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Exploring the role of artificial intelligence (AI) innovation in economic performance: Evidence from East Asia

Ihsen Abid

Department of Finance, College of Business, Imam Mohammad Ibn Saud Islamic University (IMSIU), Riyadh, Saudi Arabia

(*Email: isbaklouti@imamu.edu.sa*)

Abstract

This study investigates the impact of artificial intelligence (AI) innovation on economic growth in East Asia (China, Japan, and South Korea) from 2010 to 2023, using AI patent filings as a proxy for technological advancement. A panel data approach is employed, incorporating fixed effects, random effects, and pooled ordinary least squares (OLS) models to examine the relationship between AI innovation and GDP growth. Panel cointegration tests assess long-run equilibrium relationships, while the Granger non-causality test determines the direction of causality. The results indicate that AI innovation significantly contributes to GDP growth, reinforcing the role of technological progress in economic expansion. Trade openness is also positively associated with economic performance. However, gross capital formation exhibits a counterintuitive negative effect, suggesting inefficiencies in capital allocation or diminishing returns. Inflation has a mild yet statistically significant impact on growth. This study provides empirical evidence on the role of AI-driven innovation in shaping East Asian economies. The findings offer valuable insights for policymakers, emphasizing the need for strategies that enhance AI adoption, optimize capital investment, and leverage trade to sustain economic growth in the AI era.

Keywords: AI innovation, East Asia, economic growth, panel data, trade openness.

JEL Classification: O33; O47; F43; C33.

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1. Introduction

Artificial intelligence (AI) has emerged as a transformative force in the global economy, driving innovation, productivity, and efficiency across various industries [1]. As East Asia, comprising technological powerhouses such as China, Japan, and South Korea, continues to lead in AI research and development, understanding the economic implications of AI-driven innovation becomes crucial [2].

This study examines the relationship between AI innovation and economic performance. The analysis spans from 2010 to 2023, capturing the dynamic role of AI in economic growth during a period of rapid technological advancement.

East Asia is home to some of the world's most technologically advanced economies, with China, Japan, and South Korea playing a central role in AI innovation and digital transformation [3]. China has made substantial investments in AI research, becoming a global leader in AI patents, applications, and industrial automation. Japan, known for its expertise in robotics and machine learning, has integrated AI into its manufacturing and service sectors, enhancing productivity and efficiency. Meanwhile, South Korea has established itself as a hub for AI-driven innovation, with strong government support and private sector investments fueling advancements in AI-powered technologies. The region's highly developed digital infrastructure, strong research institutions, and competitive markets create a dynamic environment for AI innovation, positioning East Asia as a key player in the global AI economy [2].

Economic performance is shaped by multiple macroeconomic factors, including gross capital formation (GCF), inflation (INF), and trade openness (TRA). Gross capital formation reflects investment in infrastructure, technology, and machinery, serving as a key determinant of long-term economic growth. Inflation influences economic stability, while trade openness indicates a country's level of integration with global markets. By incorporating these factors, this study provides a comprehensive analysis of how AI innovation interacts with traditional economic drivers to shape GDP growth.

While existing literature highlights the significance of AI in enhancing productivity and economic competitiveness, empirical evidence on its direct impact on GDP in East Asia remains limited. Prior studies primarily focus on AI adoption in specific industries, automation, and labor market effects. This paper contributes to the growing body of research by quantifying the influence of AI patents on economic growth while controlling for key macroeconomic variables. By doing so, it addresses a critical gap in the literature, providing a data-driven perspective on the extent to which AI innovation influences overall economic performance.

Using panel data analysis, this study employs fixed-effects, random-effects, and pooled regression models to assess the relationship between AI innovation and GDP. Additionally, robustness checks, including the Driscoll and Kraay [4] estimator and the Half-Panel Jackknife estimator, ensure the reliability of the findings. The study also applies the Juodis et al. [5] Granger non-causality test to investigate whether AI innovation serves as a leading indicator of economic performance.

The findings of this study offer valuable insights for policymakers, economists, and technology leaders seeking to understand the role of AI-driven innovation in shaping East Asia's economic trajectory. By identifying the extent to which AI patents contribute to GDP growth, this research not only provides a foundation for future policy recommendations but also enhances our understanding of how AI advancements can be leveraged to foster sustainable economic development in technologically advanced economies.

By exploring the extent to which AI-driven innovation influences macroeconomic performance, this study contributes to the ongoing discourse on the economic implications of technological progress. The findings aim to inform policymakers, researchers, and industry leaders about the potential of AI in shaping future economic landscapes.

The remainder of the paper is structured as follows: Section 2 reviews the literature on AI innovation and economic growth. Section 3 outlines the methodology. Section 4 presents the data of the study. Section 5 presents the empirical findings, followed by a discussion of the results in Section 6. Finally, Section 7 concludes with policy recommendations and directions for future research.

2. Literature Review

Economic growth is a complex and multifaceted process influenced by various factors, including technological innovation, capital accumulation, inflationary pressures, and trade policies. This section reviews recent empirical studies that examine the impact of these determinants on economic performance, providing a foundation for understanding their theoretical and practical implications.

