

AI Talent and Economic Growth: Insights from OECD Economies

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Abstract

This study examines the relationship between AI talent concentration and economic growth across 34 OECD countries over the 2016–2024 period. As artificial intelligence increasingly reshapes labour markets and productive structures, understanding whether and how AI absorption translates into macroeconomic growth remains an open empirical question. We operationalise AI absorption through AI talent concentration, the share of LinkedIn members with AI engineering skills or AI-related occupations, disaggregated across eight economic sectors, and estimate its effect on GDP growth using two complementary panel estimators: Driscoll-Kraay fixed effects, which provide robust baseline estimates, and system GMM, which addresses the endogeneity arising from the reverse feedback between economic growth and AI talent attraction. The Driscoll-Kraay results show positive but largely insignificant associations between AI talent and growth, with only the Transportation and Logistics sector reaching marginal significance. The system GMM estimates reveal a strikingly different picture: once endogeneity is corrected, aggregate AI talent and manufacturing-specific AI talent exhibit negative and significant short-run effects on GDP growth, consistent with AI functioning as a structural transformation technology that imposes adjustment costs before delivering long-run productivity gains. Foreign direct investment emerges as the single most robust driver of short-run growth across all specifications. This study contributes to the literature by providing sector-level causal evidence on AI talent's growth effects within a homogeneous club of advanced economies, addressing the endogeneity challenge that most prior studies overlook. The findings carry policy implications for OECD governments seeking to calibrate AI talent strategies: simply accumulating AI skills is insufficient without the complementary institutional and structural conditions needed to convert AI capacity into growth.

Keywords

AI talent concentration, economic growth, OECD, system GMM, sectoral analysis, endogeneity, general-purpose technology

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Introduction

Artificial intelligence has emerged as one of the most consequential technological developments of the early twenty-first century, with far-reaching implications for productivity, labour markets, and aggregate economic performance. Unlike previous waves of automation, AI possesses the characteristics of a general-purpose technology. It diffuses across sectors, generates complementary innovations, and reshapes the organisation of production at multiple scales (Sood & Khanna, 2024). Yet the literature reveals a landscape that is considerably more nuanced than the popular narrative of AI as a straightforward engine of growth. Research consistently demonstrates that AI's economic impact is multifaceted: while it fuels productivity and output increases, it can simultaneously exacerbate inequalities and reshape workforce composition in complex ways (Sood & Khanna, 2024; Georgieff & Hyee, 2022).

This paper addresses these questions by focusing on AI talent concentration, the share of a country's workforce possessing AI engineering skills or performing AI-related occupations, as a direct measure of an economy's absorptive capacity for artificial intelligence. Unlike patent counts or aggregate investment indicators, which capture innovation output or expenditure, AI talent concentration reflects the human capital infrastructure that determines whether AI technologies can be effectively deployed across productive structures. Using data from OECD.AI and the World Bank for 34 OECD countries over the 2016–2024 period, we disaggregate AI talent across eight economic sectors and estimate its effect on GDP growth through Driscoll-Kraay fixed effects and system GMM, the latter explicitly addressing the endogeneity that arises when faster-growing economies attract more AI talent rather than the reverse.

The study makes three contributions to the existing literature. First, it provides sector-level evidence on the AI–growth relationship within a homogeneous group of advanced economies, moving beyond the aggregate, cross-income-group analyses that dominate the field. Second, it directly confronts the causal identification challenge by employing system GMM, revealing that the positive raw correlation between AI talent and growth disappears, and reverses, once reverse causality is accounted for. Third, it demonstrates that AI talent operates as a structural transformation variable rather than a short-run growth engine, a finding with direct implications for the design of national AI strategies in OECD economies. The remainder of the paper is structured as follows: the next section reviews the relevant literature and identifies the research gap, followed by the research methodology, results and discussion, and conclusions.

