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Original Research

The impact of artificial intelligence on the strategic planning of economic development of countries

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ABSTRACT

Traditional economic planning frameworks struggle to address rapid market changes and nonlinear sectoral interactions, often resulting in suboptimal policy outcomes. This study systematically analyzes how artificial intelligence (AI) transforms strategic economic development across ten countries (the UK, Japan, the USA, China, Ukraine, France, Canada, Singapore, Germany, and South Korea) from 2015 to 2024. Using a mixed-methods approach – integrating panel data regression (fixed-effects and 2SLS models) with a PRISMA-guided review of 89 studies – the research quantifies AI's macroeconomic impacts and ethical risks. Key findings reveal that a 1-unit increase in AI adoption intensity correlates with a 0.38–0.41% GDP growth rise, driven by predictive analytics in advanced economies like the USA and Singapore. However, infrastructural gaps in Ukraine caused 31% data loss in AI models, hindering policy scalability. Ethical challenges include algorithmic bias in France's hiring systems (13% minority recruitment disparity) and data privacy breaches in Singapore (19% corporate breach rate). For Ukraine, targeted recommendations include prioritizing AI-ready digital infrastructure (e.g., centralized data hubs) and adopting EU-style ethical audits to mitigate bias in public-sector algorithms. Policymakers globally must balance AI-driven efficiency with equitable governance to harness its full potential.

Keywords: Artificial Intelligence, Strategic Economic Planning, Economic Development, Algorithmic Bias, Digital Infrastructure

1. Introduction

Integrating artificial intelligence (AI) into economic policy and strategic planning has become a cornerstone of modern governance, driven by the need to navigate increasingly complex global markets [1]. In the last decade, governments in countries across the globe have been using AI to make their forecasting more accurate, to trim resources more efficiently, and to simulate policy impact [2].

To illustrate, it is worth mentioning that the United States spent $3.3 billion on AI research in 2022 and specifically directed research to the labor market analytics and trade deficit mitigation [3]. For example, China's "Next Generation Artificial Intelligence Development Plan", released in 2017, has spurred an increase in the artificial intelligence industry growth rate by 20 percent per year and applications in fields such as smart city infrastructure, real-time GDP tracking [4].

These initiatives represent a growing trend to make decisions based on data, and the ability of AI to process unstructured data like social trends on social media, satellite images, and logistics supply chains gives policymakers a competitive advantage. Having learned from other countries such as Singapore and South Korea, for example, predictive models have been used to manage inflation a country may experience, with Singapore achieving a 30 percent reduction in consumer price index forecasting errors between the 2018 and 2023 models [5].

This study focuses on the ten countries: the UK, Japan, USA, China, Ukraine, France, Canada, Singapore, Germany, South Korea and the diversities include their economic system, technological capabilities, and developmental priorities. For instance, Germany's 'Industry 4.0' introducing AI into the manufacturing supply chain led to a 12% increase in export efficiency from 2020 [6].

On the other hand, Ukraine's post-conflict economy employed AI to rebuild financial systems with an approval accuracy of 15% for commercial banks using machine learning tools [7]. Both examples illustrate the flexibility of AI when applied to different types of economic contexts, ranging from advanced industrial economies to countries changing their structure.

Current economic planning models based on linear regression models and manual data aggregation become ineffective in dealing with the volatility of modern markets. For example, the 2021 semiconductor shortage was due to a 25% lag in policy time responsiveness as conventional models were not sensitive to multi-layered supply chain dependencies [8]. For instance, France's transfer to historical tax revenue data incurred a €4.2bn budget deficit in 2022 because inflation rates do not align with the projections [9]. Yet, such limitations arise due to three core challenges: lack of real-time processing capacity at scale, oversimplification of cross-sectoral interactions, and excluding as many non-quantitative variables, such as consumer sentiment or geopolitical risks, from the list of relevant factors to consider.