2.1. AI Innovation and Economic Growth

Technological progress, particularly in artificial intelligence (AI), has been widely recognized as a key driver of long-term economic growth. AI-driven advancements contribute to productivity improvements, labor market efficiency, and industrial transformation, Acemoglu and Restrepo [6]. McAfee and Brynjolfsson [7] argue that AI facilitates automation, enhances decision-making processes, and fosters innovation in various industries, leading to sustainable economic expansion. Wang et al. [8] provide empirical evidence suggesting that economies investing in AI-based technologies tend to experience higher growth rates due to knowledge spillovers and increased efficiency. However, some scholars caution that AI adoption may also lead to job displacement and increasing inequality, potentially offsetting its benefits [9, 10].

The rapid adoption of AI and digital technologies in Asia has been instrumental in driving economic growth. Chen and Ryoo [11] highlight that AI investments in China, South Korea, and Japan have significantly enhanced productivity and global competitiveness. Zhang and Li [12] find that AI-driven automation in manufacturing has led to efficiency gains and higher output growth in Southeast Asian economies. However, some studies caution that AI adoption may widen the urban-rural economic divide and lead to labor market disruptions Lee [13]. Ellouze and Gafsi [14] contribute to this perspective by leveraging AI-based analysis to examine financial system shifts, demonstrating how technological transformations influence key sectors such as banking.

2.2. Gross Capital Formation and Economic Performance

Classical economic theories emphasize capital accumulation as a fundamental driver of growth [15, 16]. Investment in physical capital, such as infrastructure, machinery, and buildings, enhances productivity and facilitates economic expansion

[17]. Recent empirical findings by Stiglitz et al. [18] suggest that while capital investment remains crucial, its effectiveness depends on efficient allocation and absorptive capacity. Misallocation of resources, overinvestment in unproductive sectors, and financial constraints can diminish the positive effects of capital formation [19]. In some cases, excessive reliance on fixed asset investments can lead to diminishing returns, stagnation, or financial instability [20].

Investment-led growth has been a defining feature of many Asian economies. Studies by Wang [21] indicate that large-scale infrastructure projects in China, India, and ASEAN countries have significantly contributed to GDP growth. However, research by Zhang and Kong [22] suggests that overinvestment in real estate and state-owned enterprises may lead to inefficiencies and potential financial risks. The effectiveness of capital formation depends on institutional quality, governance, and the ability to allocate resources efficiently [23]. In the Gulf region, Abid [24] finds that targeted capital investment in conjunction with environmental policy design plays a vital role in advancing green economic growth, particularly in resource-dependent countries like Saudi Arabia.

2.3. Inflation and Economic Growth

The relationship between inflation and economic growth remains a subject of debate. Some studies suggest that moderate inflation can stimulate economic activity by encouraging consumption and investment [25, 26]. Others argue that high inflation disrupts economic stability, reduces purchasing power, and distorts investment decisions, ultimately hindering growth Ssnhadji and Khan [27]. Woodford [28] highlights that central banks play a crucial role in maintaining price stability to create a conducive environment for sustained growth. Empirical evidence from developing economies suggests that inflationary pressures have nonlinear effects, with moderate levels fostering growth while excessive inflation deters economic progress [29].

Inflation management has played a crucial role in ensuring macroeconomic stability in Asia. Studies by Park [30] show that central banks in the region have successfully implemented inflation-targeting policies to maintain economic growth while keeping inflation in check. Empirical evidence from South Korea and India suggests that moderate inflation supports economic expansion, but high inflation negatively impacts investment and consumer spending [31]. Further, Abid et al. [32] explore the interplay between political instability, inflation, and monetary policy in emerging economies, underscoring how macroeconomic volatility can hinder recovery and long-term economic performance.

2.4. Trade Openness and Economic Development

Trade openness has long been associated with economic growth, as it facilitates access to international markets, enhances competition, and promotes knowledge diffusion Frankel and Romer [33] and Dollar and Kraay [34]. Sachs et al. [35] provide strong empirical support for the positive impact of trade liberalization on growth, particularly in developing economies. Recent studies by Baldwin [36] reaffirm that trade integration fosters technological adoption, foreign direct investment inflows, and industrial specialization, all of which contribute to long-term economic prosperity. However, Rodrik [20] warns that globalization may also lead to structural vulnerabilities, with some economies experiencing adverse effects such as deindustrialization and increased income inequality.

Trade liberalization has been a key driver of Asia's economic rise. Studies by Rhee [37] confirm that trade openness has facilitated industrialization, foreign direct investment, and technology transfer across the region. China's Belt and Road Initiative (BRI) has further strengthened regional trade networks, fostering economic integration [38]. However, some scholars argue that excessive dependence on exports makes Asian economies vulnerable to global economic shocks Rodrik [20].

Within the Gulf Cooperation Council, Abid et al. [39] emphasize how energy trade dynamics, CO_2 emissions, and structural economic reforms intersect to shape trade-led growth outcomes. Additionally, Chaabouni and Abid [40] offer a panel-based analysis revealing the key drivers of energy consumption and their implications for regional trade and growth.

The literature highlights the crucial roles of AI innovation, capital formation, inflation control, and trade openness in shaping economic growth. While existing studies confirm their positive contributions under certain conditions, challenges such as investment inefficiencies, inflationary risks, and trade vulnerabilities must be carefully managed. The following empirical analysis will examine these relationships in greater detail to assess their impact on economic performance.

3. Methodology

This study employs panel data analysis to investigate the impact of artificial intelligence (AI) innovation on economic performance in East Asia. The methodological approach consists of several econometric techniques, including panel cross-sectional dependence tests, unit root and cointegration tests, panel regression models, model selection tests, and diagnostic checks.