Literature review and research gap

A growing body of empirical work examines the direct contribution of AI to economic growth at the country level. Mohamed, Henni, & Sorour (2026), analysing a panel of ten developed and developing countries between 2010 and 2024, find that both digitalisation indicators and AI investment exert significant positive effects on GDP growth, with the digitalisation coefficient significant at the one percent level and AI investment at five percent. Similarly, Gonzales (2023), using AI patent counts in a panel of OECD countries from 1970 to 2019, documents a positive and statistically significant relationship between AI-related patenting and long-run economic growth. It is one that exceeds the effect of the broader population of patents, suggesting that AI innovations carry a distinctive growth premium. Duarte, Freitas, & Simões (2025) confirm that AI adoption is already translating into faster growth in the short run across 35 OECD countries, though the long-run evidence on living standards is less consistently supported, suggesting that AI's full structural benefits may take longer to materialise.

The environmental literature adds important qualifications. Din, Khan, & Hassan (2025) find that AI exhibits a nonlinear relationship with green growth in OECD countries: it initially disrupts sustainable development due to high adoption costs, but delivers positive returns after surpassing a critical investment threshold. Aslan, Kaplan, Sarıtaş, & Büyükkör (2026) corroborate this pattern using panel CS-ARDL and wavelet coherence analysis for 38 OECD countries, showing that AI's benefits depend on complementary policy frameworks and institutional capacities. That is a finding that extends naturally to the broader AI–growth nexus. Hamadou, Wicaksono, & Hamidi (2026) reinforce this argument by demonstrating that the interaction of AI with R&D expenditure can reverse AI's otherwise positive effect on carbon emissions in OECD countries, while the same moderating effect is absent in BRICS economies, underscoring that the structural capacity of an economy fundamentally shapes whether AI translates into better outcomes. This logic applies with equal force to the human capital dimension. Mohamed et al. (2026) identify AI-related skills as the primary amplifier of AI's effect on GDP, with education and workforce training emerging as key drivers of economic resilience across business cycle phases. Green (2025) provides empirical grounding for this argument by estimating the size and profile of the AI workforce across OECD countries, finding that while it remains small, it is growing rapidly and varies significantly in scale and composition. This variation has direct implications for growth potential, as countries with thinner AI talent pools may face bottlenecks that delay or diminish the economic returns to AI adoption.

The labour market evidence reveals important nuances. Georgieff & Hyee (2022), covering 23 OECD economies, find no clear aggregate relationship between AI exposure and employment growth, but a significant positive link in occupations where computer use is high, suggesting that AI shifts task composition toward higher value-added activities. Bughin (2023) adds that employment effects depend not merely on adoption itself but on the strategic posture firms take towards AI, implying that the AI–growth relationship is shaped by organisational choices as much as by talent availability. Ahumada-Tello et al. (2023) find that AI adoption facilitates more effective decision-making, while Paul (2026) argues that AI workforce readiness functions as an economic stabiliser, identifying data and evaluation, manpower development, social safety nets, and industry-level interventions as pillars for growth integration. The

consensus is that the human capital dimension is not merely complementary to AI adoption but foundational to it. Yet several gaps persist. Empirical work has relied predominantly on occupational exposure measures, patent counts, or aggregate investment indicators, with little attention to AI talent concentration as a direct measure of absorptive capacity, even though Green (2025) confirms meaningful cross-country variation in this workforce dimension. The sector-level decomposition of AI's growth effects remains severely underexplored: while Bughin (2023) and Georgieff & Hyee (2022) demonstrate that sectoral and firm-level context matters, rigorous cross-country analyses disaggregating AI talent across industries are largely absent. Moreover, the literature provides very limited evidence distinguishing between AI's effects during different macroeconomic phases, and the OECD as a coherent club of advanced economies has not been studied as a self-contained analytical unit.

Finally, the causal identification challenge remains insufficiently addressed. Much of the existing work documents correlations, but reverse causality (faster-growing economies attracting more AI talent) is rarely rigorously controlled for. The moderating role of structural capacity, while established in the environmental literature (Hamadou et al., 2026; Aslan et al., 2026), has not been systematically tested in the AI–growth relationship across sectors and development levels. A rigorous causal assessment that addresses endogeneity, explores sectoral variation, and accounts for macroeconomic conditions is therefore needed to advance our understanding of how AI absorption shapes growth trajectories in advanced economies.

