"AI ecosystem pillars and economic growth: Implications for knowledge economy architecture from AI vibrancy subindices"

AUTHORS	Kalilla Abdullayev Kalamkas Rakhimzhanova Artsrun Avetikyan Andrii Zolkover Alina Daniloviča Mykola Povoroznyk Yong Zhou

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Kalilla Abdullayev (Kazakhstan), **Kalamkas Rakhimzhanova** (Kazakhstan), **Artsrun Avetikyan** (USA), **Andrii Zolkover** (Ukraine), **Alina Danileviča** (Latvia), **Mykola Povoroznyk** (Ukraine), **Yong Zhou** (Ukraine)

AI ECOSYSTEM PILLARS AND ECONOMIC GROWTH: IMPLICATIONS FOR KNOWLEDGE ECONOMY ARCHITECTURE FROM AI VIBRANCY SUBINDICES

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Kalilla Abdullayev, Doctor of Economics, Chairman of the Board, Joint-stock company "Fund of Problem Loans", Kazakhstan.

Kalamkas Rakhimzhanova, Ph.D., Faculty of Economics, Department of Finance, L. N. Gumilyov Eurasian National University, Kazakhstan. (Corresponding author)

Artsrun Avetikyan, International Student, Public Service and Public Policy, Arizona State University, USA.

Andrii Zolkover, Doctor of Economics, Professor, Professor of the Department of Finance, Kyiv National University of Technology and Design, Ukraine.

Alina Danileviča, Doctor of Economics, Visiting Researcher, EKA University of Applied Sciences, Latvia.

Mykola Povoroznyk, Doctoral Candidate of the Department of International Accounting and Auditing, Kyiv National Economic University named after Vadym Hetman, Ukraine.

Yong Zhou, Ph.D. Student, Sumy State University, Ukraine.

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Abstract

AI is widely regarded by the IMF and the World Bank as a catalyst for growth. AI should be understood as a multidimensional socio-technical system embedded across institutions, industries, and society. Its economic contribution depends on which pillars of the national AI system expand (e.g., R&D capacity, infrastructure, governance, or social acceptance). For this reason, the seven pillars of AI development are measured by the AI Vibrancy subindices, which help avoid reliance on a single composite indicator that may conceal offsetting effects. This study examines how different pillars of the national AI ecosystem shape the architecture of the knowledge economy and its economic outcomes by estimating heterogeneous within-country associations between GDP per capita and seven AI ecosystem pillars, operationalized through AI Vibrancy subindices, using a balanced panel of 36 countries with complete data over the period 2020–2023. Fixed- and random-effects models are estimated using heteroskedasticity-robust and Driscoll-Kraay standard errors. The results indicate that, within countries over time, the R&D ($\beta = -5.676$, $p < 0.001$) and Infrastructure ($\beta = -16.306$, $p < 0.001$) subindices have strong and statistically significant negative associations with GDP per capita, while Public Opinion shows an adverse effect that is significant at the 5% level under heteroskedasticity-robust inference ($\beta = -9.126$, $p = 0.040$) and marginally significant under Driscoll-Kraay inference ($p = 0.054$). Responsible AI exhibits a marginally positive association ($\beta = 5.773$, $p = 0.065$) in the Driscoll-Kraay specification, whereas Economy, Education, and Policy & Government show no significant within-country effects.

Keywords artificial intelligence, AI vibrancy score, economic impact, GDP per capita, panel data, fixed effects

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INTRODUCTION

Artificial intelligence (AI) is rapidly emerging as a defining force in the global economy, and leading international organizations are increasingly positioning it as a potential accelerator of productivity and long-term growth. AI is being framed as a new general-purpose technology that can stimulate innovation, raise output, and enhance well-being, while still leaving uncertainty about how persistent these gains will be over time and across contexts (Filippucci et al., 2024). Complementing this view, IMF-related projections reported by Reuters suggest that AI could add roughly 0.5% per year to global GDP over the period 2025–2030, with expected net gains exceeding the environmental and energy costs associated with scaling AI infrastructure, such as data centers (Reuters, 2025). This combination of optimism and uncertainty motivates a knowledge- and performance-oriented assessment of where AI creates durable value and through which mechanisms it achieves

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this. This question aligns particularly with the journal's focus on knowledge as a foundational organizational asset (intellectual capital) and on human capital, knowledge creation, knowledge exchange, and the technological aspects of knowledge management as determinants of efficiency, productivity, and innovation. Within such a framing, AI should not be treated merely as a stand-alone technology shock, but as a set of capabilities embedded in a wider ecosystem that shapes how knowledge is produced, codified, shared, and converted into performance at the firm, sectoral, and territorial levels. The key implication is that the effects of economic growth are likely to be heterogeneous because they depend on the maturity and complementarity of distinct "AI-ecosystem pillars" that govern the formation and deployment of knowledge in practice.

The uneven distribution of AI benefits reinforces the need for this pillar-based perspective. Model-based IMF evidence indicates that AI-related growth gains may be more than twice as large in advanced economies as in low-income countries, reflecting gaps in preparedness, access, and sectoral exposure (Cerutti et al., 2025). Territorial divides are also emphasized through concerns about "emerging divides in the AI transition" and the necessity of place-based innovation strategies that broaden participation in AI-driven development (Kergroach & Héritier, 2025). The exceptionally fast diffusion of generative AI further sharpens this contrast: adoption can spread globally within months, while low-income countries continue to lag significantly (Liu & Wang, 2024). These patterns suggest that aggregate projections can obscure significant differences in how AI enhances (or fails to enhance) knowledge economies across regions, industries, and organizational types. Recent studies further emphasize that AI-driven growth is inseparable from the problem of digital divides and uneven ecosystem maturity (Prokopenko et al., 2014). Ganushchak et al. (2025) demonstrate that AI-based solutions can support smart circular enterprises only when digital infrastructure, institutional capacity, and access to AI technologies are sufficiently aligned. Their findings highlight that AI may simultaneously act as a growth accelerator and a source of divergence, reinforcing structural inequalities across regions and sectors if ecosystem complementarities remain weak.

AI's macroeconomic relevance also extends beyond output to labor markets, inequality, and systemic stability, all of which condition whether AI-driven performance gains are sustainable. AI can intensify inequality and reinforce bias even when productivity rises, making governance and inclusion integral to the performance architecture rather than external constraints (Filippucci et al., 2024). At the same time, the expanding use of AI in trading and financial services is linked to concerns about herd behavior, correlated models, and concentration in third-party services that could amplify systemic risk (FSB, 2024). Taken together, these considerations indicate that evaluating AI's growth contribution requires disaggregation across pillars and outcomes, rather than relying on a single "AI adoption" narrative.

Against this background, a pillar-sensitive approach, operationalized through subindices such as R&D capability, infrastructure, and public opinion/trust, becomes essential for identifying which components of AI vibrancy translate into productivity and growth and which instead generate redistribution, exclusion, or risk. This orientation directly supports the emphasis on understanding how knowledge (intellectual capital) is formed and used to enhance organizational efficiency and performance, and on producing evidence that is meaningful for both scholarship and managerial and policy practice. In this study, AI is conceptualized not as the adoption of isolated algorithms or applications, but as a multidimensional socio-technical system embedded across research systems, digital infrastructure, governance frameworks, labor markets, and societal attitudes. This interpretation aligns with frameworks advanced by the OECD, International Monetary Fund, and World Bank, which emphasize that AI's economic impact depends on complementary institutional and knowledge-based conditions – pillars of the national AI ecosystem, such as research capacity, infrastructure, governance, skills, and social acceptance, rather than on technology deployment alone.

1. LITERATURE REVIEW

AI has become a central element of contemporary economic development debates, particularly in the context of the transition towards a knowledge-based economy. While international organizations and a growing body of academic literature increasingly portray AI as a potential driver of productivity growth, competitiveness, and structural transformation, there is broad agreement that its economic effects are neither automatic nor uniform across countries. Rather than acting as a single, homogeneous technology, AI operates through a constellation of interrelated technological, institutional, and societal components that jointly shape national innovation capacity and economic performance. As a result, recent research has shifted from analyzing aggregate measures of AI adoption towards examining the architecture of national AI ecosystems, emphasizing the need to disentangle the distinct channels through which AI-related capabilities are developed, governed, and diffused within economies. The ideas that economic growth effects of AI as ecosystem outcomes rather than returns to a single technology, because AI productivity gains depend on complementary pillars such as digital infrastructure, organizational capabilities, human capital, innovation finance, governance, and trust, as well as sectoral diffusion pathways are increasingly rising (Bartosova et al., 2023; Kusairi et al., 2023; Murko et al., 2024; Sitnicki et al., 2024). Within this perspective, "heterogeneity" is not an empirical nuisance but a defining property: countries, regions, firms, and sectors can face very different marginal returns to strengthening any given pillar, depending on their starting conditions, exposure to shocks, and institutional constraints (Prokopenko & Omelyanenko, 2020; Jarzębowski et al., 2024; Bouguerroumi & Belarbi, 2025; Oe et al., 2025).

A knowledge economy architecture that is fit for AI, therefore, requires an explicit mapping between pillars and growth channels, while recognizing that the same pillar may raise output in one context but merely reshuffle value (or amplify risks) in another (Bugrov et al., 2021; Prieto-Gutiérrez et al., 2023; Yarovenko et al., 2024a; Zolkover & Ovcharenko, 2024). The emerging literature supports a move from "AI adoption" as a generic proxy towards a differentiated architecture in which each pillar is linked to

1) productivity and competitiveness;
2) innovation and market valuation;
3) inclusion and public value; and
4) integrity and resilience of the economic system (Jarzębowski et al., 2024; Xue et al., 2025; Yefimenko et al., 2025a; Lyeonov et al., 2024).

Cross-country evidence typically positions digitalization as a broad enabling factor for growth, with foreign direct investment acting as a complementary channel through technology transfer and diffusion (Kusairi et al., 2023). Competitiveness gains are also repeatedly associated with digital transformation intensity; however, the effect varies depending on institutional readiness and the ability to convert digital capacity into export performance and innovation (Jarzębowski et al., 2024). This macro layer is crucial for AI because AI applications are highly complementary to data availability, connectivity, and firm-level digital maturity, making AI more of a conditional amplifier than an autonomous growth engine (Golubtsov et al., 2025; El Massaoudi et al., 2025).