3.1. Panel Cross-Sectional Dependence and Slope Heterogeneity

Before estimating the regression models, it is essential to check for cross-sectional dependence among the East Asian countries. Cross-sectional dependence arises when economic shocks in one country affect others, which is common in globally integrated economies. The Pesaran [41] cross-sectional dependence (CD) test is applied to assess the presence of dependence across countries.

Furthermore, slope heterogeneity is tested using the Pesaran and Yamagata [42] slope heterogeneity test, which determines whether the regression coefficients vary across countries. Accounting for slope heterogeneity ensures that the estimated relationships are not biased due to variations in country-specific factors.

3.2. Panel Cointegration Tests

Since the study involves both stationary and non-stationary variables, we assess the long-run equilibrium relationship between AI innovation and GDP using panel cointegration tests. The following tests are applied:

- Kao [43] residual-based test, which assumes homogeneous cointegration relationships across panel units.
- Pedroni [44] and Pedroni [45] cointegration test, which accounts for heterogeneity across panel members by estimating individual-specific cointegration relationships.
- Westerlund [46] error correction-based test, which provides robust inference by allowing for structural breaks and cross-sectional dependence in the data.
- Panel Unit Root and Stationarity Tests

To avoid spurious regression results, we test for the presence of unit roots in the data using the Augmented Cross-Sectional IPS (CIPS) test proposed by Pesaran [47]. The CIPS test accounts for cross-sectional dependence while assessing the stationarity of panel data. If variables are found to be non-stationary at levels, they are differenced to achieve stationarity.

3.3. Panel Data Regression Models

To estimate the impact of AI innovation on economic performance, the study employs the following panel data regression models:

- Pooled Ordinary Least Squares (OLS) Regression: This model does not account for country-specific heterogeneity but serves as a baseline comparison model [48].

$$Y_{it} = \beta_0 + \beta_1 X_{it} + \varepsilon_{it} \qquad (1)$$

Where:

Y_{it}: Dependent variable for entity i at time t.

X_{it}: Independent variables for entity i at time t.

β_0: Overall intercept (constant term).

β_1: Vector of coefficients for the independent variables.

ε_{it}: Error term.

- Fixed Effects Model (FEM): This model accounts for country-specific factors that do not vary over time, eliminating potential omitted variable bias. It assumes that individual country effects are correlated with the independent variables [49].

$$Y_{it} = \beta_0 + \beta_1 X_{it} + \mu_{it} + \varepsilon_{it} \qquad (2)$$

Where:

μ_{it} : Unobserved individual effect that is constant over time.

- Random Effects Model (REM): Unlike FEM, REM assumes that country-specific effects are uncorrelated with the regressors. This model is more efficient if the random effects assumption holds (Hausman, 1978).

$$Y_{it} = \beta_0 + \beta_1 X_{it} + \mu + \upsilon_{it} \qquad (3)$$

Where:

μ: Overall mean effect.

υ_{it} : Error term that captures both individual and idiosyncratic error components.

- Model Selection and Validity Tests

To determine the most appropriate model for the panel data, the following statistical tests are conducted:

- Breusch-Pagan LM Test [50]: This test assesses whether pooled OLS is preferable to random effects by examining the significance of random effects.
- F-test for Fixed Effects: This test compares pooled OLS and fixed effects, verifying whether country-specific differences justify the use of FEM.
- Hausman Test [51]: This test determines whether fixed effects or random effects is the preferred model. If the null hypothesis is rejected, FEM is chosen, as REM produces biased estimates in the presence of correlation between the regressors and country-specific effects.
- Diagnostic Tests

To ensure the reliability of the model estimates, diagnostic tests for autocorrelation and heteroscedasticity are applied:

- Wooldridge [52] test for autocorrelation in panel data, which checks for serial correlation in the residuals.
- Modified Wald test for heteroscedasticity in fixed effects models [53].

Additionally, to correct for potential heteroscedasticity and autocorrelation issues, we apply Driscoll and Kraay [4] standard errors, which provide robust standard errors in the presence of cross-sectional dependence.

3.4. Panel Causality Test

Finally, to investigate whether AI innovation Granger-causes economic growth, we apply the Juodis et al. [5] panel Granger non-causality test. This test is designed to accommodate heterogeneity and cross-sectional dependence in panel data, providing stronger causal inferences.

4. Data

This study examines the influence of AI innovation on economic performance in East Asia, focusing on China, Japan, and South Korea from 2010 to 2023.

The dependent variable, GDP (constant 2015 US$), represents the total value of goods and services produced within a country, adjusted for inflation, and serves as a key measure of economic performance and growth. The primary independent variable, Artificial Intelligence Patents Submitted per Million (AIP), captures technological advancement by measuring the number of AI-related patents filed per million people, reflecting the role of AI-driven innovation in economic development. Additionally, Gross Capital Formation (GCF, constant 2015 US$) is included as a measure of investment in fixed assets such as infrastructure, machinery, and technology, indicating the expansion of productive capacity and long-term growth potential. The study also considers Inflation, Consumer Prices (INF, annual %), which reflects changes in the general price level of goods and services, providing insight into macroeconomic stability and its impact on economic performance. Lastly, Trade (TRA, % of GDP) measures the sum of exports and imports as a percentage of GDP, indicating the degree of economic openness and integration with global markets. Data for these variables are sourced from reliable international organizations such as the World Bank and the World Intellectual Property Organization (WIPO). This study aims to explore the extent to which AI innovation contributes to economic growth while accounting for key macroeconomic factors.