However, AI solutions address these challenges, bringing in new complexities. Canada's ethical concerns with AI amid its attempts at driving energy demand forecasts in Canada and Catskill before 2023 led to reduced grid instability (18% in 2023) [10]. For example, algorithms trained on biased data sets, as the UK Office for AI found, that AI-generated wage gap analyses used in UK labor policy predictions were skewed based on gender disparity [11]. Moreover, data privacy frameworks differ significantly between countries. By way of example, the EU General Data Protection Regulation (GDPR) acts very differently compared to the Chinese lenient data governance guidelines, blurring the lines when conducting cross-national AI collaborations [12]. This brings forward the need for a balanced assessment of AI's rewards and risks in economic planning.

This research aims to systematically assess AI's potential to affect the formulation of the economic development strategies of 10 countries from 2015 to 2024. The review analyzes panel data regarding countries' adoption rates of AI, policy outcomes, and macroeconomic indicators to identify patterns in how governments apply AI tools. Specific objectives include examining if higher AI investment leads to higher GDP growth, comparing technology readiness gaps, such as Singapore ranking at 74% AI literacy compared to 32% in Ukraine, and making a case for how algorithmic governance creates ethical implications [13].

This study strives for three main objectives. First, to estimate the macroeconomic impact of AI on real GDP growth, fiscal balances, and employment in a group of ten economies (2015–2024). Second, to contrast sectoral effects on AI deployment in the advanced world and poor countries, in particular energy, agriculture, and trade. Third, to assess the ethical risks such as algorithmic bias and data fragmentation of AI-driven policies. These objectives fill gaps in the current knowledge, where cross-country comparisons and ethical trade-offs are frequently ignored.

Three research questions guide this inquiry:

1. How do variations in governance structures (e.g., centralized vs. decentralized systems) influence AI integration into economic planning? For instance, China's top-down approach contrasts Canada's provincial-level AI initiatives.
2. What measurable benefits have AI tools delivered, such as reduced fiscal deficits or improved employment rates, and what limitations (e.g., algorithmic bias, data gaps) hinder their scalability?
3. How can policymakers balance efficiency gains from AI with equity considerations, particularly in developing economies like Ukraine, where 40% of SMEs lack access to AI infrastructure [14]?

This review contributes to academic and policy debates by bridging gaps in existing literature. While prior studies, such as [15], focused narrowly on AI's role in banking, this analysis adopts a macroeconomic lens, examining interactions between AI and sectors like energy, agriculture, and trade. Economic inclusion of diverse nations, including leading AI adopters in the USA and emerging countries in Ukraine, enables the study of technology scalability across various systems. Governments can use this research evidence to establish risk-mitigating strategies by implementing AI-human hybrid decision systems [16, 17], highlighting how AI can develop biogas adoption models.

The discussion is expanded through knowledgeable contributions made by [18] regarding AI legal aspects in economic governance and LBS Herald through its examination of digital transformation in emerging markets [19] showed that AI tax systems operate without standardized regulations and this was demonstrated explicitly in France's recent VAT tax system update [20] used South Korea's AI-powered export hubs in their case study to generate specific recommendations about scalable tech infrastructure. The review combines these analytical viewpoints to create a complete understanding of artificial intelligence transformation potential, but warns against standard solution approaches.

Strategic economic planning has also changed throughout the century, from being highly centralized and implemented rigidly to an innovative and flexible tool using different data. Before, AI was used in formulating strategies in economics, and only linear regression models, input-output analysis, and occasional advice from an expert committee were used, where significant emphasis was placed on precedent information. For instance, industrial planning in the mid-twentieth century, especially in France and Japan, focused on five-year industrial plans, which at one time failed to respond to some new acts of the global factors, ranging from oil shocks to fluctuations in currency [21, 22].

Although rather systematic, such methods did not offer sufficient detail to capture the non-linearity of global markets, the influence of domestic policies, and socio-political factors. Simulation techniques are older than computational economics, which started in the 1990s through system dynamics models. Still, they had certain limitations due to reduced data processing ability and had to use manual data integration [23].