Macroeconomic regimes further shape the realized growth returns to AI investments, because adoption decisions and productivity impacts are exposed to cyclical dynamics, energy-price volatility, and sectoral reallocation (Bouguerroumi & Belarbi, 2025; Abou-Moghli, 2025). This helps explain why the same "AI pillar" can be growth-enhancing in one period or sector yet appear neutral (or even disruptive) elsewhere, particularly when firms delay capital deepening and skills investment under heightened uncertainty (Bouguerroumi & Belarbi, 2025; Yarovenko et al., 2024a).

A consistent strand of evidence treats ICT investment, especially in network industries, as a strategic precondition for broad organizational change and competitive adaptation, implying that the infrastructure pillar can exhibit high growth elasticity where connectivity constraints are binding (Sahnouni & Kadri, 2025). At the organizational

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level, digital transformation can reshape management control, measurement, and decision cycles, which becomes particularly relevant once AI is integrated into monitoring and forecasting functions (El Massaoudi et al., 2025).

Supply chain studies reinforce this logic by indicating that AI-enabled digital technologies can increase operational efficiency. However, the magnitude depends on data integration and process standardization, suggesting strong heterogeneity by firm maturity and sectoral complexity (Golubtsov et al., 2025). In Industry 4.0 settings, immersive and cyber–physical manufacturing configurations (including digital twins and robotics) point to further productivity pathways, yet these remain contingent on high-quality infrastructure and complementary skills (Tymoshenko et al., 2023; Lazaroiu et al., 2024). Consequently, the infrastructure pillar is likely to deliver the largest marginal growth gains where digital bottlenecks constrain diffusion, while offering diminishing returns in already-connected environments unless paired with organizational innovation (Sahnouni & Kadri, 2025; El Massaoudi et al., 2025).

Human capital emerges as a central driver of heterogeneity because AI value creation depends on skills for implementation, interpretation, and governance rather than on tool availability alone (Zimosz & Ober, 2025; Prieto-Gutierrez et al., 2023). Evidence from the energy sector highlights how AI training can support sustainable digital transformation and align technology deployment with green growth strategies, illustrating a pathway from targeted upskilling to sectoral productivity and sustainability outcomes (Abou-Moghli, 2025). Workplace-focused studies similarly link AI use to employee engagement and productivity, implying that human capital interacts with organizational design and incentives rather than acting as a standalone input (Ayu Gusti et al., 2024).

Heterogeneity is also evident in adoption across demographic groups, where the acceptance of AI-enabled digital services (e.g., in insurance) varies due to age-related barriers and trust constraints, suggesting that growth effects may be limited by inclusion gaps even when technologies are available (Chandran & Tholath, 2025). At the macro level, AI-driven job displacement and labor productivity growth are jointly emphasized, implying that growth benefits can co-exist with transitional labor-market pressures and distributional consequences that feed back into political support for AI strategies (Lazaroiu & Rogalska, 2023; Yarovenko et al., 2024a). This positions education and lifelong learning not only as productivity infrastructure but also as a stabilizer of adoption legitimacy and social sustainability (Zimosz & Ober, 2025; Haley, 2025).

AI-related growth effects often materialize through entrepreneurial dynamism, innovation systems, and finance channels that convert capabilities into scalable business models (Mursalov et al., 2023; Ziane et al., 2025). The synergy between entrepreneurial ecosystems and digitalization indicates that ecosystem density and supportive institutions matter for translating technology into new ventures and productivity growth (Mursalov et al., 2023). In knowledge economy settings under stress and reconstruction, targeted support for domestic entrepreneurship is viewed as a mechanism for sustaining innovation capacity and employment, thereby linking ecosystem design to macroeconomic resilience (Sitnicki et al., 2024; Yurchyk et al., 2023).

Financial services transformation provides a particularly clear lens on heterogeneity. The digitalization of finance reshapes market structure and service delivery, but the efficiency and welfare impacts depend on regulatory design and consumer adoption patterns (Kozhushko, 2023; Chandran & Tholath, 2025). Fintech services supported by AI and big data are framed as value co-creation systems, implying that growth contributions depend on platform governance, data access, and partner ecosystems rather than on firm-level adoption alone (Khaddam & Alhanatleh, 2024). InsurTech integration with e-commerce likewise underlines that complementary ecosystem alignment (standards, interoperability, customer experience) can be more decisive than any single technology (Khrais, 2025). Forward-looking analyses of digital economy recovery and fintech trajectories further reinforce that the finance pillar can accelerate diffusion, but also introduces systemic and integrity risks if governance lags behind innovation speed (Polishchuk, 2023; Lyeonov et al., 2024).

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Measurement-focused bibliometric work on efficiency methods in insurance suggests that the evaluation toolkit (e.g., DEA-based assessments) is itself part of the architecture, as credible measurement influences investment allocation and regulatory learning (K. Kumar & J. Kumar, 2024). This supports the argument that the finance pillar encompasses not only capital availability but also the methodological capacity for performance and risk assessment (K. Kumar & J. Kumar, 2024; El Massaoudi et al., 2025).

Governance frameworks are increasingly presented as economic inputs because they shape trust, compliance costs, and the feasibility of scaling AI across sectors (Murko et al., 2024; Haley, 2025). Public governance models integrating AI can influence socioeconomic welfare outcomes; however, the benefits depend on institutional capacity, transparency, and accountability mechanisms, thereby reinforcing cross-country heterogeneity in public-sector returns to AI readiness (Murko et al., 2024; Kuzior et al., 2025). The linkage between government AI readiness and energy security further demonstrates that public capability can shape strategic sectors and thereby influence macro stability and growth potential (Kuzior et al., 2025).

Ethical dimensions are considered material to economic performance when AI is used in enforcement and public health-related contexts, as perceived unfairness or bias can undermine legitimacy and exacerbate inequality, thereby reducing the sustainable component of growth (Haley, 2025). Parallel work connecting digital innovation to energy justice highlights that the distribution of AI-enabled benefits (affordability, access, reliability) matters for equity and long-run welfare (Kirichok et al., 2025).

Integrity and security literatures add another layer: AI and machine learning are positioned as tools against illegal financial operations, but effectiveness depends on institutional coordination, data quality, and regulatory enforcement capacity (Lyeonov et al., 2024; Yarovenko et al., 2024b). Digitalization can also increase cybercrime risks, implying that growth gains from digital and AI adoption may be partially offset by higher security costs and losses if protective institutions lag (Yarovenko et al., 2025). Broader system perspectives connect education, digitalization, and national security, suggesting that knowledge economy architecture must treat security and integrity as core pillars rather than externalities (Samusevych et al., 2021). Structural analyses linking digitalization and technological development to corruption reduction suggest that governance quality and transparency gains can serve as a growth channel, especially where rent-seeking constraints are binding (Yefimenko et al., 2025a; 2025b).

Sectoral studies demonstrate that AI's growth contribution is not uniform, as each sector has distinct production functions, regulations, and data environments. In traditional sectors such as agriculture, AI is presented as enabling better modelling and forecasting, implying productivity gains through improved decision quality and risk management (Hadouga, 2023). In municipal waste management and Industry 4.0 settings, AI-driven automation is linked to operational efficiency and sustainability. However, the investment and governance requirements imply uneven adoption across municipalities and industrial structures (Kajda & Karwot, 2025).

In marketing and commerce, AI appears as both a diffusion accelerant and a value reallocation mechanism (Ustik et al., 2023; Potwora et al., 2024). The normalization of AI in marketing practice is associated with changing competitive dynamics. In contrast, influencer marketing research mapping indicates rapid expansion and shifting tools, implying that gains may concentrate among data-rich platforms and early adopters (Dabija & Frau, 2025; Pilelienė & Bogoyavlenska, 2025). Consumer-side digital behavior research in the fourth industrial revolution suggests that online shopping dynamics evolve with technology intensity, shaping demand patterns and business model innovation (Xuan et al., 2025). These patterns suggest heterogeneous growth effects, depending on whether AI primarily expands total factor productivity or redistributes market share (Dabija & Frau, 2025; Xuan et al., 2025).

The creative and cultural industries provide a further contrast, where expert-based evidence highlights both opportunities and constraints, implying that intangible value creation and IP regimes may dominate over scale efficiencies, there-

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by producing heterogeneous growth responses (Schinello, 2025). Strategic management of creative industries in university information institutions also suggests that knowledge intermediaries and cultural infrastructure are integral to the broader architecture that influences the diffusion of innovation (Bugrov et al., 2021).

High-regulation and science-intensive sectors show distinct heterogeneity. In pharmaceutical R&D, the potential of AI is mediated by investment horizons, researcher incentives, and regulatory validation, implying that the growth channel is long-cycle innovation rather than immediate productivity (Kritikos et al., 2025). Evidence from the enterprise market in China suggests that AI applications can be capitalized into firm valuations, but with likely heterogeneity by sector, governance, and investor expectations (Xue et al., 2025). Construction safety applications utilizing AI-based image analytics highlight that productivity-adjacent benefits may materialize through reduced accidents and improved compliance, rather than output expansion per se (Zaryczańska & Karwot, 2025). The linkage between public health and the digital economy similarly highlights welfare and system performance channels that may not be fully captured by GDP measures, complicating cross-study comparisons of "growth effects" (Kuzior et al., 2024; Haley, 2025).

Bibliometric analyses indicate that AI-related research is expanding across various domains, albeit with uneven maturity, which reflects the heterogeneity of ecosystem pillars. Mapping in project management suggests rising attention to AI-enabled planning and control, indicating that managerial capability is becoming a critical complement to technical deployment (Ibadildin et al., 2025). Bibliometric work in the social sciences indicates a growing methodological engagement with AI, which can strengthen policy design but also highlights fragmentation and varying standards across fields (Prieto-Gutierrez et al., 2023). Bibliometric evidence in illegal financial operations suggests the rapid institutionalization of AI tools in integrity and compliance domains, reinforcing the importance of governance pillars for "safe diffusion" (Lyeonov et al., 2024). These mapping exercises suggest that knowledge economy architecture must consider the research-production interface, where scientific attention, standards, and training pipelines are thin; pillar strengthening may not translate into scalable economic outcomes (Prieto-Gutierrez et al., 2023; Ibadildin et al., 2025).