This correlation matrix presents the relationships between GDP, AI patents (AIP), gross capital formation (GCF), inflation (INF), and trade (TRA) in East Asia from 2010 to 2023 (Table 1).

Table 1.
Correlation matrix.

Variable	GDP	AIP	GCF	INF	TRA
GDP	1.0000				
AIP	-0.1422	1.0000			
GCF	0.9857	-0.1026	1.0000		
INF	0.0193	-0.2822	0.0691	1.0000	
TRA	-0.7996	0.1214	-0.7031	0.3177	1.0000

There is an extremely strong positive correlation between GDP and GCF. This suggests that higher investment in fixed assets, such as infrastructure and machinery, is closely linked to economic growth in East Asia. This aligns with economic theory, where capital accumulation plays a crucial role in driving GDP expansion. The correlation between AI innovation and GDP is weakly negative, implying that an increase in AI patent filings does not strongly align with GDP growth in this dataset. This could indicate that AI innovation takes time to translate into economic gains or that its benefits are not immediately reflected in GDP. The relationship between inflation and GDP is nearly zero, suggesting that inflationary changes have little direct impact on economic growth in the studied countries. This could mean that inflation has been relatively stable over the period, with no significant disruptive effects on GDP. There is a strong negative correlation between trade openness and GDP, suggesting that higher trade as a percentage of GDP is associated with lower economic performance. This could indicate that excessive reliance on trade may be linked to economic volatility or that trade imbalances affect domestic production and growth. Overall, gross capital formation appears to be the strongest driver of GDP, while AI innovation and trade show negative correlations.
In Table 2, we provide a summary of the variables used in the analysis.

Table 2.
Descriptive Statistics.

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
GDP	33	29.1426	0.8873	27.9544	30.4745
AIP	33	2.5995	1.4980	-0.1278	5.1594
GCF	33	27.9968	1.0480	26.6958	29.5789
INF	33	1.5499	1.2040	-0.2334	5.0895
TRA	33	3.8859	0.3897	3.4439	4.5845

The descriptive statistics provide insights into the distribution of the key variables in the study. GDP shows relatively stable values with minimal fluctuations, indicating consistent economic performance across the observed years. AI patent filings exhibit noticeable variability, suggesting differing levels of AI innovation efforts among the countries in East Asia. Gross capital formation remains fairly stable, reflecting steady investment patterns in infrastructure and capital assets. Inflation demonstrates some dispersion, with both positive and negative values, indicating occasional periods of deflation or low inflation. Trade openness appears to be relatively stable, with moderate fluctuations over time. These statistics highlight the economic and technological dynamics of the region, suggesting the need for further analysis to understand the relationships between AI innovation, investment, inflation, trade, and GDP growth.

5. Results

Before proceeding with the model estimation, we first conduct several diagnostic tests to ensure the validity and robustness of our panel data analysis. These tests include panel cross-sectional dependence estimations to check for correlation across entities; tests for slope heterogeneity to determine whether the relationship between variables differs across units; and co-integration tests to examine potential long-run relationships among non-stationary variables. The results of these tests inform the appropriate model specification and estimation technique, ensuring that subsequent analyses are reliable and accurate.

Table 3 summarizes the results of Pesaran's test, Friedman's test, and Frees' test for cross-sectional dependence.

Table 3.
Cross-sectional dependence (CSD) tests results.

Test	Test Statistic	p-value	Critical Values (Frees' Test)
Pesaran's Test (CD)	2.9600	0.0031	—
Friedman's Test	19.0910	0.0001	—
Frees' Test (Q)	0.5750	—	Alpha = 0.10: 0.2333
			Alpha = 0.05: 0.3103
			Alpha = 0.01: 0.4649

The results from the cross-sectional dependence (CSD) tests indicate significant dependence among the panel units, meaning that economic and technological variables in one country are influencing others within the East Asian panel (China, Japan, and South Korea).

Pesaran's test shows a statistically significant result, rejecting the null hypothesis of cross-sectional independence. This confirms that the variables in the dataset are interrelated across countries. Friedman's test also yields a highly significant result, further supporting the presence of cross-sectional dependence. Frees' test shows a test statistic higher than all critical values, reinforcing the rejection of the null hypothesis and confirming interdependence.

Since all three tests suggest strong cross-sectional dependence, standard panel estimation techniques (such as fixed or random effects) may produce biased results. To address this issue, econometric methods that account for cross-sectional dependence should be considered, such as Driscoll-Kraay standard errors, common correlated effects (CCE) estimators, or spatial econometric models.

The results from the Pesaran and Yamagata [42] test for slope heterogeneity provide insights into whether the slope coefficients of the panel data model are homogeneous across the countries in your sample (Table 4).

Table 4.
Pesaran and Yamagata [42] test results.

Statistic	Value	p-value
Delta	1.2100	0.2260
Adjusted Delta	1.7950	0.0730

Based on these results, the evidence suggests that slope coefficients are homogeneous across the countries in the sample (China, Japan, and South Korea). The slight evidence of heterogeneity at the 10% level (from the adjusted Delta) does not strongly suggest a need for separate slope coefficients for each country. Therefore, a model assuming homogeneous slopes might be more appropriate for this dataset.
Table 5 summarise the Pedroni, Pedroni and Westerlund tests results for cointegration.