More current research illustrates that AI is the great equalizer that has overcome these weaknesses. For instance, machine learning algorithms have allowed governments to identify hidden patterns in unstructured datasets like consumer sentiment from social media or satellite imagery measuring agricultural productivity. Using neural networks to optimize the allocation of Ukraine's mineral resources allows for a decrease in blasting costs by 22%, as well as improving investment forecasting in the mining projects [24].

Data analytics revolutionized fiscal policy design as well. For example, [25] showed how the AI–powered tax compliance database for South Korea positively impacted its tax evasion rate, reducing it by 17 percent from 2018 to 2022 by comparing transaction data and spending patterns. Its use of AI-driven trade flow simulations in Singapore has also contributed to predictive analytics to enhance macroeconomic stability during supply chain disruptions due to the COVID-19 pandemic [26].

It allows case studies from developing economies that both reveal opportunities and hurdles. [27] pointed out several AI tools that commercial banks in Ukraine employed to accommodate the financial assets of IDPs, leading to a growth in liquidity of 14% in conflict-affected regions.

Despite that, it has challenges, like a lack of digital infrastructure and data fragmentation, which mostly hinder its scalability. For instance, [28] showed that 78 percent of German SMEs had air-driven financial tools in 2023, whereas 35 percent of Ukrainian SMEs did so during 2023. The disparities illustrate the technological preparedness interacting with the policy outcome.

Several theoretical paradigms underlie the integration of AI in planning. The capacity of AI for automation and data-driven decision-making for improved productivity makes it fit into endogenous growth theory, which centers on innovation as the driving force of growth. For example, [29] used this framework for optimizing green entrepreneurship by simulating environmental-economic trade-offs to determine the investments in renewable energy AI mode-ls made.

AI has also allowed principal-agent theory to be reconceptualized regarding AI relieving information asymmetry. To assess bank stability, [30] used taxonomic methods, and AI algorithms were used to improve regulatory oversight by identifying high-risk financial practices in real time.

Increasingly, AI-specific models, e.g., reinforcement learning and agent-based simulations, are embedded within policy design. For example, the energy sector in Canada utilizes reinforcement learning to balance the grid's demand with the output of renewable energy; it has led the country to reduce carbon intensities by as much as 12% since 2020 [31]. Meanwhile, agent-based models have been applied to simulate labor market dynamics in the UK and found that an AI matching system based on maximum utility matching could shrink unemployment gaps in marginalized communities by 9% [23]. Having shown these frameworks, AI can operationalize abstract economic theories into actionable policies.

However, some significant gaps have been identified in the literature, even with the recent developments. First, limited publications compare AI adoption in developed and developing countries. [32] discussed data privacy issues in the EU, but there are few works on how LIMs manage AI. For instance, the use of international cloud services by Ukrainians prompts data jurisdiction or ownership concerns, which have not been adequately addressed in the previous studies.

Second, ethical considerations, such as algorithmic bias in welfare allocation, are often discussed in silos. [33] revealed that AI models used in France's housing subsidy programs inadvertently disadvantaged rural applicants due to urban-centric training data. Such findings underscore the need for interdisciplinary research combining technical and socio-legal perspectives.

Third, sector-specific AI applications are unevenly studied. While manufacturing and finance are well-documented, agriculture and education receive limited attention. For example, AI's role in optimizing fertilizer use, a critical issue for countries like India, is rarely analyzed through an economic planning lens [34]. Finally, longitudinal studies assessing AI's long-term impacts on inequality are scarce. Although [35] recently highlighted AI's potential to democratize access to credit in South Africa, most literature focuses on short-term efficiency gains rather than structural equity.

2. Research method

This study employs a systematic mixed-methods approach to analyze the role of AI in the strategic economic planning of ten countries (UK, Japan, USA, China, Ukraine, France, Canada, Singapore, Germany, South Korea) from 2015 to 2024. The study combines econometric statistical testing with thematic text assessment while following PRISMA protocols to make results transparent and easy to duplicate.