The literature supports an architecture in which

1) infrastructure and organizational transformation enable baseline diffusion;

2) human capital governs absorption and productivity realization;

3) innovation–entrepreneurship-finance channels convert capabilities into scalable growth; and

4) governance, ethics, and integrity determine legitimacy and resilience, while sectoral pathways define where and how gains appear in the national accounts (Kusairi et al., 2023; Sahnouni & Kadri, 2025; Zimosz & Ober, 2025; Murko et al., 2024; Golubtsov et al., 2025; Koldovskyi et al., 2025).

Heterogeneity across these pillars implies that "one-size-fits-all" AI strategies are likely to underperform: marginal returns to skills investments are higher where infrastructure is adequate but adoption capability is weak. In comparison, returns to infrastructure are higher where connectivity remains the binding constraint (El Massaoudi et al., 2025; Jarzębowski et al., 2024). Similarly, growth strategies that overlook integrity and security may incur hidden costs through cybercrime, persistent corruption, and trust deficits that hinder sustainable diffusion (Yarovenko et al., 2025; Yefimenko et al., 2025a; 2025b; Lyeonov et al., 2024).

A further implication is that public-private coordination matters for pillar alignment, particularly in regional revitalization and traditional industries where market incentives alone may not generate interoperable ecosystems or inclusive outcomes (Oe et al., 2025; Kirichok et al., 2025). Finally, policy relevance is heightened in fragile contexts, where entrepreneurship support and social programs can stabilize labor markets and sustain knowledge economy functions, shaping the feasibility of AI-driven growth (Sitnicki et al., 2024; Yurchyk et al., 2023).

The accumulated evidence suggests that AI contributes to economic growth primarily through complementarities among ecosystem pillars, and the observed cross-country and cross-sector variation is best explained by differences in pillar balance rather than by AI adoption alone. Knowledge economy architecture should therefore be designed as a pillar-sensitive system that jointly develops infrastructure, skills, innovation, finance, and trustworthy governance, because weaknesses in any single pillar can cap the growth returns to advances in the others. A key limitation of the existing empirical literature is the frequent reliance on aggregate AI indicators, which implicitly assume homogeneous economic effects. Such aggregation risks masking opposing mechanisms: investments in AI-related R&D and infrastructure may initially impose adjustment costs, whereas governance, trust, or responsible AI frameworks may yield benefits only over longer horizons. This study, therefore, adopts a pillar-based approach, disaggregating AI development into seven ecosystem dimensions to identify which components contribute to short-term economic performance and which reflect transitional or redistributive dynamics.

This study aims to examine how different pillars of the national AI ecosystem shape the architecture of the knowledge economy and its economic outcomes by estimating heterogeneous within-country associations between GDP per capita and seven AI ecosystem pillars, operationalized through AI Vibrancy subindexes, using a balanced panel of 36 countries with complete data over the period 2020–2023.

2. METHODOLOGY

This study examines the relationship between AI development, as measured by the AI Vibrancy Score and its subindexes, and economic performance, represented by GDP per capita (in constant 2015 US dollars), using a balanced panel of 36 countries from 2020 to 2023. The empirical sample comprises all countries for which complete and consistent data on GDP per capita and the AI Vibrancy Index, including all seven subindexes, were available for the period 2020–2023. The full list of the 36 countries included in the balanced panel is provided in Appendix A. These countries represent a diverse set of advanced and emerging economies, enabling comparative analysis across different stages of AI ecosystem development while maintaining a balanced panel structure. The dependent variable (y) is GDP per capita, sourced from the World Bank (n.d.). The main explanatory variables are the overall AI Vibrancy Score (x) and its seven subindexes obtained from Stanford University (n.d.): Research & Development (R&D, x1), Responsible AI (x2), Economy (x3), Education (x4), Policy and Government (x5), Public Opinion (x6), and Infrastructure (x7). Table 1 summarizes the variables and their sources.

Table 1. Variables and their sources

Variable	Definition	Source
y	GDP per capita (constant 2015 US$)	World Bank, n.d.
x	Vibrancy Score	Stanford University, n.d.
x1	R&D	Stanford University, n.d.
x2	Responsible AI	Stanford University, n.d.
x3	Economy	Stanford University, n.d.
x4	Education	Stanford University, n.d.
x5	Policy and Government	Stanford University, n.d.
x6	Public Opinion	Stanford University, n.d.
x7	Infrastructure	Stanford University, n.d.

Given the skewness and outliers in several variables, transformation procedures were applied to improve normality and variance stability before econometric modelling. The Box–Cox test for GDP per capita suggested an optimal transformation parameter. All seven AI Vibrancy subindexes were transformed using the Yeo-Johnson method, an extension of the Box-Cox procedure that accommodates zero and negative values without arbitrary shifts. This approach effectively reduced skewness and kurtosis, aligning the data more closely with the assumptions of linear panel models.

From an economic perspective, the applied transformations allow the analysis to focus on marginal changes in AI ecosystem intensity rather than absolute scale differences between countries. This is particularly important given the presence of extreme outliers in AI indicators, which reflect global frontier economies and would otherwise dominate the estimation results.

Panel regression analysis was conducted using fixed effects (FE) and random effects (RE) speci-

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fications, with model choice evaluated via the Hausman test. Diagnostic tests for heteroskedasticity, autocorrelation, and cross-sectional dependence were performed. Where violations were detected, robust inference procedures were applied. From an economic perspective, the applied transformations allow the analysis to focus on marginal changes in AI ecosystem intensity rather than absolute scale differences between countries. This is particularly important given the presence of extreme outliers in AI indicators, which reflect global frontier economies and would otherwise dominate the estimation results. The analysis focuses on within-country variation over time to identify the temporal association between changes in AI development dimensions and changes in GDP per capita, while controlling for unobserved country-specific effects.

The empirical strategy prioritizes fixed effects estimation to isolate within-country temporal variation in AI ecosystem development, thereby controlling for time-invariant structural characteristics such as geography, historical development paths, and institutional quality. This approach enables the analysis to distinguish short-run adjustments associated with changes in AI pillars from long-standing cross-country income differences. By focusing on within-country variation and disaggregated AI ecosystem pillars, this study contributes to the literature by explaining why AI may appear growth-enhancing in cross-sectional comparisons yet neutral or negative in short-run panel settings.

The estimated coefficients should be interpreted as short-run within-country associations, not as long-term growth elasticities. Negative coefficients do not imply that AI development is economically harmful per se; rather, they may capture transition costs, reallocation effects, or delayed productivity payoffs that arise during periods of rapid technological restructuring. Given the macro-panel setting and the presence of common global shocks, robust inference using Driscoll-Kraay standard errors is essential to ensure that statistical significance is not driven by cross-sectional dependence or serial correlation.

To account for unobserved heterogeneity across countries, the analysis employs country fixed effects, which control for time-invariant structural characteristics such as historical development paths, institutional quality, and long-run productivity differences. In addition, explicit year dummies are included to capture common global shocks affecting all countries simultaneously during the 2020–2023 period, including post-pandemic recovery dynamics and macroeconomic policy responses.

Statistical inference is based on Driscoll-Kraay standard errors, ensuring robustness to heteroskedasticity, serial correlation, and cross-sectional dependence in the presence of both country-specific and time-specific effects.

All calculations and econometric estimations were performed in RStudio using R version 4.4.0, with the plm, lmtest, and sandwich packages employed.

3. RESULTS

The descriptive statistics (Table 2) from R Studio provide an overview of the variables used in the analysis, with particular focus on the AI Vibrancy Score (x) and GDP per capita in constant 2015 US dollars (y). The dataset covers 252 observations across 36 countries from 2017 to 2023. The variable 'country' has a mean of 18.5, reflecting the coding of 36 countries, while 'year' has a mean of 2020, corresponding to the midpoint of the time span, with an equal distribution across the period.

Table 2. Descriptive statistics (from R Studio)

Statistic indicator	AI Vibrancy Score (x)	GDP per capita (constant 2015 USD y)
Obs (n)	252	252
Mean	18.46	39,151.71
Std. Dev.	85.63	24,860.40
Median	11.18	40,501.44
Trimmed Mean	11.86	36,826.43
MAD	9.02	27,050.43
Min	0.34	1,788.70
Max	1363	110,425.9
Range	1,362.66	108,637.19
Skewness	15.36	0.68
Kurtosis	238.22	0.18
Std. Error	5.39	1,566.00

The AI Vibrancy Score (x) exhibits a mean of 18.46, but its standard deviation (85.63) is substantially higher than the mean, indicating extreme variability between countries and years. The median val-

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ue (11.18) is far lower than the maximum (1,363.0), and the high positive skewness (15.36) combined with extremely high kurtosis (238.22) confirms a heavy-tailed distribution with a few extreme outliers. This suggests that while most countries have relatively low AI Vibrancy Scores, a small number demonstrate exceptionally high values, which can significantly influence the averages. Such distributional properties imply that transformations (e.g., logarithmic) or robust statistical techniques may be needed before applying parametric models.

GDP per capita (y) has a mean of USD 39,151.71, with a standard deviation of USD 24,860.40, indicating significant differences in economic prosperity among the countries. The median (USD 40,501.44) is close to the mean, and skewness (0.68) is moderate, suggesting a slightly right-skewed distribution. The kurtosis value (0.18) indicates a near-normal shape, though the range is wide (from USD 1,788.70 to USD 110,425.90), reflecting the presence of both high-income and low-income economies in the sample. Compared to x, the distribution of y is more balanced, which may lead to more stable regression estimates without requiring strong transformations.

The diagnostic analysis of variable distributions indicated the necessity of data transformation to improve normality and stabilize variance before econometric modelling. For the dependent variable, GDP per capita (y), the Box-Cox transformation was applied to a pooled OLS specification with country and year effects. The estimated transformation parameter was $\lambda \approx 0.10$, close to zero and within the confidence bounds for a log transformation. This suggests that GDP per capita exhibits moderate right skewness and that applying a logarithmic transformation is appropriate. Log transformation not only improves the distributional properties of the residuals but also enables the interpretation of elasticity for regression coefficients, allowing for the assessment of percentage changes in GDP per capita in response to changes in explanatory variables.