Table 5.
Cointegration test results [45].

Test	Statistic	p-value
Pedroni Test		
Modified Phillips-Perron t	2.0714	0.0192*
Phillips-Perron t	-6.6543	0.0000***
Augmented Dickey-Fuller t	-2.8260	0.0024***
Kao Test		
Modified Dickey-Fuller t	-1.8181	0.0345*
Dickey-Fuller t	-3.0158	0.0013***
Augmented Dickey-Fuller t	-2.4888	0.0064***
Westerlund Test		
Variance Ratio	0.5072	0.3060

The combined results from the Pedroni, Kao, and Westerlund cointegration tests provide a comprehensive view of the relationship among the variables. The Pedroni [45] test reveals strong evidence of cointegration with significant p-values for the Phillips-Perron t, Augmented Dickey-Fuller t, and Modified Phillips-Perron t tests, all indicating cointegration at 1% or 10% significance levels. The Kao test further confirms this, with significant p-values for both the Dickey-Fuller and Augmented Dickey-Fuller tests, signaling cointegration at 1% or 10% levels. However, the Westerlund test, specifically the variance ratio statistic, does not support cointegration, as the p-value (0.3060) exceeds the 0.05 threshold, suggesting no cointegration among the variables. Therefore, while the Pedroni and Kao tests suggest cointegration, the Westerlund test does not, highlighting the differing results across the tests and the need for careful consideration when interpreting cointegration in panel data.

Following the diagnostic tests, we proceed with the Pesaran Panel Unit Root Test (CIPS test) to examine the stationarity of the variables. This test helps to determine whether the variables in the panel dataset are non-stationary or stationary, which is crucial for ensuring the validity of our model. Non-stationary data could lead to spurious results, and thus, testing for unit roots is an essential step before conducting further estimation. Pesaran Panel Unit Root Test (CIPS test) results are presented in Table 6.

Table 6.
Pesaran Panel Unit Root test results (CIPS test).

Variable	CIPS (Level)	Variable in difference	CIPS (First Difference)
GDP	-1.3250	ΔGDP	-2.3130***
AIP	-1.8240	ΔAIP	-3.7210***
GCF	-3.9760***	ΔGCF	-4.2880***
INF	-1.5800	ΔINF	-3.1270***
TRA	-3.8810***	ΔTRA	-2.1020**

Note: *** and ** imply the significance at 1% and 5% level, respectively.

The results of the Pesaran Panel Unit Root Test (CIPS test) indicate that GDP, AIP, and INF are non-stationary at level, as their test statistics are not significant. In contrast, GCF and TRA are stationary at level, showing significance at the 1% level. However, after taking the first difference, all variables become stationary, with GDP, AIP, GCF, and INF showing significance at the 1% level, while TRA is significant at the 5% level. These findings suggest that GDP, AIP, and INF are integrated of order one (I(1)) and should be used in their first-differenced form in regression models to avoid spurious results. Meanwhile, GCF and TRA can be used in level form if necessary. Given the mix of stationary and non-stationary variables, further cointegration analysis may be necessary to determine potential long-run relationships among them.

Having established the stationarity of the variables, we proceed with the model estimation. Table 7 outlines the estimation results for the Fixed-Effects, Random-Effects, and Pooled regression models, providing insights into the relationships between the variables of interest.

Table 7.
Regression results.

Fixed-Effects (Within) Regression			
Variable	**Coefficient**	**Std. Err.**	**p-value**
daip (AI Innovation)	0.0088	0.0040	0.0390
gcf (Gross Capital Formation)	0.0027	0.0357	0.9400
dinf (Inflation)	-0.0021	0.0026	0.4290
tra (Trade Openness)	0.1265	0.0430	0.0070
_cons (Constant)	-0.5362	1.0932	0.6280
Random-Effects GLS Regression			
Variable	Coefficient	Std. Err.	p-value
daip (AI Innovation)	0.0060	0.0030	0.0490
gcf (Gross Capital Formation)	0.0306	0.0041	0.0000
dinf (Inflation)	-0.0003	0.0025	0.9000
tra (Trade Openness)	0.0622	0.0115	0.0000
_cons (Constant)	-1.0701	0.1491	0.0000
Pooled OLS Regression			
Variable	Coefficient	Std. Err.	p-value
daip (AI Innovation)	0.0060	0.0031	0.0600
gcf (Gross Capital Formation)	0.0306	0.0041	0.0000
dinf (Inflation)	-0.0003	0.0025	0.9010
tra (Trade Openness)	0.0622	0.0115	0.0000
_cons (Constant)	-1.0701	0.1491	0.0000

The results of the fixed-effects regression model suggest that AI innovation plays a significant role in driving economic growth. The positive and statistically significant coefficient (0.0088, $p = 0.039$) for AI-related patents per million people indicates that increased AI innovation contributes to higher GDP, supporting the notion that technological advancements fuel economic expansion. However, gross capital formation (0.0027, $p = 0.940$) does not show a significant relationship with GDP, implying that investment in fixed assets alone may not directly influence economic growth within the observed period. Inflation (-0.0021, $p = 0.429$) also appears to have an insignificant effect, suggesting that moderate price fluctuations do not strongly impact GDP in this context. In contrast, trade openness (0.1265, $p = 0.007$) exhibits a significant positive relationship with GDP, highlighting the importance of global economic integration in fostering growth. The constant term (-0.5362, $p = 0.628$) is not statistically significant, reinforcing that the included variables sufficiently explain variations in economic performance. Overall, the findings underscore the critical role of AI-driven innovation and trade openness in shaping economic growth, while traditional investment and inflationary effects appear less influential in this model.

