.75859	13.35523
AIPATENT	430	3.114078	8.057904	-3.337185	60.83865
PATENT	430	188.0274	334.6151	1.82286	2128.237
UNEMP	430	7.570379	5.206791	2.015	34.007
GOVTEXP	430	4.922992	1.154055	2.48892	8.49443
GFCF	430	22.28148	5.057389	10.68743	44.51876
POPGRO	430	.4900112	1.133005	-14.31654	3.30862
INFLA	430	3.238464	5.3592	-1.735888	72.30884

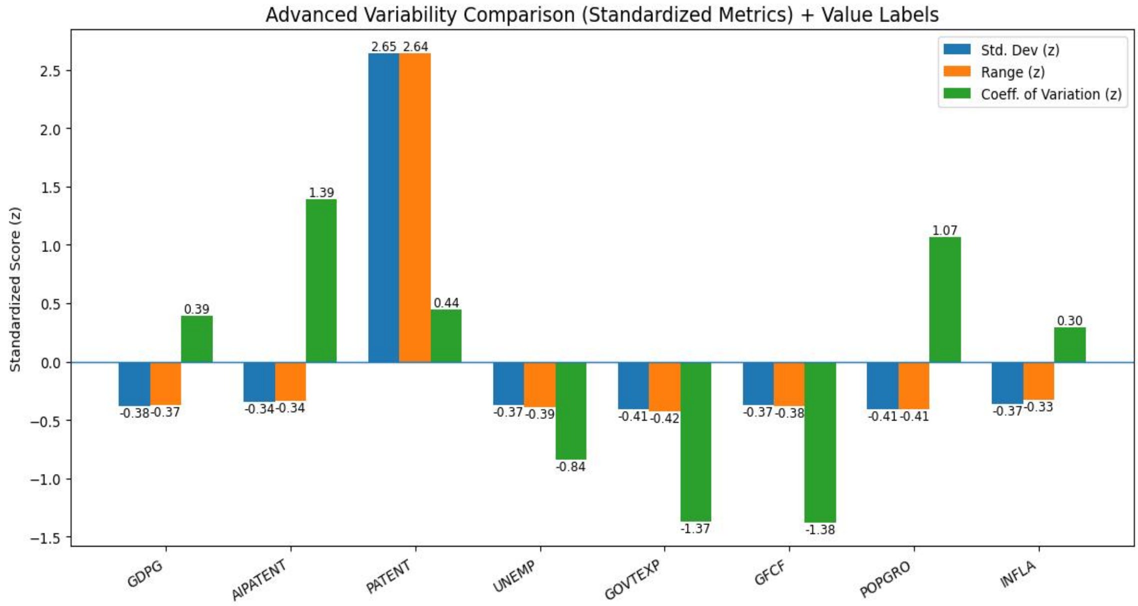

Figure 3: Descriptive statistics

Correlation

Correlation describes the foundational association between the predictor variables, Muhammad, N., et, al. (2025). The correlation table shows the relationships between GDP growth (GDP) and several key variables. AI patents (AIpatent) and patent applications (patent) have weak negative correlations with GDP growth (-0.007 and -0.025, respectively); unemployment (unemp) shows a mild negative correlation with GDP growth (-0.148), while government expenditure (govexp) has a slightly stronger negative correlation (-0.186). Thus, gross fixed capital formation (GFCF) exhibits a positive correlation with GDP growth (0.319), suggesting that investment in physical capital may play a more significant role in driving economic growth. Population growth shows a moderate positive correlation (0.293), and inflation has a very weak correlation (0.002).

Table 2: Correlation

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) GDPG	1.000							
(2)	-	1.000						

AIPATENT	0.007							
(3) PATENT	-0.025	0.531	1.000					
(4) UNEMP	-0.148	-0.173	-0.247	1.000				
(5) GOVTEXP	-0.186	-0.107	-0.115	0.041	1.000			
(6) GFCF	0.319	0.291	0.272	-0.428	-0.080	1.000		
(7) POPGRO	0.293	0.010	-0.055	-0.106	0.145	0.277	1.000	
(8) INFLA	0.002	-0.116	-0.133	0.044	-0.109	0.015	-0.123	1.000