For the primary explanatory variable, the AI Vibrancy Score (x), the Yeo–Johnson transformation was employed due to the presence of values close to zero, which precluded the use of a simple Box-Cox transformation. The estimated transformation parameter was $\lambda \approx -0.08$, rounded to zero, with the confidence interval fully encompassing zero. This result indicates that a log-type transformation is suitable for x. Given the distribution's extreme right skewness, a log1p(x) transformation (i.e., log(x + 1)) was chosen, as it accommodates zero or near-zero values while compressing the influence of extreme outliers. This approach substantially reduces skewness and kurtosis, contributing to more robust and reliable coefficient estimates in the panel regression framework.

The one-way (individual) FE model (Table 3), using the log-transformed GDP per capita (y_trans) as the dependent variable and the log-transformed AI Vibrancy Score (x_log1p) as the main regressor, covers 36 countries over seven years (252 balanced panel observations). The estimated coefficient for x_log1p is −0.0346 ($p < 0.001$), indicating that, within a country over time, a 1% increase in the AI Vibrancy Score (approximately) is associated with a 0.0346% decrease in GDP per capita, holding unobserved country-specific effects constant. The within R^2 is relatively low (0.077), which is common in macro-panel settings with a small number of regressors. The F-statistic confirms the joint significance of the included variables ($p < 0.001$).

The one-way RE model (Table 3) produces a slightly smaller (in absolute value) coefficient of −0.0276 ($p < 0.01$). Here, the interpretation reflects both within- and between-country variation. The R^2 value is lower (0.031), but the model retains statistical significance at the 1%.

The Hausman test statistic ($\chi^2 = 1.755$, $p = 0.185$) fails to reject the null hypothesis that the RE estimator is consistent, implying that the RE model is preferable under the maintained assumptions. However, given the similarity in coefficients and significance levels across both estimators, the substantive conclusion of a small but statistically significant negative association between AI Vibrancy Score and GDP per capita remains robust to the model choice.

The diagnostic tests for the RE model indicate several violations of the classical panel data assumptions, suggesting the need for robust inference. The studentized Breusch–Pagan test for heteroskedasticity returns a statistically significant result (BP = 8.94, $p = 0.0028$), indicating that the variance

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Table 3. Summary table of results of FE and RE models

Model Type	FE (1-way)	RE (1-way)
Coefficient (x_log1p)	−0.0346465	−0.027611
Std. Error	0.0081941	0.009765
t/z-value	−4.2282	−2.8275
p-value	0.0000348 ***	0.004691 **
R^2 (within) / Overall	0.0768 (within)	0.0310 (overall)
N (Obs)	252	252
Countries	36	36
Years	7	7
Hausman p-value		0.1853

Note: '***' – 0.001; '**' – 0.01; '*' – 0.05; '.' – 0.1; 'no symbol' – insignificant.

of the idiosyncratic errors is not constant across observations. This heteroskedasticity can lead to biased standard errors if uncorrected, potentially affecting statistical inference.

The Breusch-Godfrey/Wooldridge test strongly rejects the null hypothesis of no serial correlation in the idiosyncratic errors ($\chi^2 = 91.77$, df = 7, $p < 0.0001$). This implies the presence of autocorrelation within the panel units over time, which can further distort standard errors and test statistics if left unaccounted for. In addition, the Pesaran CD test reveals highly significant cross-sectional dependence ($z = 38.65$, $p < 0.0001$), meaning that residuals are correlated across countries. Such dependence may be driven by standard shocks, spillover effects, or unobserved global factors influencing all panel units simultaneously.

Finally, the Breusch-Pagan Lagrange Multiplier test for significant effects is highly significant ($\chi^2 = 301.27$, $p < 0.0001$), confirming the appropriateness of a panel model structure over a pooled OLS model. Taken together, these results suggest that while the RE specification is justified, the presence of heteroskedasticity, serial correlation, and cross-sectional dependence necessitates the use of robust variance-covariance estimators, such as Driscoll-Kraay or cluster-robust standard errors, to obtain reliable statistical inference.

In the baseline RE estimation without robust corrections, the coefficient for the log-transformed AI Vibrancy Score (x_log1p) is −0.0276 and is marginally insignificant at the 10% level ($p = 0.067$). This suggests a weak negative association between AI Vibrancy Score and GDP per capita when standard errors are computed under classical assumptions.

However, after applying Driscoll-Kraay standard errors (robust to heteroskedasticity, serial correlation, and cross-sectional dependence, Table 4), the standard error for x_log1p decreases substantially (from 0.0150 to 0.00884), and the coefficient becomes statistically significant at the 1% level ($p = 0.002$). This indicates that, once model violations are corrected, there is strong evidence of a negative relationship between AI Vibrancy Score and GDP per capita in the panel.

The magnitude of the coefficient implies that, holding other factors constant, a 1% increase in the AI Vibrancy Score is associated with approximately a 0.0276% decrease in GDP per capita, when both variables are log-transformed (elasticity interpretation).

The two-step System GMM estimation (Table 5) was employed to investigate the dynamic relationship between GDP per capita (y_trans) and the AI

Table 4. Outputs of the Driscoll-Kraay and cluster-robust standard errors

Model / SE Type	Variable	Estimate	Std. Error	t-value	p-value	Significance
RE (classical SE)	Intercept	10.364464	0.149979	69.1063	< 2e-16	***
	x_log1p	−0.027611	0.015010	−1.8394	0.06704	.
RE (Driscoll-Kraay robust SE)	Intercept	10.364464	0.334077	31.024	< 2e-16	***
	x_log1p	−0.027611	0.008841	−3.123	0.00200	**

Note: '***' – 0.001; '**' – 0.01; '*' – 0.05; '.' – 0.1; 'no symbol' – insignificant.

Table 5. System GMM estimation results

Variable	Coefficient	Std. Error	z-value	p-value	Significance
lag(y_trans, 1)	1.0019	0.0010	978.73	<0.001	***
lag(x_log1p, 1)	–0.0018	0.0042	–0.4391	0.6606	

Note: '***' – 0.001; '**' – 0.01; '*' – 0.05; '.' – 0.1; 'no symbol' – insignificant.

Vibrancy Score (x_log1p) in a balanced panel of 36 countries spanning seven years. The coefficient on the first lag of GDP per capita is extremely close to unity (1.002, $p < 0.001$), indicating a very high degree of persistence in economic performance over time. In contrast, the coefficient on the first lag of the AI Vibrancy Score is small (–0.0018) and statistically insignificant ($p = 0.661$), suggesting no evidence that past AI vibrancy levels exert a measurable short-term impact on GDP per capita once persistence and other factors are accounted for in the dynamic panel framework.

The diagnostic tests provide mixed signals regarding model validity. The Sargan overidentification test does not reject the null hypothesis of instrument validity ($p = 0.099$), implying that the chosen lag structure for instruments is acceptable. However, the Arellano-Bond serial correlation tests reveal significant first-order autocorrelation in the differenced residuals (AR(1) $p < 0.001$), which is expected, but also significant second-order autocorrelation (AR(2) $p = 0.0066$), which violates a core assumption of the Arellano-Bond estimator. AR(2) suggests that the chosen set of instruments and lag depth may not fully address dynamic misspecification, potentially biasing coefficient estimates. This limitation should be considered when interpreting the insignificant relationship between AI vibrancy and GDP per capita. Alternative specifications with longer lags or different instrument sets may be required to confirm the robustness of the result.

In reconciling these findings, the Random Effects model suggests a positive association between AI vibrancy and GDP per capita, considering both cross-sectional and temporal variations. However, the System GMM estimation does not provide evidence of a statistically significant short-run causal effect once GDP persistence and potential endogeneity are controlled. This divergence suggests that the observed relationship reflects structural, long-term differences across countries rather than short-term within-country dynamics.

3.1. Subindices of the AI Vibrancy score

The dataset consists of 144 observations for 36 cross-sectional units over the period 2020–2023, covering GDP per capita (constant 2015 US$) as the dependent variable (y) and seven explanatory variables (x1–x7), which are subindexes of the AI Vibrancy Score: x1 – Research and Development (R&D), x2 – Responsible AI, x3 – Economy, x4 – Education, x5 – Policy and Government, x6 – Public Opinion, and x7 – Infrastructure.

The AI Vibrancy subindexes display notable variation in their central tendency and dispersion. Mean values range from 0.65 for Responsible AI (x2) to 5.84 for R&D (x1), with substantial differences between minimum and maximum observations across countries and years. Most subindexes exhibit pronounced right-skewness and high kurtosis, indicating distributions dominated by a small number of significant values. This is especially pronounced for x4 (Education), x6 (Public Opinion), and x7 (Infrastructure), with skewness values exceeding 2.9, 11.4, and 3.4, respectively, and extremely high kurtosis, pointing to the influence of extreme outliers. The Infrastructure subindex (x7) and Public Opinion subindex (x6) exhibit highly non-normal distributions.

The dependent variable, GDP per capita (y), has a mean of $39,711.26 (constant 2015 US dollars), ranging from $1,806.50 to $110,425.89. Its skewness (0.70) and kurtosis (0.11) indicate a near-symmetric distribution without substantial heavy-tailedness, which is favorable for econometric modelling.

The descriptive statistics (Table 6) reveal that while GDP per capita is relatively well-behaved in terms of distributional shape, the AI Vibrancy subindexes are heavily skewed and leptokurtic in most cases. These characteristics suggest the presence of outliers and potential heteroscedasticity, implying

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Table 6. Descriptive statistics

Variable	x1	x2	x3	x4	x5	x6	x7	y
Obs	144	144	144	144	144	144	144	144
Mean	5.84	0.65	2.25	0.92	0.97	1.35	1.49	39,711.26
Std. Dev.	4.09	1.01	2.87	1.18	1.44	6.5	2.12	25,440.42
Median	5.06	0.24	1.1	0.47	0.38	0.52	0.84	40,844.03
Min	0.34	0	0.02	0	0	0	0	1,806.5
Max	23.09	5.04	12.08	9	9.05	78	12.9	110,425.9
Range	22.75	5.04	12.06	9	9.05	78	12.9	108,619.4
Skewness	1.58	2.46	1.79	2.92	2.45	11.41	3.41	0.7
Kurtosis	3.77	6.43	2.46	13.98	7.12	131.65	12.88	0.11
Std. Error	0.34	0.08	0.24	0.1	0.12	0.54	0.18	2,120.03

that log or other variance-stabilizing transformations may be necessary for some subindexes to improve the robustness of regression analysis.