The random-effects GLS regression model provides further insights into the relationship between AI innovation, investment, inflation, and trade openness with economic growth. The results indicate that AI innovation (0.0060, $p = 0.049$) has a positive and statistically significant effect on GDP, reinforcing the notion that advancements in AI contribute to economic expansion, though the effect size is slightly lower compared to the fixed-effects model. Gross capital formation

(0.0306, p = 0.000) is strongly significant, suggesting that investment in infrastructure, machinery, and technology plays a crucial role in economic growth. Conversely, inflation (-0.0003, p = 0.900) is not statistically significant, indicating that changes in consumer prices do not meaningfully impact GDP in this model. Trade openness (0.0622, p = 0.000) remains a significant driver of economic growth, emphasizing the importance of international trade and economic integration. The constant term (-1.0701, p = 0.000) is statistically significant, suggesting that factors beyond those included in the model may also influence GDP. Overall, these findings highlight the key roles of AI-driven innovation, capital investment, and trade in fostering economic growth, while inflation appears to have a negligible effect.

The pooled OLS regression results indicate that AI innovation (0.0060, p = 0.060) has a positive effect on GDP, but its statistical significance is marginal (just above the conventional 5% threshold). This suggests that AI-driven technological advancements may contribute to economic growth, though the effect is weaker compared to the fixed and random-effects models. Gross capital formation (0.0306, p = 0.000) remains highly significant, reinforcing the crucial role of investment in infrastructure, machinery, and technology in driving economic expansion. Inflation (-0.0003, p = 0.901) continues to show an insignificant relationship with GDP, indicating that short-term price fluctuations do not significantly impact economic performance. Trade openness (0.0622, p = 0.000) is strongly significant, underscoring the importance of international trade and economic integration in promoting growth. The constant term (-1.0701, p = 0.000) is also significant, suggesting that additional unobserved factors influence GDP. Overall, these findings align with the random-effects model, highlighting the pivotal roles of capital investment and trade openness, while AI innovation shows a weaker effect in this specification.

We now proceed to model selection. This step involves determining the most suitable model specification by comparing alternative estimation techniques, such as Pooled OLS, Fixed Effects, and Random Effects models. The decision is informed by tests such as the Breusch-Pagan LM test, the Hausman test, and the F-test for fixed effects, which assess the appropriateness of random effects versus fixed effects and the presence of heterogeneity across cross-sectional units. The chosen model is then used to analyze the relationships between the variables more accurately and effectively (Table 8).

Table 8.
Model selection test results.

Test	Null Hypothesis (H_0)	Test Statistic	p-value	Decision	Preferred Model
Hausman Test (Fixed Effects vs. Random Effects)	Difference in coefficients is not systematic	4.9900	0.0825	Fail to reject H_0	Random Effects
Breusch-Pagan LM Test (Pooled OLS vs. Random Effects)	Var(u) = 0	0.0000	0.9900	Fail to reject H_0	Pooled OLS
F-test for Fixed Effects (Pooled OLS vs. Fixed Effects)	No fixed effects	0.2400	0.6285	Fail to reject H_0	Pooled OLS

The Breusch-Pagan LM test suggested that there is no significant random effect in the model, favoring Pooled OLS over Random Effects. Similarly, the F-test for Fixed Effects indicated that there are no fixed effects to account for, further supporting the use of Pooled OLS. While the Hausman test suggested that Random Effects might be more appropriate than Fixed Effects, its recommendation was not in conflict with the results of the other two tests. Given that both the Breusch-Pagan and F-tests pointed towards Pooled OLS, this model is the best choice for our analysis. Therefore, Pooled OLS should be used, as it is the most efficient and consistent model for our data.

Once the appropriate model is selected, we conduct a series of diagnostic tests to validate the robustness of the model's assumptions. These tests include the Wooldridge test for autocorrelation, to examine first-order serial correlation; the Breusch-Pagan / Cook-Weisberg test for heteroskedasticity, to check for constant variance across observations. The results from these diagnostic tests are crucial in determining whether any model adjustments or corrections are necessary, ensuring the reliability and consistency of the estimated relationships (Table 9).

Table 9.
Diagnostic tests results.

Test	Null Hypothesis (H_0)	Test Statistic	p-value	Decision	Conclusion
Wooldridge Test for Autocorrelation	No first-order autocorrelation exists	0.0000	0.9926	Fail to reject H_0	No first-order autocorrelation detected
Breusch-Pagan / Cook-Weisberg Test for Heteroskedasticity	Constant variance (Homoskedasticity)	0.0600	0.8042	Fail to reject H_0	No heteroskedasticity detected

Wooldridge test for autocorrelation results confirm that there is no evidence of first-order autocorrelation in the panel dataset. The Breusch-Pagan / Cook-Weisberg test results confirm that there is no evidence of heteroskedasticity in the dataset. Both tests indicate that the Pooled OLS assumptions hold (no autocorrelation and no heteroskedasticity); this reinforces the validity of using Pooled OLS.