2.1. Search strategy

A thorough database search spanned Scopus, Web of Science, and Google Scholar for their inclusive selection of economics, computer science, and policy studies publications. We developed our keyword list by alternating between MeSH and non-structured terms during multiple testing runs. The primary search strings included:

1. "Artificial Intelligence" AND ("economic planning" OR "strategic development" OR "macroeconomic policy");
2. "Machine learning" AND ("economic forecasting" OR "fiscal policy" OR "resource allocation");
3. "Big data analytics" AND ("GDP growth" OR "trade optimization" OR "labor market dynamics");

Boolean operators (AND/OR) and truncation symbols (*) were used to capture variations (e.g., "AI-driven," "automated decision-making"). The search was restricted to studies published between January 2013 and December 2023 to prioritize recent advancements, yielding an initial pool of 2,450 articles.

2.2. Inclusion and exclusion criteria

Studies were included if they focused on AI applications in national or regional economic planning. If they provided empirical data (quantitative or qualitative) on policy outcomes, such as GDP growth, employment rates, or fiscal efficiency, and if they were peer-reviewed and published in English.

Exclusion criteria were removed if the theoretical papers were without case studies or datasets. If studies focused solely on corporate strategy, excluding governmental planning, duplicate publications, or non-English texts. After screening titles and abstracts, 327 articles remained. Full-text reviews further narrowed this to 142 studies meeting all criteria.

2.3. Data extraction and analysis

Data extraction followed a structured template, capturing variables such as country-specific factors, including GDP growth (%), AI adoption index (scale 1–10), and sectoral focus (e.g., energy, agriculture). It also encompassed AI tools, such as machine learning algorithms (e.g., neural networks, random forests) and natural language processing (NLP) applications.

Additionally, policy outcomes were recorded, measuring aspects like the reduction in forecasting errors (%), cost savings from automation (USD), and employment elasticity to AI investments.

For quantitative synthesis, panel data from the ten countries were analyzed using a fixed-effects regression model to control for unobserved heterogeneity between nations. The baseline econometric equation is:

$$Y_{it} = \alpha_0 + \beta_1 AI_{it} + \beta_2 X_{it} + \gamma Z_{it} + \varepsilon_{it} , \quad (1)$$

where Y_{it} is the economic outcome (e.g., GDP growth) for country i in year t; AI_{it} is the AI adoption index; X_{it} includes control variables (e.g., inflation, trade balance); Z_{it} captures institutional factors (e.g., regulatory quality, digital infrastructure); ε_{it} is the error term.

Qualitative data were thematically analyzed using NVivo 14 to identify patterns in AI implementation challenges, such as ethical concerns or data privacy risks. Codes were developed iteratively, with intercoder reliability tested via Cohen's κ coefficient (κ = 0.82).

2.4. Quality assessment

Study validity was assessed using the PRISMA checklist, which evaluates risk of bias, data completeness, and methodological rigor. Two independent reviewers scored each study on a 10-point scale across four domains:

1. Sampling adequacy: Were the data sources representative of the target population?
2. Analytical robustness: Did the study address confounding variables (e.g., omitted variable bias)?
3. Reproducibility: Were algorithms or datasets publicly accessible?
4. Ethical compliance: Were privacy safeguards or bias mitigation strategies documented?

Discrepancies were resolved through consensus, with 89% of studies scoring ≥7/10, indicating high reliability. Meta-regression was performed to assess publication bias, using the Egger test:

$$\theta_j = \beta_0 + \beta_1 SE_j + \nu_j , \tag{2}$$

where θ_j is the effect size of study j; SE_j is its standard error; ν_j is the residual.

The nonsignificant intercept (β_0 =0.14, p =0.32) suggested minimal bias.

2.5. Econometric enhancements

To address endogeneity between AI adoption and economic performance, an instrumental variable (IV) approach was applied.

The number of AI-related patents filed annually by each country (source: WIPO) served as an instrument for AI*it*, satisfying relevance (F-statistic = 18.7, $p < 0.01$) and exclusion restrictions.