Research methodology

This empirical study uses cross-country data from 34 OECD countries over the 2016–2024 period, with annual frequency. The dependent variable is the GDP growth rate (GDPG), expressed as a percentage and sourced from the World Bank. The primary explanatory variable is AI talent concentration, operationalised as the share of LinkedIn members holding at least two AI engineering skills or performing an AI-related occupation, as a percentage of total LinkedIn members, collected from OECD.AI. Nine specifications of this variable are employed: one aggregate measure covering all economic sectors (AI) and eight sector-specific measures capturing AI talent in Transportation and Logistics (AITL), Technology, Information and Media (AITIM), Professional Services (AIPS), Manufacturing (AIM), Hospitals and Healthcare (AIHH), Financial Services (AIFS), and Education (AIED).

Five control variables collected from World Bank are included: foreign direct investment (FDI), measured as net inflows as a share of GDP, and trade openness (TRD), measured as total trade as a share of GDP, both capturing the degree of integration among OECD economies. The stock of secure internet servers per million people (SIS) proxies the level of digitalisation, while high-technology exports as a share of manufactured exports (HTEC) reflects countries' innovation capacity. Finally, the unemployment rate (UNEM) as percentage of total labour force, is included to control for prevailing macroeconomic conditions. Descriptive statistics for all variables are reported in Table no. 1, revealing significant heterogeneity across OECD members during the time frame of the analysis.

Table no. 1. Descriptive statistics

Variable	No.obs.	Mean	Std. dev.	Min	Max
GDPG	423	2.404	3.629	-10.94	16.26
AI	432	0.557	0.319	0.07	1.98
AITL	300	0.740	0.380	0.16	2.44
AITIM	300	2.796	1.492	0.59	9.29
AIPS	300	1.984	0.815	0.49	4.43
AIM	290	1.156	0.722	0.2	5.09
AIHH	300	0.527	0.413	0.07	3.19
AIFS	300	2.057	0.990	0.5	5.78
AIED	300	1.784	0.982	0.37	6.38
FDI	414	3.733	41.228	-391.56	431.79
TRD	413	103.055	70.999	23.4	412.18
SIS	414	40827.55	58836.09	37.74	557174.3
HTEC	413	16.007	10.292	0.3	59.43
UNEM	460	6.860	4.681	1.64	34.01

Source: Authors' work

Correlations among variables were in general positive and at levels that do not indicate concerns regarding multicollinearity in the estimated models (they are available from the authors). As expected, correlations

were high between AI talent variables in economic sectors, ranging between 0.691 (AIFS and AIED) and 0.925 (AITIM and AIPS), suggesting that the concentration of AI talent in an economy tends to be rather homogeneous across sectors.

The estimation strategy was preceded by a sequence of pre-estimation diagnostic tests, summarised in Table 2. The Pesaran (2021) cross-sectional dependence (CSD) test rejects the null of cross-sectional independence for all variables at the one percent significance level, rendering first-generation panel estimators inappropriate and requiring estimators robust to CSD. The Pesaran (2007) CIPS panel unit root test reveals mixed orders of integration, with variables either $I(0)$ or $I(1)$, which rules out cointegration-based estimators. The Pesaran and Yamagata (2008) slope homogeneity test does not reject the null of homogeneous slopes, indicating that a pooled estimation is appropriate for our data set.

Table no. 2. Pre-estimation diagnostics

Diagnostic test	Result	Implication
Pesaran (2021) CD test	H_0 rejected at 1% for all variables	First-generation estimators invalid Second-generation unit root test required
Pesaran (2007) CIPS test	Mixed orders of integration: $I(0)/I(1)$	Cointegration estimators ruled out GMM appropriate for mixed integration orders
Pesaran-Yamagata (2008) test	H_0 of slope homogeneity not rejected	Pooled estimation