Given the presence of cross-sectional dependence identified in earlier tests, we apply Driscoll-Kraay standard errors to correct for this issue. This method provides robust standard errors that account for heteroskedasticity, autocorrelation, and dependence across cross-sectional units, ensuring more reliable inference in panel data settings. By implementing this correction, we enhance the robustness of our estimated coefficients, reducing the risk of biased statistical inference.

Table 10 reflects the results of the Driscoll-Kraay standard errors, providing more robust estimates for the regression coefficients.

Table 10.
Regression with Driscoll-Kraay standard errors.

Variable	Coefficient	Std. Err.	p-value
daip (AI Innovation)	0.0060	0.0016	0.0050
gcf (Gross Capital Formation)	0.0306	0.0036	0.0000
dinf (Inflation)	-0.0003	0.0015	0.8340
tra (Trade Openness)	0.0622	0.0090	0.0000
_cons (Constant)	-1.0701	0.1337	0.0000

The regression results using Driscoll-Kraay standard errors, which account for cross-sectional dependence and heteroskedasticity, provide robust estimates of the relationships between AI innovation, investment, inflation, and trade openness with economic growth. AI innovation (0.0060, $p = 0.005$) remains positive and statistically significant, indicating that advancements in AI contribute to economic growth, with a stronger level of confidence compared to the pooled OLS model. Gross capital formation (0.0306, $p = 0.000$) continues to have a significant positive effect, reinforcing the importance of investment in infrastructure, machinery, and technology. Inflation (-0.0003, $p = 0.834$) remains statistically insignificant, suggesting that inflationary fluctuations do not meaningfully impact GDP in this model. Trade openness (0.0622, $p = 0.000$) remains a key driver of economic growth, with its strong significance reaffirming the role of global market integration. The constant term (-1.0701, $p = 0.000$) is also statistically significant, suggesting that unobserved factors beyond the included variables influence GDP. Overall, these results align with previous models, particularly the random-effects and pooled OLS models, confirming the crucial roles of AI innovation, investment, and trade openness in economic growth while showing inflation as an insignificant factor.

To further explore the dynamic relationships between the variables, we conduct the Juodis et al. [5] Granger Non-Causality Test. This test allows us to determine whether past values of one variable can predict changes in another. Table 11 presents the results from the Juodis et al. [5] Granger non-causality test results.

Table 11.
Juodis et al. [5] Granger non-causality test results

Variable	Coefficient	Std. Err.	p-value
daip (AI Innovation, lagged)	0.0307	0.0073	0.0000
gcf (Gross Capital Formation, lagged)	-0.4739	0.0449	0.0000
dinf (Inflation, lagged)	0.0083	0.0032	0.0090
tra (Trade Openness, lagged)	0.2661	0.0729	0.0000

The Granger non-causality test examines whether past values of the independent variables predict future GDP, providing insights into causal relationships. The positive and highly significant coefficient of AI Innovation (0.0307, $p = 0.000$) suggests that past AI-related patent activity Granger-causes economic growth, indicating that technological advancements have a predictive and causal impact on GDP. This supports the argument that AI innovation drives long-term economic expansion. Interestingly, the coefficient is negative and highly significant for Gross Capital Formation (-0.4739, $p = 0.000$), suggesting that past investment in fixed assets negatively predicts future GDP growth. This counterintuitive result may indicate diminishing returns to investment, inefficient capital allocation, or time lags between investment and economic gains. The positive and significant coefficient of Inflation (0.0083, $p = 0.009$) suggests that past inflation levels have a mild predictive effect on future GDP, potentially reflecting short-term economic adjustments or price stability influencing future economic activity. The strong positive and significant coefficient of Trade Openness (0.2661, $p = 0.000$) implies that greater historical trade openness predicts future economic growth, reinforcing the idea that global market integration has long-term benefits for economic performance.

Overall, the results highlight AI innovation and trade openness as strong predictors of future economic growth, while investment in fixed assets appears to have a negative predictive effect, potentially pointing to inefficiencies or delayed returns. Inflation, though statistically significant, has a relatively weaker impact.

6. Discussion

The results of the regression with Driscoll-Kraay standard errors provide robust insights into the relationship between AI innovation, investment, inflation, and trade openness with economic growth.

The positive and statistically significant effect of AI innovation on GDP aligns with a growing body of literature emphasizing the transformative role of AI in economic development, Tam et al. [54], and Abbas Khan et al. [1]. McAfee and Brynjolfsson [7] argue that AI enhances productivity, fosters innovation, and creates new business opportunities, leading to economic expansion. Similarly, Aghion et al. [17] highlight that AI-driven automation increases efficiency and accelerates technological progress, contributing to GDP growth. More recent studies [55, 56] confirm that AI adoption leads to gains in productivity, labor market dynamics, and industrial efficiency, ultimately driving long-term economic performance.

The highly significant impact of gross capital formation is consistent with classical and modern growth theories, which emphasize investment as a key driver of economic expansion. The neoclassical growth model [15] posits that capital accumulation increases productive capacity, while empirical studies by Levine and Renelt [57] and Barro [16] confirm a strong link between investment in infrastructure, machinery, and technology with GDP growth. More recent evidence from Asongu and Odhiambo [58] and the World Bank [59] underscores that strategic capital investments in emerging economies significantly enhance long-run economic growth, particularly when complemented by innovation and technology.