The Box-Cox test for the dependent variable, GDP per capita, produced an optimal transformation parameter of $\lambda \approx 0.505$. This value is close to 0.5, indicating that a square root transformation is most suitable for stabilizing variance and improving the normality of residuals. Applying this transformation is expected to enhance the robustness and reliability of subsequent regression estimates.

All seven AI Vibrancy subindexes (x1 – R&D, x2 – Responsible AI, x3 – Economy, x4 – Education, x5 – Policy and Government, x6 – Public Opinion, and x7 – Infrastructure) were transformed using the Yeo–Johnson transformation. This method, an extension of the Box–Cox procedure, was selected because it accommodates zero and negative values without an arbitrary constant shift while addressing skewness and stabilizing variance. Applying the Yeo–Johnson transformation ensures that the distributional properties of the variables are better aligned with the assumptions of the econometric models, thereby improving the robustness and interpretability of the results.

The panel regression results for the transformed dependent variable (y_sqrt) and Yeo-Johnson-transformed AI Vibrancy subindexes (x1_yj–x7_yj) reveal notable differences between the fixed effects (FE) and random effects (RE) specifications.

The FE model (Table 7) explains approximately 46.3% of the total variation in y_sqrt ($R^2 = 0.463$), with the within variation accounting for a substantial share of the explanatory power. Statistically significant adverse effects are found for the R&D subindex (x1_yj, $\beta = -5.676$, $p < 0.001$) and the Infrastructure subindex (x7_yj, $\beta = -16.306$, $p < 0.001$), indicating that, within countries over time, higher scores in these dimensions are associated with lower GDP per capita (after square root transformation). The remaining subindexes do not exhibit statistically significant within-country effects at the 5% level.

In the RE model (Table 7), the intercept is large and highly significant, capturing between-country differences in GDP per capita. Here, R&D (x1_yj, $\beta = -4.467$, $p = 0.041$), Responsible AI (x2_yj, $\beta = 12.976$, $p = 0.028$), and Infrastructure (x7_yj, $\beta = -12.784$, $p = 0.006$) emerge as significant predictors, suggesting that both cross-sectional and temporal variation drive these associations. However, the RE model's R^2 is substantially lower (0.173), reflecting its broader scope but weaker explanatory power within units.

The Hausman test ($\chi^2 = 16.986$, $p = 0.017$) indicates that the FE estimator is preferred, as the null hypothesis of no systematic difference between FE and RE is rejected. This implies that the RE model's estimates are likely inconsistent due to the correlation between the regressors and unobserved individual effects. Consequently, the FE model provides a more reliable basis for inference in this context.

Diagnostic testing of the fixed effects model indicates several violations of classical panel regression assumptions. The Breusch-Pagan tests confirm the presence of heteroskedasticity across entities, with the standard specification (BP = 23.43, df = 7, p = 0.0014) and the panel-specific form accounting for individual effects (BP = 70.69, df = 35, p = 0.00033) both rejecting the null hypothesis of homoskedasticity.

Table 7. Panel regression results for GDP per capita (square root transformation) and Yeo-Johnson-transformed AI Vibrancy subindexes

Variable	FE Coefficient	FE Std. Error	FE p-value	RE Coefficient	RE Std. Error	RE p-value
R&D (x1_yj)	−5.6756	1.4772	0.0002 ***	−4.4672	2.1838	0.0408 *
Responsible AI (x2_yj)	5.7735	4.0205	0.1541	12.9763	5.9202	0.0284 *
Economy (x3_yj)	−0.5177	2.0318	0.7994	3.0033	3.0009	0.3169
Education (x4_yj)	−2.0999	3.0570	0.4937	0.8960	4.5263	0.8431
Policy & Government (x5_yj)	−4.8410	4.5095	0.2856	1.1322	6.6378	0.8646
Public Opinion (x6_yj)	−9.1257	5.7067	0.1129	2.0549	8.3478	0.8056
Infrastructure (x7_yj)	−16.3065	3.1661	0.0000 ***	−12.7839	4.6874	0.0064 **

Note: '***' – 0.001; '**' – 0.01; '*' – 0.05; '.' – 0.1; 'no symbol' – insignificant.

Tests for autocorrelation in the idiosyncratic errors also yield significant results. The Breusch-Godfrey/Wooldridge test ($\chi^2 = 44.35$, df = 4, $p < 0.0001$) and the Wooldridge test for serial correlation in fixed effects panels ($F = 16.94$, $p < 0.0001$) both indicate strong evidence of first-order autocorrelation.

Furthermore, Pesaran's CD test for cross-sectional dependence rejects the null hypothesis of independence ($z = 5.54$, $p < 0.0001$), suggesting that unobserved shocks are likely correlated across countries in the sample.

These results collectively indicate that the model suffers from heteroskedasticity, serial correlation, and cross-sectional dependence, necessitating the use of robust inference procedures, such as Driscoll-Kraay or panel-corrected standard errors, to obtain consistent and reliable statistical inferences.

Given the evidence of heteroskedasticity, autocorrelation, and cross-sectional dependence, the fixed effects model was re-estimated using heteroskedasticity-robust standard errors and Driscoll-Kraay standard errors, which are robust to all three issues. The results remain broadly consistent with the initial estimates, confirming the stability of the coefficient signs and magnitudes.

The fixed effects estimation with heteroskedasticity-robust standard errors (Table 8) reveals that only three AI Vibrancy subindexes exhibit statistically significant within-country effects on GDP per capita (after taking the square root transformation). The R&D subindex (x1_yj) exhibits a strong and significant negative association ($\beta = -5.676$, $p < 0.001$), indicating that, holding other factors constant, an increase in R&D scores is associated with a decrease in GDP per capita within a country over time. The Infrastructure subindex (x7_yj) also demonstrates a large and highly significant negative relationship ($\beta = -16.306$, $p < 0.001$), indicating that higher infrastructure scores are associated with lower GDP per capita within the dimension. Public Opinion (x6_yj) presents a statistically significant adverse effect ($\beta = -9.126$, $p = 0.040$), implying that public opinion scores are associated with reduced GDP per capita.

The remaining subindexes (Responsible AI (x2_yj), Economy (x3_yj), Education (x4_yj), and Policy & Government (x5_yj)) do not display statistically significant within-country effects, suggesting their influence on GDP per capita is either mini-

Table 8. Fixed effects model with heteroskedasticity-robust standard errors

Variable	Estimate	Std. Error	t-value	p-value	Significance
R&D (x1_yj)	−5.6756	1.6228	−3.497	0.0007	***
Responsible AI (x2_yj)	5.7735	3.7484	1.540	0.1266	
Economy (x3_yj)	−0.5177	1.3034	−0.397	0.6921	
Education (x4_yj)	−2.0999	4.2623	−0.493	0.6233	
Policy & Government (x5_yj)	−4.8410	4.2734	−1.133	0.2600	
Public Opinion (x6_yj)	−9.1257	4.3906	−2.078	0.0402	*
Infrastructure (x7_yj)	−16.3065	2.8623	−5.697	<0.0001	***

Note: '***' – 0.001; '**' – 0.01; '*' – 0.05; '.' – 0.1; 'no symbol' – insignificant.

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mal or operates primarily through between-country variation not captured by the FE estimator.

For Driscoll-Kraay standard errors, the R&D subindex (x1_yj) retains a significant negative association with GDP per capita ($\beta = -5.676$, $p = 0.001$), indicating that within-country increases in R&D scores are linked to lower GDP per capita after accounting for the square root transformation of the dependent variable. The Infrastructure subindex (x7_yj) also remains highly significant and negative ($\beta = -16.306$, $p < 0.001$), indicating that higher infrastructure scores are associated with lower GDP per capita within the country.

Responsible AI (x2_yj) becomes marginally significant ($\beta = 5.773$, $p = 0.065$), pointing to a possible positive relationship that warrants further investigation. Public Opinion (x6_yj) also approaches marginal significance ($\beta = -9.126$, $p = 0.054$), indicating a potential negative association. The remaining subindexes (x3_yj, x4_yj, x5_yj) show no statistically significant within-country effects.

The within-country analysis (Table 10) reveals that three AI Vibrancy subindexes have a statistically significant impact on GDP per capita. R&D and Infrastructure consistently display strong negative associations, suggesting that increases in these scores are linked to lower GDP per capita over time within countries. Public Opinion also exhibits an adverse effect, although its significance is less robust across specifications. The remaining subindexes (Responsible AI, Economy, Education, and Policy & Government) do not demonstrate significant within-country effects, implying their relationship with GDP per capita is either weak or driven mainly by between-country differences rather than temporal variation within countries.

The estimated country-specific effects from the fixed effects model reveal substantial heterogeneity in baseline economic performance after controlling for within-country changes in AI ecosystem pillars. These effects capture time-invariant structural characteristics, such as historical development paths, institutional quality, industrial structure, and long-term productivity levels, that systematically differentiate countries in terms of GDP per capita. The highest positive effects are observed for Luxembourg (369.6), Ireland (337.2), Switzerland (328.8), Norway (311.2), Singapore (296.8), and the United States (283.9), reflecting their advanced knowledge-economy structures, strong institutional frameworks, and sustained high-income levels. These values indicate that, ceteris paribus, these economies operate at significantly higher baseline levels of economic performance than the average of the panel.

A second group of countries, including Denmark, Australia, Sweden, the Netherlands, Finland, the United Kingdom, Canada, Germany, Austria, Belgium, and France, also exhibits strong positive country effects, suggesting well-established but more diversified economic structures. These economies combine advanced AI ecosystems with mature industrial and service sectors, where productivity gains are more incremental. Their intermediate-to-high fixed effects are consistent with the literature, which emphasizes that advanced economies may experience diminishing short-run returns to technological expansion once a high development threshold has been reached.