Source: Authors' work

Against this diagnostic background, two complementary estimators were employed. First, Driscoll and Kraay (1998) fixed-effects regressions (DK-FE) are used to obtain baseline estimates that are robust to CSD, heteroskedasticity, and autocorrelation in the error structure, while controlling for unobserved country-level heterogeneity through fixed effects. Second, the system Generalized Method of Moments (GMM) estimator of Blundell and Bond (1998) is applied to address the dynamic nature of economic growth and the potential endogeneity of AI talent concentration. The system GMM specification augments the standard first-differenced GMM with level equations, using lagged levels and lagged differences as instruments, and includes the lagged dependent variable (L.GDPG) to capture conditional convergence. Instrument validity was assessed through the Hansen J test of overidentifying restrictions (Hansen, 1982) and the Arellano-Bond AR(1)/AR(2) tests for serial correlation in the differenced residuals (Arellano and Bond, 1991). For each estimator, eight parallel models are estimated, one for the aggregate AI measure and one for each sector-specific AI variable, thus providing a comprehensive cross-sectoral assessment of AI talent's growth effects across OECD economies over the 2016–2024 period.

The general model used in the estimation of the relationship between AI and economic growth is the following:

$$GDPG = \alpha_{it} + \beta_{it}AI + \delta_{it}Controls + \epsilon_{it} \quad (1)$$

Where: GDPG is the dependent variable, AI designates AI talent, Controls is a vector of control variables as explained above, while α_{it} , β_{it} , δ_{it} and ϵ_{it} are the intercept (constant), the AI talent coefficient, control variables coefficients and model error.

Results and discussion

Figure no. 1 shows three distinct phases in the evolution of GDP growth in OECD countries between 2016–2024: a stable pre-pandemic expansion (2016–2019), the COVID shock and rebound (2020–2021), and a post-pandemic deceleration (2022–2024). The two last stages were accompanied by high heterogeneity among OECD economies, signalling a stark impact of the pandemic on countries' growth prospects.

The left panel in Figure no. 2 depicts the steady and uninterrupted upward trend in AI talent concentration across OECD countries over the studied period – the median rises from approximately 0.37% in 2016 to around 0.8% in 2024, more than doubling over nine years. This signals that AI talent is not a cyclical variable that tracks the business cycle, but a stock variable that accumulates over time and continued to rise through the pandemic. However, the progressive increase of the boxes and whiskers from 2016 to 2024 means that OECD countries were diverging in their AI talent accumulation, with some countries moving ahead rapidly and others lagging behind.

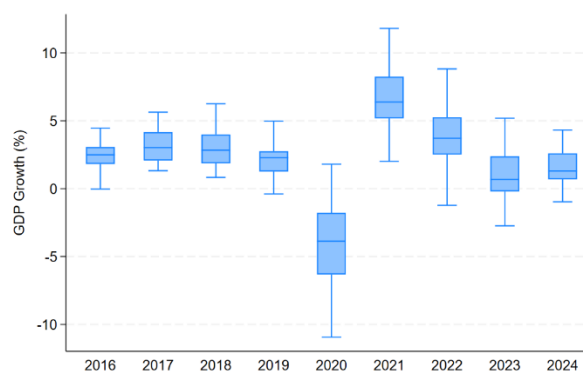


Figure no. 1. Economic growth across 2016-2024

Source: Authors' work in Stata 19

The right panel in Figure no. 2 indicates significant variation in AI talent levels across sectors, from below 0.5% in Healthcare to above 2.5% in Technology at median levels, which means that aggregating AI talent at economy level may hide very different structural realities. This justifies our estimation approach where AI talent variables are included in estimations of the relationship with economic growth.