Trade openness remains a significant determinant of economic growth, reinforcing theories that highlight the benefits of globalization and international integration [60, 61]. Empirical research by Frankel and Romer [33] and Sachs et al. [35] has demonstrated that trade liberalization fosters economic expansion by facilitating access to technology, increasing competition, and improving resource allocation. More recent studies, including Rodrik [20] and Dollar and Kraay [34] confirm that trade openness contributes to sustained economic growth, particularly in knowledge-intensive sectors that benefit from global innovation spillovers.

Conversely, inflation is found to be statistically insignificant, indicating that inflationary fluctuations do not significantly impact GDP in this model. This finding is supported by empirical evidence from Barro [62] and Fischer [63], which suggests that while excessive inflation can be detrimental to growth, moderate inflation has little to no adverse effect. More recently, studies by Ssnhadji and Khan [27] and Mishkin [25] reaffirm that inflation-growth relationships are context-dependent, with stable inflation rates generally exerting minimal influence on long-run GDP trajectories.

Overall, these results confirm that AI innovation, capital investment, and trade openness are key drivers of economic growth, while inflation appears to have a limited impact. These findings align with recent empirical research, reinforcing the importance of policies that support AI development, investment efficiency, and trade liberalization to sustain economic performance in the digital era.

The results of the Granger non-causality test provide essential insights into the causal relationships between AI innovation, capital investment, inflation, trade openness, and economic growth.

The positive and highly significant coefficient of AI innovation confirms that past AI-related patent activity Granger-causes economic growth. This finding aligns with extensive literature emphasizing the role of AI in driving long-term economic expansion through productivity gains, automation, and technological progress [7, 64].

The negative and highly significant coefficient of Gross Capital Formation presents a counterintuitive result, suggesting that past investment in fixed assets negatively predicts future GDP growth. While traditional growth theories emphasize capital accumulation as a key driver of economic expansion [15, 16], this result may reflect diminishing returns to investment, inefficient capital allocation, or time lags in realizing economic benefits from infrastructure and machinery investments [17, 19]. More recent research by Stiglitz et al. [18] suggests that in some economies, excessive or misallocated capital investment, such as overinvestment in real estate or inefficient state-led projects, can lead to lower productivity growth and financial imbalances, explaining the observed negative effect.

The positive and significant coefficient of Inflation suggests that past inflation levels have a mild predictive effect on future GDP. While high inflation is typically associated with economic instability, moderate levels of inflation can sometimes reflect rising demand, leading to short-term economic adjustments that stimulate growth [25, 27]. Empirical studies by Dornbusch and Fischer [26] and Woodford [28] indicate that in some cases, inflationary pressures may lead to increased consumption and investment in anticipation of rising prices, temporarily boosting economic activity. However, the relatively small coefficient suggests that this effect is limited.

The strong positive and significant coefficient of Trade Openness reinforces the idea that historical trade integration predicts future economic growth. This result is consistent with prior studies by Frankel and Romer [33] and Sachs et al. [35], which highlight the long-term benefits of trade liberalization, including technology diffusion, competitive efficiency, and access to larger markets. More empirical research by Dollar and Kraay [34] confirms that trade openness is a key driver of economic resilience, particularly in knowledge-intensive industries that benefit from global market participation. Additionally, Rodrik [20] and Baldwin [36] emphasize that countries with open economies tend to experience sustained growth through improved capital flows, innovation spillovers, and enhanced industrial specialization.

Overall, the findings underscore AI innovation and trade openness as strong predictors of future economic growth, while gross capital formation appears to have a negative predictive effect, potentially due to inefficiencies or delayed returns. Inflation, though statistically significant, has a relatively weaker impact on future GDP. These results highlight the need for efficient capital investment policies, continued AI-driven innovation, and greater trade integration to sustain long-term economic growth.

7. Conclusion

This study investigates the determinants of economic growth, focusing on the roles of AI innovation, gross capital formation, inflation, and trade openness. The findings provide empirical evidence that AI-driven technological advancements significantly contribute to economic expansion, aligning with the broader literature emphasizing the transformative role of artificial intelligence in productivity growth and innovation-led development. This underscores the necessity for policymakers to foster AI research, incentivize technological diffusion, and enhance digital infrastructure to sustain long-term economic progress.

The results also reveal a counterintuitive negative relationship between gross capital formation and future GDP growth. This suggests the presence of diminishing returns to investment, inefficient capital allocation, or extended lag effects in capital-intensive economies. Such findings call for strategic investment policies that emphasize efficiency, productivity enhancement, and effective capital utilization rather than mere capital accumulation. Inflation demonstrates a statistically significant but relatively mild predictive effect on economic growth, highlighting its role as a short-term adjustment mechanism. Policymakers should balance price stability with growth-oriented strategies to avoid excessive inflationary pressures while maintaining economic momentum. Moreover, the strong positive impact of trade openness on future GDP growth reinforces the argument that greater integration into the global economy facilitates knowledge transfer, innovation diffusion, and market expansion. Policymakers should continue to pursue trade liberalization policies while ensuring complementary domestic policies that enhance competitiveness and productivity.

In summary, this study highlights AI innovation and trade openness as key drivers of economic growth, while also revealing complexities in the relationship between capital formation and economic performance. Future research should further explore the interplay between these factors, considering structural reforms, institutional quality, and sectoral dynamics to provide deeper insights into sustainable economic development strategies.

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