In contrast, emerging and middle-income economies such as India (52.5), South Africa (90.0), Brazil (100.9), Mexico (110.2), Russia (110.3), China (118.1), Malaysia (126.9), and Turkey (131.4) display markedly lower country effects. These val-

Table 9. Fixed effects model with Driscoll-Kraay robust standard errors

Variable	Estimate	Std. Error	t-value	p-value	Significance
R&D (x1_yj)	−5.6756	1.6867	−3.365	0.0011	**
Responsible AI (x2_yj)	5.7735	3.0896	1.869	0.0646	
Economy (x3_yj)	−0.5177	1.2713	−0.407	0.6847	
Education (x4_yj)	−2.0999	4.1935	−0.501	0.6176	
Policy & Government (x5_yj)	−4.8410	4.6776	−1.035	0.3032	
Public Opinion (x6_yj)	−9.1257	4.6865	−1.947	0.0543	.
Infrastructure (x7_yj)	−16.3065	3.0262	−5.389	<0.0001	***

Note: '***' – 0.001; '**' – 0.01; '*' – 0.05; '.' – 0.1; 'no symbol' – insignificant.

Table 10. Country-specific fixed effects from the fixed effects model

Country	Fixed Effect	Country	Fixed Effect	Country	Fixed Effect
Luxembourg	369.608	Canada	236.610	Saudi Arabia	170.406
Ireland	337.238	Austria	235.798	Portugal	169.865
Switzerland	328.779	United Arab Emirates	234.613	Estonia	173.973
Norway	311.200	Belgium	229.913	Poland	140.026
Singapore	296.848	Israel	227.814	Turkey	131.396
United States	283.906	New Zealand	228.254	Malaysia	126.857
Denmark	271.796	Germany	231.088	China	118.129
Australia	269.067	France	216.550	Russia	110.276
Sweden	259.200	Japan	209.944	Mexico	110.216
Netherlands	251.098	South Korea	204.454	Brazil	100.876
Finland	247.542	Italy	199.130	South Africa	89.965
United Kingdom	241.120	Spain	180.264	India	52.477

Note: Fixed effects are estimated from the within (fixed effects) panel model with GDP per capita (square root transformed) as the dependent variable. Higher values indicate stronger time-invariant baseline economic performance relative to the panel mean.

ues do not imply weaker AI potential but rather reflect structural constraints and developmental gaps, including lower capital intensity, institutional frictions, and incomplete knowledge-economy architectures, that shape long-term income levels. Overall, the dispersion of country effects underscores the importance of distinguishing between structural (between-country) differences and dynamic (within-country) AI-related adjustments, reinforcing the methodological choice to focus on within-country variation when estimating the economic impact of AI ecosystem pillars.

The estimated model (Table 11) is a one-way (individual) fixed effects specification augmented with explicit year dummies to control for common temporal shocks. This approach isolates within-country variation while flexibly capturing time-specific effects without imposing a full two-way fixed effects structure.

Once year dummies are introduced, none of the AI ecosystem pillars exhibit statistically significant within-country effects on GDP per capita. This finding is robust to inference based on Driscoll-Kraay standard errors, indicating that the lack of significance is not driven by heteroskedasticity, serial correlation, or cross-sectional dependence. Compared with earlier specifications without time controls, the attenuation of AI coefficients suggests that part of the previously observed variation reflects common macroeconomic dynamics rather than country-specific changes in AI ecosystem development.

By contrast, the estimated time dummies are large and highly significant across all specifications. Relative to the base year (2020), GDP per capita increased substantially in 2021 ($\beta \approx 5.84$), 2022 ($\beta \approx 8.05$), and 2023 ($\beta \approx 8.33$), with all coefficients remaining significant under Driscoll-Kraay inference ($p < 0.001$). These results capture global shocks that affect all countries simultaneously, such as the post-pandemic recovery, coordinated fiscal and monetary responses, and broad investment cycles. The high explanatory power of the model (within $R^2 = 0.70$) confirms that short-term economic dynamics during 2020–2023 were dominated by time-specific global factors rather than by contemporaneous adjustments in national AI ecosystem pillars.

Table 11. One-way fixed effects model with time dummies and Driscoll-Kraay standard errors

Observations: 144		Countries: 36	Within R^2: 0.702	
Variable	**Estimate**	**FE Std. Error**	**DK Std. Error**	**DK p-value**
Year 2021	5.843***	0.935	1.219	<0.001
Year 2022	8.050***	0.932	1.240	<0.001
Year 2023	8.330***	1.081	1.202	<0.001

Notes: The model includes country fixed effects and explicit year dummies. Driscoll-Kraay standard errors are robust to heteroskedasticity, serial correlation, and cross-sectional dependence. *** denotes significance at the 1% level.

The estimated country fixed effects reveal pronounced structural differences in baseline economic performance across countries, reflecting long-standing disparities in institutional quality, productive capacity, and the maturity of nation-

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al knowledge economies. In contrast, the strong and statistically significant time effects suggest that short-term fluctuations in GDP per capita from 2020 to 2023 were primarily driven by common global shocks rather than contemporaneous changes in national AI ecosystem pillars.

4. DISCUSSION

The results of this study offer nuanced insights into the economic implications of AI development, aligning with, yet also diverging from, the expectations established by prior research. At the macroeconomic level, earlier studies by the OECD (Filippucci et al., 2024) and IMF (Cerutti et al., 2025) emphasized AI's potential to boost productivity and contribute positively to GDP growth, albeit with uneven distribution across countries. However, the fixed effects results here suggest that, within countries over time, specific AI dimensions (specifically, R&D and Infrastructure) are associated with statistically significant adverse effects on GDP per capita. This finding contrasts with the general macro-level optimism, suggesting that the short-term within-country dynamics of AI investment may involve transitional costs, resource reallocation, or lags between capability building and economic payoff, as also hinted by Yarovenko et al. (2025) in their work on digitalization's transitional impacts.

At the sectoral and organizational level, prior literature has documented efficiency gains from AI adoption in manufacturing, logistics, marketing, and public administration (Golubtsov et al., 2025; Dabija & Frau, 2025). The lack of significant within-country effects for Economy, Education, and Policy & Government subindexes in this study suggests that these benefits, while potentially significant in cross-sectional comparisons, may not translate into measurable short-term GDP per capita gains in panel settings. This echoes findings from Kusairi et al. (2023) and Jarzębowski et al. (2024), who emphasize that sectoral AI benefits can be offset by adjustment costs, uneven adoption, or insufficient absorptive capacity at the national level.

The negative within-country association between Public Opinion and GDP per capita also warrants attention. While Yarovenko et al. (2024a) and Kuzior et al. (2024) emphasize the importance of public trust and acceptance for the successful integration of AI, the results presented here may suggest that heightened public engagement or concern could reflect societal resistance, ethical debates, or regulatory interventions that slow the pace of economic gains. This interpretation aligns with OECD warnings (Kergroach & Héritier, 2025) about the potential drag on AI-driven growth from unresolved governance and ethical issues. Ethical considerations are increasingly emerging as economically relevant dimensions of AI deployment, rather than purely normative constraints. Bashynska (2025) argues that ethical AI practices in the circular economy influence not only social acceptance but also long-term efficiency and value creation by reducing reputational risks, regulatory friction, and misallocation of resources. This supports the interpretation that Responsible AI may generate positive economic effects primarily over longer horizons, while short-term growth indicators may fail to capture these benefits.

Finally, the marginally positive but statistically weak relationship between Responsible AI and GDP per capita in robust specifications supports the argument advanced by Kuzior et al. (2024) and Haley (2025) that embedding ethical and inclusive AI practices may enhance economic outcomes over time. The divergence between short-term panel estimates and the cross-sectional or simulation-based optimism in IMF and OECD projections underscores the analytical value of disaggregating AI into its subcomponents. By distinguishing between AI dimensions that may temporarily depress GDP during adaptation phases and those that could yield net gains, this study provides empirical evidence in support of the call by Golubtsov et al. (2025) and Yarovenko et al. (2025) to tailor AI strategies according to specific development stages and institutional contexts.

This study is subject to several limitations that should be acknowledged. First, the analysis is based on a balanced panel covering only 36 countries over the 2020–2023 period, which constrains the temporal scope and may limit the generalizability of findings to longer-term dynamics. Second, while using Yeo-Johnson and Box-Cox transformations improves normality and variance stability, interpreting transformed coefficients may be less intuitive for policymakers and practitioners. Third, the fixed effects approach captures only within-country variation and does not account for potential long-run relationships that alternative modelling strategies, such as dynamic panel methods or cointegration techniques, might better capture. Fourth, despite the application of Driscoll-Kraay robust standard errors to address heteroskedasticity, autocorrelation, and cross-sectional dependence, other sources of endogeneity, such as reverse causality between GDP per capita and AI Vibrancy subindexes, cannot be entirely ruled out. Finally, the study relies on composite indices from publicly available sources, such as those from Stanford University (n.d.) and the World Bank (n.d.), which, although authoritative, may contain measurement biases or methodological limitations inherent in their construction.

CONCLUSION

This study aims to examine how different pillars of the national AI ecosystem shape the architecture of the knowledge economy and its economic outcomes by estimating heterogeneous within-country associations between GDP per capita and seven AI ecosystem pillars, operationalized through AI Vibrancy subindexes, using a balanced panel of 36 countries with complete data over the period 2020–2023.

The study uses a balanced panel dataset from the World Bank with AI Vibrancy indicators from Stanford University. Fixed- and random-effects models were estimated, with the Hausman test supporting the fixed-effects specification. Robust and Driscoll–Kraay standard errors were applied to address heteroskedasticity, serial correlation, and cross-sectional dependence.

The results show that short-run economic effects of AI development are highly heterogeneous across ecosystem pillars. Within countries, increases in AI-related R&D and Infrastructure are associated with statistically significant declines in GDP per capita ($\beta = -5.676$ and $\beta = -16.306$, both $p < 0.001$), indicating the presence of transitional adjustment costs rather than immediate growth gains. Responsible AI displays a marginally positive association ($\beta = 5.773$, $p \approx 0.065$), suggesting that governance- and ethics-oriented AI development may yield more favorable economic effects even in the short term. At the same time, strong country fixed effects (e.g., Luxembourg 369.6 vs. India 52.5) and sizable common time shocks (+5.84 in 2021, +8.05 in 2022, +8.33 in 2023) confirm that structural differences and global macroeconomic dynamics dominate short-term GDP movements relative to contemporaneous changes in AI ecosystem pillars.

From a policy perspective, the results highlight the importance of aligning AI-related investments and strategies with broader economic and social priorities. Policymakers should ensure that R&D activities are effectively translated into productivity gains, infrastructure investments are balanced with economic absorptive capacity, and public opinion is managed through transparent and inclusive AI governance. Furthermore, policies promoting responsible AI practices may yield positive economic outcomes, underscoring the value of ethical frameworks and trust-building in maximizing the benefits of AI adoption.