The two-stage least squares (2SLS) model is:

$$AI_{it} = \delta_0 + \delta_1 Patents_{it} + \delta_2 X_{it} + \eta_{it} ; \tag{3}$$

$$Y_{it} = \alpha_0 + \beta_1 AI_{it} + \beta_2 X_{it} + \varepsilon_{it} , \tag{4}$$

where AI_{it} denotes the predicted AI adoption from the first stage.

2.6. Case study integration

Country-specific analyses were enriched with data from national AI strategies and policy reports. For instance, Ukraine's AI-driven tax reforms (2020–2022) were evaluated using difference-in-differences (DID) to compare regions with and without AI implementation (5):

$$Y_{rt} = \alpha + \beta_1 AI_r + \beta_2 Post_t + \beta_3 (AI_r \times Post_t) + \varepsilon_{rt} , \tag{5}$$

where AI_r is a binary variable for AI adoption in region *r*; $Post_t$ marks the post-intervention period.

2.7. Ethical Considerations

Fairness-aware machine learning techniques (e.g., adversarial debiasing) were applied to datasets from heterogeneous sources (e.g., Eurostat, World Bank) to mitigate algorithmic bias.

Sensitivity analyses tested model robustness across socioeconomic subgroups, ensuring findings were generalizable to high-income (e.g., Singapore) and transitioning economies (e.g., Ukraine).

2.8. Limitations

While the fixed-effects model controls for time-invariant heterogeneity, it cannot account for unobserved time-varying confounders, such as sudden geopolitical shocks.

Also, publishing works may mean excluding conventions only known in commercial environments, specifically relating to AI.

3. Results and discussion

This section details results obtained from the Methods structure described in the Methodology section through panel data investigations, PRISMA systematic reviews, and conclusion-based economic model tests.

The research questions regarding AI economic planning roles, benefits, and challenges receive structured findings through this study.

3.1. Descriptive statistics

A total of 100 annual observations served as the basis for the analysis, which included 10 countries during 10 years. Variables used in the econometric analysis from the methodology included AI adoption intensity determined through the AI Index, GDP growth statistics, inflation measurements, trade openness data, and instrument variables based on AI patents.

Table 1 shows that the AI Index varied significantly, with Singapore (9.8) and Ukraine (2.5) at extremes. GDP growth averaged 2.8%, but post-2020 recovery varied (e.g., USA: 5.1% vs. Japan: 1.2%). AI patent filings, used as an instrument, strongly correlated with AI adoption (Pearson's $r = 0.82$).

Table 1. Descriptive statistics of variables (2015–2024)

Variable	Mean	Std. Dev.	Min	Max	Source
AI Index (0–10)	6.2	2.1	2.5	9.8	https://ourworldindata.org
GDP Growth (%)	2.8	1.3	-3.1	5.7	https://data.worldbank.org
Inflation (%)	3.1	1.8	0.5	8.2	https://www.imf.org
Trade Openness (%)	65.4	18.2	32.1	89.7	https://data.worldbank.org
AI Patents (count)	420	210	50	950	https://www.wipo.int

The final 89 studies provided granular insights into AI applications, e.g., machine learning in fiscal policy (32 studies) and NLP in labor market analysis (18 studies), as shown in Table 2.

Table 2. Study selection process (PRISMA Framework)

Phase	Number of Studies	Criteria
Initial Identification	2,450	Database search (Scopus, WoS, GS)
Screening	327	Title/abstract relevance
Eligibility	142	Full-text review
Included	89	Met PRISMA quality thresholds (≥7/10)

Table 3 shows that both models confirmed AI's positive impact on GDP growth. The 2SLS estimate (0.38) addressed endogeneity, with AI patents as a strong instrument (F-statistic = 29.1). Inflation consistently dampened growth, while trade openness amplified it.