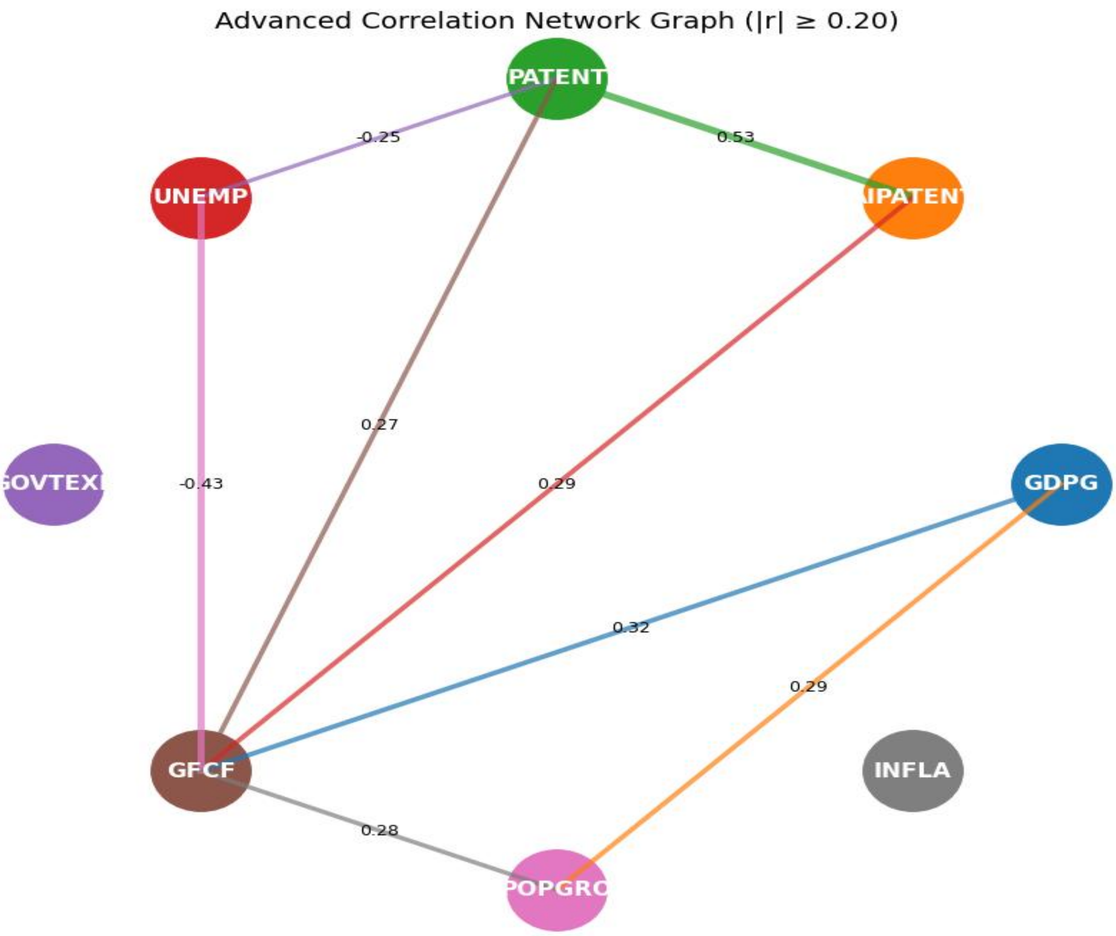

Figure 4: correlation

OLS FE and Difference GMM Results

The results from the OLS, Fixed Effects (FE), and Difference GMM models provide insight into the relationships between the variables and GDP growth. In the OLS model, the lagged L.GDPG is negative and statistically significant, meaning that past GDP growth negatively influences current growth. AIPATENT is negatively correlated with GDP growth, but the correlation is not statistically significant at the 5% level. UNEMP is also negatively correlated with GDP growth, but remains insignificant. GOVEXP has a strong negative impact on GDP growth, statistically significant at the 1% level. GFCF positively affects GDP growth, with a highly significant coefficient. POPG has a positive and significant impact on GDP growth, while INFLA shows a very weak negative correlation.

In the fixed effects model, the coefficients for L.GDPG, AIPATENT, GOVEXP, GFCF, and POPG are all statistically significant, with the same direction of effects as in the OLS model, though with stronger magnitudes for GOVEXP and GFCF. The variable INFLA becomes insignificant, suggesting that fixed effects account for most of the inflation variation. The Difference GMM results, which treat GDP growth and GFCF as endogenous variables, show a much weaker relationship for L.GDPG, with a non-significant coefficient. The coefficient for AIPATENT is negative but not statistically significant, whereas the coefficient for GOVEXP remains negative and significant. GFCF shows a stronger positive impact on GDP growth, similar to the OLS and FE results, but with an even larger magnitude. Population growth remains positively significant. INFLA becomes significantly negative, highlighting its potential to constrain growth. The results suggest that the GMM estimator is most effective at capturing the relationships among key economic variables while addressing endogeneity, as evidenced by the Hansen test and the AR2 p-value.

Table 3 OLS Fixed Effects, Difference GMM, and System GMM Results (Dependent Variable: GDP Growth)