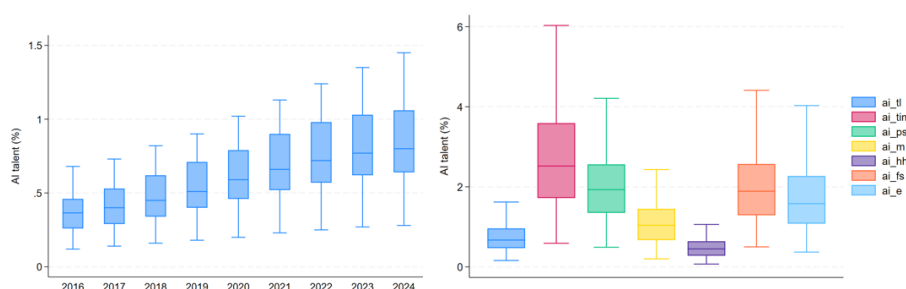


Figure no. 2. AI talent across years and economic sectors

Source: Source: Authors' work in Stata 19

The DK-FE estimator produces positive estimates for most AI variables but achieves statistical significance only marginally for AITL (β of 1.186, p-value 0.098) – see Table no. 3. All other AI talent variables, including AI, have positive coefficients but they are not statistically insignificant. The significance of AITL is economically meaningful, as transport and logistics in OECD economies is characterised by more digitalised supply chains, higher automation readiness, and greater integration of AI-driven optimisation tools, as also evidenced by Tetteh et al. (2026). For the control variables, FDI coefficient is positive and highly significant at 1% across all eight models, which is the single most robust finding that reinforces the role of foreign capital flows are the primary short-run driver of GDP growth variation across OECD members. HTEC has negative and significant coefficients at 5% across most models, which means that economies specialised in high-technology goods exports exhibit lower average GDP growth rates. UNEM is significant and negative in the AI Model 1 but loses significance in sector-specific models, however the direction is consistent.

Table no. 3. Results of Driscoll-Kraay fixed effects panel estimations

	All sectors	AITL	AITIM	AIPS	AIMAN	AIHH	AIFS	AIED
AI talent	1.506	-0.604	1.186*	2.518	-0.233	-0.442	-0.047	-0.050
FDI	0.010***	0.010***	0.010***	0.010***	0.010***	0.010***	0.010***	0.010***
TRD	0.009	0.008	0.008	0.005	0.009	0.006	0.006	0.006
UNEM	-0.0217**	-0.192	-0.210	-0.165	-0.198	-0.194	-0.192	-0.191
SIS	-0.133	-0.100	-0.132	-0.088	-0.112	-0.055	-0.060	-0.056
HTEC	-0.091**	-0.099**	-0.097**	-0.094**	-0.104**	-0.094*	-0.097**	-0.097**
Constant	7.499	5.639	7.082	5.446	5.534	4.683	5.280	5.250
Observations	305	260	260	260	251	260	260	260
No. of groups	34	29	29	29	28	29	29	29
Within R2	0.704	0.700	0.698	0.699	0.694	0.697	0.697	0.697

Note: ***, ** and * indicate statistical significance at 1%, 5% and 10% levels, respectively.

Source: Source: Authors' work in Stata 19

The GMM estimations, which correct for endogeneity by instrumenting the AI variable, produce a very different picture from the DK-FE results, presented in Table no. 4. AI shows a negative coefficient (β of -3.280^*) that is significant at 10%, and AIM also has a negative and significant coefficient at 5% (β of -2.766^{**} , p-value 0.032). Once the endogenous feedback from growth to AI talent attraction is removed in the GMM estimations, the average causal effect of aggregate AI talent on short-run GDP growth within OECD countries becomes negative. This illustrates the difference between the short-run impact of a general-purpose technology that is negative while structural transformation costs are being absorbed, while long-run positive effects are waiting to be captured. All other sector-specific AI variables are statistically insignificant in the GMM estimation, with the exception of the AIFS model which fails the Hansen test and cannot be interpreted.

Table no. 4. Results of dynamic panel estimations (GMM)

Models of	AI	AITL	AITIM	AIPS	AIMAN	AIHH	AIFS	AIED
L.GDPG	0.189	0.225	0.195	0.154	0.223	0.142	0.184	0.184
AI talent	-3.280*	-0.598	0.325	-2.237	-2.766**	4.178	-2.183	-1.740
FDI	0.007***	0.008***	0.008***	0.007***	0.008***	0.006***	0.008***	0.007***
TRD	0.008*	0.002	0.001	0.002	0.005*	-0.002	0.002	0.004
SIS	0.334	0.138	0.004	0.211	0.374	-0.672	0.176	0.203
HTEC	0.036	0.021	0.003	0.041	0.055*	-0.093	0.051	0.029
UNEM	0.013	0.028	0.025	0.067	0.015	0.103	0.008	0.106
Constant	7.500	5.639	7.082	5.446	5.534	4.683	5.280	5.250
Observations	272	232	232	232	224	232	232	232
No. of groups	34	29	29	29	28	29	29	29
No. of instruments	19	19	19	19	19	19	19	19
F-statistic	29.94***	18.35***	21.05***	72.06***	43.69***	20.01***	30.00***	31.42***
AR(1): p-value	0.001	0.002	0.002	0.002	0.001	0.001	0.001	0.003
AR(2): p-value	0.073	0.151	0.113	0.059	0.116	0.065	0.14	0.101
Hansen J: p-value	0.086	0.099	0.224	0.242	0.13	0.227	0.03	0.122