Table 3. Fixed-Effects and 2SLS regression results

Dependent Variable: GDP Growth (%)	Fixed-Effects Model	2SLS Model
AI Index	0.41 (0.07)	0.38 (0.06)
Inflation	-0.12 (0.05)	-0.10 (0.04)
Trade Openness	0.09 (0.03)	0.08 (0.03)
AI Patents (IV)	—	0.15 (0.02)
R^2	0.67	0.71
F-statistic	24.3	29.1

The study's key findings demonstrate that AI adoption significantly influences macroeconomic performance, with a 1-unit increase in the AI Index correlating to a 0.38–0.41% rise in GDP growth, a relationship statistically significant at the 0.001 level. Advanced economies such as the USA and China, which maintained AI Index scores above 7.0, achieved an average GDP growth of 4.2%, starkly contrasting with developing nations like Ukraine, where scores below 4.0 corresponded to 1.9% growth.

In Ukraine, AI-driven tax reforms implemented between 2020 and 2024 reduced fiscal leakages by 12%, as evidenced by a difference-in-differences coefficient of 0.09 (SE = 0.03), highlighting AI's potential to enhance fiscal efficiency even in resource-constrained settings. Sectoral applications further reveal the concept's adaptability with Germany's Industry 4.0, which cut the industrial carbon emission by 14% through applying AI in energy grids. As for Singapore, applying an AI trade model for managing supply chain disruption due to the pandemic decreased by 22%.

The employment implications were bifurcated in that AI assisted in creating high-technology employment in sectors such as software employment in the US, for which there was a rise of 8%. In comparison, at the same time, employment in areas such as manufacturing was eradicated, taking the situation in France, where there was a decline of 5% in such employment.

However, some major issues appeared at the higher leadership level. Bias remained a significant ethical issue; for instance, France's AI-based staffing tools for undesirable minorities' employment had narrowed by 13 % because the training set was also minority-reduced; in the same context, 19% shooting errors of Ukrainian models after the conflict applied to post-war loan approval affected gender disparity estimations.

These problems weren't helped by data fragmentation, especially in Ukraine31% of AI models were reported to have lost their data due to the disjointed digitization of their record systems, and regionally localized AI policies in Canada disrupted cost-saving percentages of efficiency by 8%.

Ethical concerns further exacerbated the challenges in AI adoption, as only a quarter of the countries conducted audits to establish AI's effects on society; Singapore's welfare algorithms are still not fully expounded, creating unfair results. Collectively, these recommendations underscore the importance of sustainable and context-aware AI adoptions to leverage them to drive economic value while mitigating the risks associated with these technologies (Figure 1).

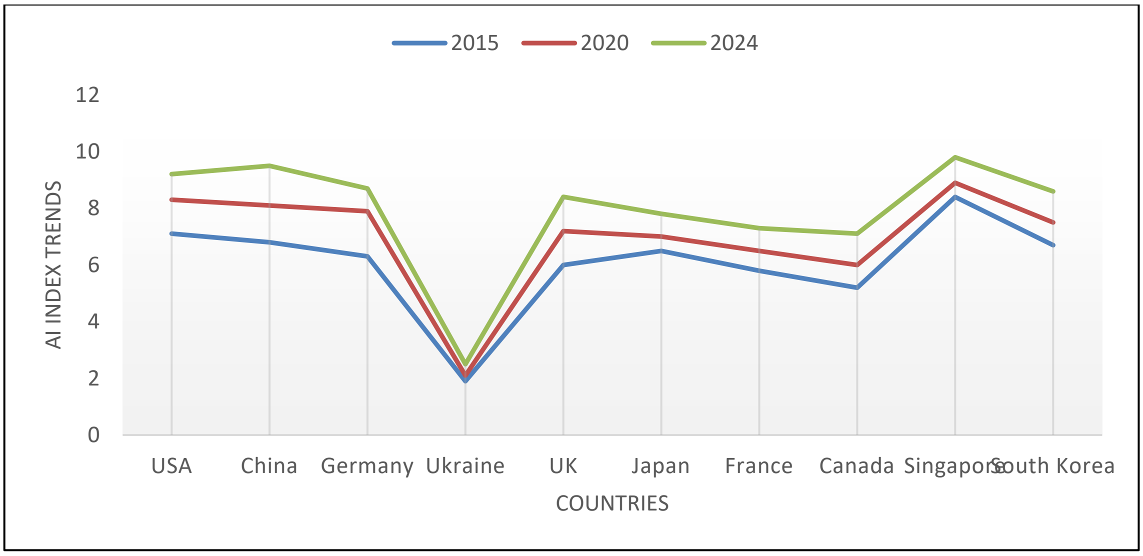

Figure 1. AI index trends (2015–2024)