Variables	OLS (1)	FE (2)	Diff-GMM (3)	Sys-GMM (4)	Sys-GMM (5)
L.GDPG	-0.212*** (-3.88)	-0.367*** (-6.64)	-0.0261 (-0.15)	0.108 (1.13)	0.0789 (0.78)
AIPATENT	-0.0389 (-1.49)	-0.0765** (-2.37)	-0.0374 (-0.88)	-0.0822** (-3.08)	-
PATENT	-	-	-	-	-0.00238* (-2.36)
UNEMP	-0.0311 (-0.79)	-0.112 (-0.95)	0.187 (0.85)	0.164 (1.49)	0.206 (1.58)
GOVEXP	-0.861*** (-5.23)	-2.557*** (-5.14)	-1.250** (-2.10)	-0.516* (-2.24)	-0.547* (-2.38)
GFCF	0.247*** (5.46)	0.475*** (3.55)	1.245** (2.83)	0.565* (2.48)	0.739* (2.54)
POPG / POPGRO	0.840*** (5.09)	0.837*** (4.08)	1.547** (2.34)	0.517 (1.07)	0.384 (0.67)
INFLA	-0.00347 (-0.10)	0.0139 (0.33)	-0.108** (-3.03)	-0.128** (-2.82)	-0.143** (-3.47)
Constant	1.658 (1.20)	4.282 (1.05)	-	-9.074 (-1.59)	-8.357 (-1.14)
N	378	378	336	378	378

R^2	0.220	0.237	-	-	-
Prob (F-test)	0.000	0.000	-	-	-
AR(2) p-value	-	-	0.225	0.810	0.810
Hansen p-value	-	-	0.194	0.247	0.247
No. of Countries	42	42	42	42	42
No. of Instruments	-	-	31	33	33

Note: t: statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. GDPG and GFCF are treated as endogenous instrument and all other is treated as exogenous instrument.

The results presented in columns (4) and (5) provide insight into the factors influencing GDPG. The lagged GDP growth shows a positive but statistically insignificant relationship with GDPG in both models, suggesting that past GDP growth does not significantly predict future growth in this context. The key findings include a negative, statistically significant impact of AI patents on GDP growth in column (1), with a coefficient of -0.0822, indicating that AI patents, at least in the short run, may not drive economic growth. Similarly, patent applications also show a negative, statistically significant effect on GDP growth, with a coefficient of -0.00238, suggesting that while innovation may be present, it does not translate directly into growth. The negative and statistically significant relationship between AI patents and GDP growth suggests that AI-related innovations may not yet be a major driver of economic growth at the national level. This could be attributed to the early stage of AI adoption and the high initial costs associated with AI technologies. Other significant results include the negative effects of government expenditure (GOVEXP) and inflation (INFLA) on GDP growth in both models. The coefficients for GOVEXP are -0.516 and -0.547, suggesting that higher government expenditure may not be conducive to economic growth, possibly due to inefficiencies. INFLA also has a negative effect, with coefficients of -0.128 and -0.143, which aligns with the view that inflation can hinder economic growth by creating uncertainty. Meanwhile, GFCF is consistently positive and statistically significant in both columns, with coefficients of 0.565 and 0.739, suggesting that investment in physical capital remains an important driver of growth. Similar conclusions can be drawn for UNEMP and POPGRO, as both have no statistically significant effects and therefore make little immediate contribution to GDP growth. The Hansen tests with p-values of 0.247 and the AR2 tests with p-values of 0.810 also confirm the model's reliability, with no over-identification and no serial correlation issues. The results highlight the difficulty in deciphering economic growth, in which more old-fashioned variables like investment and inflation still appear to be the key players, as the effects of newer variables, like AI patents, are far from straightforward.

CONCLUSION

To sum up, the current studies provide the basic impetus for envisaging a relationship between AI and economic growth and focus on the effect of AI patents on GDP growth. Using a variety of econometric models (OLS, FE, Difference GMM, and System GMM), they found powerful evidence that AI patents negatively correlate with GDP growth across a plurality of specifications. These findings suggest that although AI may enhance long-term economic growth, the current stage of AI adoption, combined with the high upfront costs of developing AI, may still constrain GDP growth contributions in the near term. The inverse relationship between AI patents and GDP growth may also reflect the fact that the economic benefits of AI are not yet realized as firms and governments adapt to these emergent technologies. In contrast, macroeconomic factors, including gross fixed capital formation (GFCF), population growth (POPGRO), and government expenditure (GOVEXP), have a substantial positive impact on GDP growth. These results underscore the case for investing in physical capital, population growth, and sound fiscal policy as leading determinants of short-run economic performance. And GFCF consistently contributes to GDP growth, underscoring the importance of infrastructure and long-term investments for economic growth. Both inflation and GDP growth are widely studied economic indicators, often considered together to understand the interplay between price levels and economic output. An increasing inflation rate can lead to a decline in GDP, as higher prices reduce consumers' overall spending power, thereby slowing GDP growth. Thus, the negligible effect of unemployment (UNEMP) on GDP growth found in this study suggests that, in the nations dissected, labor market dynamics may not be directly affecting short-run economic output, likely because of stronger effects such as investment and government expenditures.

Policy recommendation

1. The inverse short-run link between AI copyrights and GDP growth indicates the early-stage adoption of AI innovations. Governments must invest in initiatives that bring AI innovation closer to practical execution.
2. The remarks on gross fixed capital formation4 shows the influence of infrastructure and physical investments on GDP growth.
3. The adverse effects of inflation on economic growth highlight the importance of prudent macroeconomic policies aimed at achieving price stability. Other leakages occur when policymakers need not rely on monetary and fiscal policies in controlling inflation and ensuring economic stability

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