AUTHOR CONTRIBUTIONS

Conceptualization: Kalilla Abdullayev, Kalamkas Rakhimzhanova, Artsrun Avetikyan, Andrii Zolkover, Alina Danileviča, Mykola Povoroznyk, Yong Zhou.
Data curation: Yong Zhou.
Formal analysis: Yong Zhou.
Funding acquisition: Alina Danileviča.
Investigation: Yong Zhou.
Methodology: Yong Zhou.

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Project administration: Kalamkas Rakhimzhanova.
Resources: Alina Danileviča, Yong Zhou.
Software: Yong Zhou.
Supervision: Kalilla Abdullayev.
Validation: Andrii Zolkover, Yong Zhou.
Visualization: Artsrun Avetikyan, Yong Zhou.
Writing – original draft: Kalilla Abdullayev, Kalamkas Rakhimzhanova, Artsrun Avetikyan, Andrii Zolkover, Alina Danileviča, Mykola Povoroznyk, Yong Zhou.
Writing – review & editing: Kalilla Abdullayev, Kalamkas Rakhimzhanova, Artsrun Avetikyan, Andrii Zolkover, Alina Danileviča, Mykola Povoroznyk, Yong Zhou.

REFERENCES

1. Abou-Moghli, A. (2025). Sustainable digital transformation in the energy sector: The role of artificial intelligence training in achieving Jordan's green growth strategy. *Environmental Economics, 17*(1), 1-11. https://doi.org/10.21511/ee.17(1).2026.01
2. Ayu Gusti, M., Satrianto, A., Candrianto, Juniardi, E., & Fitra, H. (2024). Artificial intelligence for employee engagement and productivity. *Problems and Perspectives in Management, 22*(3), 174-184. https://doi.org/10.21511/ppm.22(3).2024.14
3. Bartosova, V., Drobyazko, S., Bielialov, T., Nechyporuk, L., & Dzhyhora, O. (2023). Company strategic change management in the open innovation system. *Journal of Open Innovation: Technology, Market, and Complexity, 9*(2), 100087. https://doi.org/10.1016/j.joitmc.2023.100087
4. Bashynska, I. (2025). Ethical aspects of AI use in the circular economy. *AI & Society* https://doi.org/10.1007/s00146-025-02436-1
5. Bouguerroumi, H., & Belarbi, Y. (2025). Cyclicality and Economic Growth Dynamics: Business Cycles' Typologization, Dating, and Matching with Oil Price Fluctuations. *Financial Markets, Institutions and Risks, 9*(1), 59-73. https://doi.org/10.61093/fmir.9(1).59-73.2025
6. Bugrov, V., W. Sitnicki, M., & Serbin, O. (2021). Strategic management of creative industries: A case study of university information institutions. *Problems and Perspectives in Management, 19*(2), 453-467. https://doi.org/10.21511/ppm.19(2).2021.36
7. Cerutti, E., García Pascual, A., Kido, Y., Li, L., Melina. G., Tavares, M. M., & Wingender, P. (2025). *The Global Impact of AI: Mind the Gap* (IMF Working Paper No. 25/76). Retrieved from https://www.imf.org/-/media/files/publications/wp/2025/english/wpiea2025076-print-pdf.pdf
8. Chandran, K. R. P., & Tholath, D. I. (2025). Digital insurance acceptance among older adults in the context of AI. *Insurance Markets and Companies, 16*(1), 131-145. https://doi.org/10.21511/ins.16(1).2025.11
9. Dabija, D. C., & Frau, M. (2025). Leveraging artificial intelligence in marketing: Trend or the new normal? *Oeconomia Copernicana, 15*(4), 1173-1181. https://doi.org/10.24136/oc.3390
10. El Massaoudi, E. M., El Hammoumi, A., Seghyar, N., & El Ouali, A. (2025). Digital transformation and improvement of management control: Empirical study in financial institutions. *Investment Management and Financial Innovations, 22*(3), 455-469. https://doi.org/10.21511/imfi.22(3).2025.34
11. Filippucci, F., Gal, P., Jona-Lasinio, C., Leandro, A., & Nicoletti, G. (2024). The impact of Artificial Intelligence on productivity, distribution and growth: Key mechanisms, initial evidence and policy challenges. *OECD Artificial Intelligence Papers, 15*. Retrieved from https://www.oecd.org/content/dam/oecd/en/publications/reports/2024/04/the-impact-of-artificial-intelligence-on-productivity-distribution-and-growth_d54e2842/8d900037-en.pdf
12. Financial Stability Board (FSB). (2024). *The Financial Stability Implications of Artificial Intelligence*. Financial Stability Board Reports to the G20. Retrieved from https://www.fsb.org/uploads/P14112024.pdf
13. Ganushchak, I., Bashynska, I., Ognjanovic, I., Duda, J., & Kusa, R. (2025). AI-driven approaches to bridging the digital divide and advancing smart circular enterprises. *Journal of Intelligent and Fuzzy Systems,* 0(0). https://doi.org/10.1177/18758967251392651
14. Golubtsov, D., Kedziora, J., Kozhakhmetova, A., & Kedziora, D. (2025). Assessing the impact of digital technologies and artificial intelligence (AI) on the efficiency of supply chain. *Economics and Sociology, 18*(1), 149-173. https://doi.org/10.14254/2071-789X.2025/18-1/8
15. Hadouga, H. (2023). Leadership in Agriculture: Artificial Intelligence for Modelling and Forecasting Growth in the Industry. *Business Ethics and Leadership, 7*(3), 13-19. https://doi.org/10.61093/bel.7(3).13-19.2023
16. Haley, P. (2025). Artificial Intelligence and Ethical Dimensions of Automated Traffic Enforcement: Implications for Public Health, Healthcare Equity, and Social Justice. *Health Economics and Management Review, 6*(2),

32-49. https://doi.org/10.61093/hem.2025.2-03

17. Ibadildin, N., Kenzhin, Z., Yeshenkulova, G., Ismailova, R., Nurguzhina, A., Nassanbekova, S., & Kadyrova, A. (2025). Artificial intelligence in project management: A bibliometric analysis. *Problems and Perspectives in Management, 23*(2), 252-264. https://doi.org/10.21511/ppm.23(2).2025.17

18. Jarzębowski, S., Bozhenko, V., Didorenko, K., Tkachenko, O., Blyznyukov, A., Melnyk, M., & Cieslik, J. (2024). The Impact of Digitalisation on the Competitiveness of European Countries. *SocioEconomic Challenges, 8*(3), 238-261. https://doi.org/10.61093/sec.8(3).238-261.2024

19. Kajda, K., & Karwot, J. (2025). The Role of Artificial Intelligence in Revolutionizing Industrial Automation for Municipal Waste Management in Industry 4.0. *Green Transition and Sustainable Development, 1*(1), 37-63. https://doi.org/10.61093/gtsd.1(1).37-63.2025

20. Kergroach, S. & J. Héritier (2025). *Emerging divides in the transition to artificial intelligence* (OECD Regional Development Papers No. 147). Paris: OECD Publishing. https://doi.org/10.1787/7376c776-en

21. Khaddam, A., & Alhanatleh, H. (2024). Role of artificial intelligence and BIG DATA capabilities on fintech services: Value cocreation theory. *Innovative Marketing, 20*(4), 219-233. https://doi.org/10.21511/im.20(4).2024.19

22. Khrais, L. (2025). Bridging gaps in InsurTech and e-commerce integration: Insights from Saudi Arabia. *Insurance Markets and Companies, 16*(1), 64-73. https://doi.org/10.21511/ins.16(1).2025.06

23. Kirichok, O., Orlovska, Y., Zhanseitova, G., Oriekhova, A., Babaiev, D., Havrylenko, O., & Vasylieva, T. (2025). Bridging digital innovation and energy justice: The role of artificial intelligence in advancing energy equity. *Environmental Economics, 16*(4), 166-181. https://doi.org/10.21511/ee.16(4).2025.11

24. Koldovskyi, A., Babenko, K., Shafranova, K., & Dyvynska, Y. (2025). The Role of AI in Enhancing Sustainable Business Leadership and Organizational Resilience. *Business Ethics and Leadership, 9*(2), 188-199. https://doi.org/10.61093/bel.9(2).188-199.2025

25. Kozhushko, I. (2023). Transformation of the Financial Services Industry in the Context of Digital Economy. *Financial Markets, Institutions and Risks, 7*(4), 189-200. https://doi.org/10.61093/fmir.7(4).189-200.2023

26. Kritikos, I., Sarantopoulos, A., Roumeliotis, A., Vasiliades, J., & Matsinas, I. (2025). Unlocking the Potential of Artificial Intelligence in Pharma Research and Development: Insights from Investor and Researcher Perspectives. *Health Economics and Management Review, 6*(2), 1-16. https://doi.org/10.61093/hem.2025.2-01

27. Kumar, K. S. D., & Kumar, J. P. S. (2024). Efficiency assessment and trends in the insurance industry: A bibliometric analysis of DEA application. *Insurance Markets and Companies, 15*(1), 83-98. https://doi.org/10.21511/ins.15(1).2024.07

28. Kusairi, S., Wong, Z. Y., Wahyuningtyas, R., & Sukemi, M. N. (2023). Impact of digitalisation and foreign direct investment on economic growth: Learning from developed countries. *Journal of International Studies, 16*(1), 98-111. https://doi.org/10.14254/2071-8330.2023/16-1/7

29. Kuzior, A., Bielialov, T., Morozova, O., Vasiltsova, O., Rubanov, P., Holub, I., & Lyeonov, S. (2025). Does a country's energy security increase with advances in government AI readiness? An empirical panel study. *Environmental Economics, 16*(4), 182-196. https://doi.org/10.21511/ee.16(4).2025.12

30. Kuzior, A., Marszałek-Kotzur, I., Kurovska, Y., & Chvankin, Y. (2024). The Role of Digital Economy in Transformation of Public Health: Modeling and Analysis. *Health Economics and Management Review, 5*(4), 91-109. https://doi.org/10.61093/hem.2024.4-06

31. Lazaroiu, G., & Rogalska, E. (2023). How generative artificial intelligence technologies shape partial job displacement and labor productivity growth. *Oeconomia Copernicana, 14*(3), 703-706. https://doi.org/10.24136/oc.2023.020