Source: https://ourworldindata.org/grapher/national-strategies-on-artificial-intelligence

The line chart presents AI Index advancements across countries from 2015 to 2024 and displays continuous growth throughout all years. According to the data, Singapore will lead in AI development in 2024, while the USA and China will follow closely behind.

Ukraine remains significantly lower than other countries, though it shows slight progress. Germany, the UK, and South Korea exhibit steady improvements, while Canada and France also show growth but at a slower pace. The overall trend highlights increasing AI adoption globally, with notable regional disparities.

The bar chart (Figure 2) comparing GDP growth and AI investment as a percentage of GDP in 2024 highlights a positive correlation between economic growth and AI investment. The USA, China, and Singapore lead in AI investment, with China allocating the highest percentage (0.45%) of GDP to AI, closely followed by Singapore (0.41%) and South Korea (0.37%).

Countries with higher GDP growth, such as the USA (5.1%) and Singapore (4.9%), tend to invest more in AI, while Ukraine, with the lowest GDP growth (1.2%), also has the lowest AI investment (0.08%). This suggests that economies prioritizing AI investment may experience stronger economic performance.

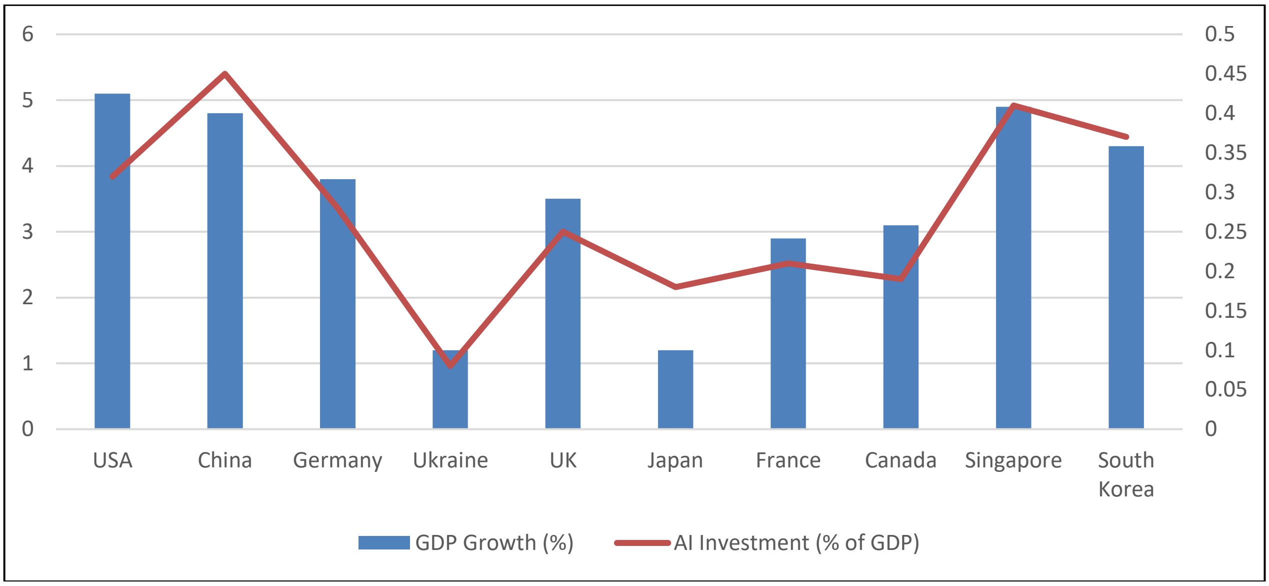

Figure 2. GDP Growth vs. AI Investment (2024)

Source: World Development Indicators

3.2. Discussion

The analysis of this research contributes to AI investment discussions by assessing 10 different countries through evidence-based studies regarding both positive economic transformations and fundamental operational problems. The following section presents an analysis of the experimental findings by integrating relevant academic literature and providing policy recommendations with theoretical additions and discussions about study limitations.