Note: ***, ** and * indicate statistical significance at 1%, 5% and 10% levels, respectively.

Source: Authors' work in Stata 19

FDI maintains its positive and significant coefficients at 1% across all valid models in the GMM estimations, confirming the findings in the DK-FE estimations and showing strong evidence that FDI inflows are a causal driver of short-run GDP growth in OECD countries. TRD becomes marginally significant in AI and AIMAN models, suggesting that once endogeneity and dynamic adjustments are accounted for, trade integration has only a modest positive causal effect on short-run economic growth.

The results indicate the need of a nuanced interpretation when contrasted with the existing literature. The predominantly positive but statistically weak AI coefficients in the DK-FE estimations are consistent with Green's (2025) finding that AI talent accumulation, while growing, remains slim in absolute terms across most OECD economies, which limits their growth contribution. The marginal significance of AITL aligns with evidence that digitally-intensive sectors such as transportation and logistics are better positioned to translate AI investment into measurable output gains (Tetteh et al., 2026; Gonzales, 2023). The GMM estimates, where the negative and significant coefficients on aggregate and manufacturing-specific AI talent suggest that, once endogeneity is considered, the short-run causal effect of AI absorption on GDP growth is contractionary. This pattern confirms the threshold dynamics documented by Din et al. (2025) and the nonlinear trajectory described by Aslan et al. (2026): AI initially imposes structural transformation costs on host economies before its productivity-enhancing effects materialise. Duarte et al. (2025) similarly stresses that short-run and long-run growth effects of AI adoption may diverge substantially.

Conclusions

This study examined the relationship between AI talent concentration and economic growth across 34 OECD countries over the 2016–2024 period, employing Driscoll-Kraay fixed effects and system GMM estimators across eight sectoral specifications. The central finding is that the positive raw association between AI talent and GDP growth, observed in the baseline estimations, disappears and reverses once endogeneity is addressed through GMM instrumentation. This sign reversal constitutes direct evidence that growing OECD economies attract AI talent, rather than AI talent causing growth in the short run. The

negative and significant GMM coefficients on aggregate and manufacturing-specific AI talent are consistent with AI functioning as a structural transformation technology that imposes adjustment costs — workforce displacement, organisational restructuring, and reallocation frictions, before its productivity-enhancing effects can materialise.

The policy implications are consequential. For OECD governments, simply scaling AI talent pipelines is insufficient: the short-run contractionary effects suggest that complementary investments in institutional capacity, innovation ecosystems, and workforce adaptation programmes are necessary to bridge the gap between AI talent accumulation and its eventual growth dividend. The robust significance of FDI across all specifications further suggests that openness to foreign capital remains a more reliable short-run growth lever than AI talent alone.

Several limitations should be acknowledged. The reliance on LinkedIn-based data, while offering cross-country comparability, may underrepresent AI talent in economies with lower LinkedIn penetration. The 2016–2024 timeframe, though capturing the critical period of AI diffusion, may be too short to observe the long-run structural effects that theory predicts. Additionally, the analysis does not account for interaction effects between AI talent and conditioning variables such as economic development or digitalisation levels.

Future research should extend this framework by incorporating interaction models and quantile regression approaches to explore whether AI talent's growth effects vary across the income distribution of OECD economies and across different macroeconomic regimes.

Generative Artificial Intelligence (GenAI) usage statement

Writefull was responsibly used for correcting grammar and spelling. After this process, the authors reviewed and edited the content as needed and take full responsibility for the content of the present article.

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