32. Lazaroiu, G., Gedeon, T., Valaskova, K., Vrbka, J., Šuleř, P., Zvarikova, K., Kramarova, K., Rowland, Z., Stehel, V., Gajanova, L., Horák, J., Grupac, M., Caha, Z., Blazek, R., Kovalova, E., & Nagy, M. (2024). Cognitive digital twin-based Internet of Robotic Things, multi-sensory extended reality and simulation modeling technologies, and generative artificial intelligence and cyber-physical manufacturing systems in the immersive industrial metaverse. *Equilibrium. Quarterly Journal of Economics and Economic Policy, 19*(3), 719-748. https://doi.org/10.24136/eq.3131

33. Liu, Y., & Wang, H. (2024). *Who on Earth Is Using Generative AI?* (World Bank Policy Research Working Paper No. 10870). Digital Development Global Practice. Retrieved from https://documents1.worldbank.org/curated/en/099720008192430535/pdf/IDU15f321eb-5148701472d1a88813ab-677be07b0.pdf

34. Lyeonov, S., Draskovic, V., Kubaščikova, Z., & Fenyves, V. (2024). Artificial intelligence and machine learning in combating illegal financial operations: Bibliometric analysis. *Human Technology, 20*(2), 325-360. https://doi.org/10.14254/1795-6889.2024.20-2.5

35. Murko, E., Babšek, M., & Aristovnik, A. (2024). Artificial intelligence and public governance models in socioeconomic welfare: some insights from Slovenia. *Administratie si Management Public, 43,* 41-60. https://doi.org/10.24818/amp/2024.43-03

36. Mursalov, M., Yarovenko, H., & Vasilyeva, T. (2023). Entrepreneurial Ecosystem and digitalization: Relationship and Synergy of Development. In: Strielkowski, W. (Eds.), *Leadership, Entrepreneur-*

ship and Sustainable Development Post COVID-19. NILBEC 2022. Springer Proceedings in Business and Economics (pp. 109-127). Springer, Cham. https://doi.org/10.1007/978-3-031-28131-0_9

37. Oe, H., Yamaoka, Y., & Weeks, M. (2025). Public-Private Partnerships in Traditional Industries: A Comparative Governance Framework for Regional Revitalization in Japan and Central Europe. *Public Governance, Regulation and Law, 1*(1), 1-15. https://doi.org/10.61093/pgrl.1(1).1-15.2025

38. Pilelienė, L., & Bogoyavlenska, Y. (2025). Artificial intelligence in influencer marketing: Current researchscape, trends and insights from a bibliometric review. *Equilibrium. Quarterly Journal of Economics and Economic Policy, 20*(2), 583-611. https://doi.org/10.24136/eq.3783

39. Polishchuk, Y. (2023). Fintech future trends. In Lubacha, J., Maihaniemi, B., & Wisła, R. (Eds.), *The European digital economy: Drivers of digital transition and economic recovery* (pp. 204-220). Routledge. https://doi.org/10.4324/9781003450160-15

40. Potwora, M., Vdovichena, O., Semchuk, D., Lipych, L., & Saienko, V. (2024). The use of artificial intelligence in marketing strategies: Automation, personalization and forecasting. *Journal of Management World, 2,* 41-49. https://doi.org/10.53935/jomw.v2024i2.275

41. Prieto-Gutierrez, J.-J., Segado-Boj, F., & Da Silva França, F. (2023). Artificial intelligence in social science: A study based on bibliometrics analysis. *Human Technology, 19*(2), 149-162. https://doi.org/10.14254/1795-6889.2023.19-2.1

42. Prokopenko, O., & Omelyanenko, V. (2020). Intellectualization of the phased assessment and use of the potential for internationalizing the activity of clusters of cultural and creative industries in the Baltic Sea regions. *TEM Journal, 9*(3), 1068-1075. https://doi.org/10.18421/TEM93-31

43. Prokopenko, O., Eremenko, Y., & Omelyanenko, V. (2014). Role of international factor in innovation ecosystem formation. *Economic Annals-XXI, 3-4*, 4-7. Retrieved from http://ea21journal.world/index.php/ea-v140-01/

44. Reuters. (2025). *AI economic gains likely to outweigh emissions cost, says IMF*. Retrieved from https://www.reuters.com/sustainability/climate-energy/ai-economic-gains-likely-outweigh-emissions-cost-says-imf-2025-04-22

45. Sahnouni, M., & Kadri, M. (2025). Investments in ICT in the Telecommunications Sector: A Strategic Imperative for Organizational Changes in Response to Market Transformations. *Financial Markets, Institutions and Risks, 9*(2), 112-122. https://doi.org/10.61093/fmir.9(2).112-122.2025

46. Samusevych, Y. V., Novikov, V. V., Artyukhov, A. Y., & Vasylieva, T. A. (2021). Convergence trends in the "economy – education – digitalization – national security" chain. *Naukovyi Visnyk Natsionalnoho Hirnychoho Universytetu, 6,* 177-183. https://doi.org/10.33271/nvngu/2021-6/177

47. Schinello, S. (2025). Challenges and opportunities in using artificial intelligence in creative economy: Insights from expert interviews. *Economics and Sociology, 18*(1), 199-216. https://doi.org/10.14254/2071-789X.2025/18-1/10

48. Sitnicki, M. W., Horbas, I., Derkach, O., Flowers, A., Wielewska, I., Tucki, K., Zuzek, D. K., & Pimenov, S. (2024). Development and Support of Ukrainian Domestic Entrepreneurship in the Knowledge Economy. *Sustainability, 16*(13), 5682. https://doi.org/10.3390/su16135682

49. Stanford University. (n.d.). *Global AI Vibrancy Tool - AI Index*. Stanford University Human-Centered Artificial Intelligence. Retrieved from https://aiindex.stanford.edu/vibrancy

50. Tymoshenko, M., Saienko, V., Serbov, M., Shashyna, M., & Slavkova, O. (2023). The impact of Industry 4.0 on modelling energy scenarios of the developing economies. *Financial and Credit Activity-Problems of Theory and Practice, 1*(48), 336-350. https://doi.org/10.55643/fcaptp.1.48.2023.3941

51. Ustik, T., Karmazinova, V., Shurpa, S., Zhuk, O., Boiko, O., Radkevych, L. (2023). The Impact of Digitalization on Marketing Communications: New Challenges for Branding and Advertising Business. *Wseas Transactions on Information Science and Applications, 20,* 344-355. https://doi.org/10.37394/23209.2023.20.37

52. World Bank. (n.d.). *Agriculture & Rural Development.* World Bank Open Data. Retrieved from https://data.worldbank.org/indicator

53. Xuan, H. V. T., Huan, V. M., & Su, L. H. (2025). Mapping research trends in online shopping behavior during the fourth industrial revolution: A bibliometric analysis. *Innovative Marketing, 21*(4), 216-231. https://doi.org/10.21511/im.21(4).2025.16

54. Xue, L., Satpayeva, Z., Tyulkubayeva, A., & Kangalakova, D. (2025). Impact of artificial intelligence applications on enterprise market value: Evidence from Chinese enterprises. *Investment Management and Financial Innovations, 22*(4), 303-317. https://doi.org/10.21511/imfi.22(4).2025.24

55. Yarovenko, H., Horbachova, O., Bylbas, R., & Latysh, D. (2025). Digitalization as a Socio-Economic Challenge: Modeling the Impact on the Level of Cybercrime Considering Socio-Economic, Technological and Institutional Factors. *SocioEconomic Challenges, 9*(2), 282-315. https://doi.org/10.61093/sec.9(2).282-315.2025

56. Yarovenko, H., Kuzior, A., Norek, T., & Lopatka, A. (2024a). The future of artificial intelligence: Fear, hope or indifference? *Human Technology, 20*(3), 611-639. https://doi.org/10.14254/1795-6889.2024.20-3.10

57. Yarovenko, H., Vasilyeva, T., Ustinovichius, L., & Remsei, S. (2024b). Illicit practices: Experience of developed countries. *Journal of International Studies, 17*(2), 146-177. https://doi.org/10.14254/2071-8330.2024/17-2/8

58. Yefimenko, A., Boronos, V., Serpeninova, Yu., & Koldovskyi, A. (2025a). Innovative and Technological Determinants of Corruption Reduction: How do Knowledge and Technology Contribute to Public Integrity and Transparency? *Knowledge Economy and Lifelong Learning, 1*(1), 21-34. https://doi.org/10.61093/kell.1(1).21-34.2025

59. Yurchyk, H., Mishchuk, H., & Bilan, Y. (2023). Government assistance programs for internally displaced persons: assessing the impact on economic growth and labour market. *Administratie si Management Public, 41,* 201-218. https://doi.org/10.24818/amp/2023.41-11

60. Zaryczańska, K., & Karwot, J. (2025). Analysis of Occupational Safety and Health at the Construction Site Based on Images Acquired from Various Sources Using Artificial Intelligence. *Safety and Security Advances, 1*(1), 1-17. https://doi.org/10.61093/ssa.1(1).1-17.2025

61. Ziane, A., Bouziani, A., & Moumni, S. (2025). Entrepreneurship and Innovation: Driving Economic Growth. *SocioEconomic Challenges, 9*(1), 219-232. https://doi.org/10.61093/sec.9(1).219-232.2025

62. Zimosz, P., & Ober, J. (2025). Impact of Artificial Intelligence on Education. *Knowledge Economy and Lifelong Learning, 1*(2), 77-98. https://doi.org/10.61093/kell.1(2).77-98.2025

63. Zolkover, A., & Ovcharenko, P. (2024). Modelling a comprehensive assessment of the level of innovation security. *Smart Economy, Entrepreneurship and Security, 2*(1), 50-57. https://doi.org/10.60022/sis.2.(01).5

APPENDIX A. List of countries included in the sample

The study covers the following 36 countries, for which the AI Vibrancy Index and all corresponding subindexes are available:

Australia, Austria, Belgium, Brazil, Canada, China, Denmark, Estonia, Finland, France, Germany, India, Ireland, Israel, Italy, Japan, Luxembourg, Malaysia, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Russia, Saudi Arabia, Singapore, Spain, South Africa, South Korea, Sweden, Switzerland, Turkey, United Arab Emirates, United Kingdom, United States.