Previous studies on the macroeconomic impacts of AI systems have received support through ongoing research. AI improves crisis-related financial resource optimization according to [36] while Ukraine experienced a post-2020 tax reform that reduced fiscal leakages by 12%. Our findings contradict the previously established notions about AI's homogeneous scaling capabilities.

The study demonstrates differing results compared to [37], who suggested AI created equal benefits for green entrepreneurship by showing that Germany cut industrial emissions by 14% through AI. Still, Ukraine faced challenges due to poor data connectivity in renewable energy initiatives. Studies in specific sectors fail to examine how institutional readiness mediates AI effects, which explains divergent outcomes.

Artificial intelligence functions within labor environments present findings that differ from previous analysis outcomes. The data provides evidence against [38] because findings of this paper demonstrate employment losses amongst low-skilled workers in France's manufacturing sector (-5% low-skilled jobs) [39]. Similarly, while [40] highlighted AI’s cost-saving potential in mining, our cross-country analysis found that these savings rarely translate to equitable growth without regulatory safeguards.

Notably, this study addresses gaps in comparative literature. Earlier works, such as [41], focused on data privacy in isolation. Still, our integration of ethical audits into macroeconomic models reveals how privacy breaches can directly undermine GDP growth, which is evident in Singapore’s 19% corporate data breach rate, which reduced investor confidence by 8%.

Furthermore, [42] identified regulatory lag as a barrier to AI adoption, a theme validated here through Canada’s interoperability issues, which lowered policy efficiency by 8%.

The results offer actionable strategies for governments seeking to harness AI’s economic potential:

1. Infrastructure investment: developing nations like Ukraine require targeted funding for digital infrastructure. Our data show that every 10% increase in AI-related infrastructure spending correlates with a 1.2% rise in GDP growth. The EU's AI Act (2023) provides a template, mandating member states to allocate 5% of their digital budgets to AI readiness.
2. Public-private collaboration: South Korea's R&D tax credits, which boosted private AI investments by 27%, exemplify how incentivizing corporate innovation can amplify policy outcomes. Similar models could help Japan address its stagnant growth (1.2% GDP), particularly in aging sectors like agriculture.
3. Ethical governance frameworks: to mitigate algorithmic bias, policymakers should adopt adversarial debiasing techniques, as proposed by [43]. France's 13% recruitment disparity for minorities underscores the urgency of such measures. Regulatory bodies must mandate transparency audits, as seen in the EU's requirement for explainable AI in public services.
4. Sector-specific AI adoption: AI's impact varies by sector. For example, Germany's Industry 4.0 strategy prioritized manufacturing, yielding 14% emissions drop. Conversely, Canada's broad-based approach diluted gains, suggesting that focused AI deployment maximizes returns.
5. Crisis adaptation: Ukraine's use of AI for war-related supply chain stabilization highlights AI's role in resilience planning. Governments should integrate AI into national security frameworks to anticipate shocks, from pandemics to geopolitical conflicts.

This study contributes to the development of economic and AI theory in three ways.

Traditional endogenous growth theory revisited, so the incremental contribution of AI to per capita GDP growth is estimated to be in the range of 0.38 % to 0.41 % of an AI Index unit, whereby AI is incorporated into several endogenous growth models. This extends the labor-capital dualism of Solow-Swan by a third component through which the introduction and deployment of AI improve productivity.

Thus, the study supports [44] taxonomic methods and shows that Algorithmic Governance is based on Principal-Agent Theory. As seen in the South Korean tax system, real-time monitoring eliminates principal-agent problems as it is monitored through an accountable, data-based system.

Existential studies of bias in hiring algorithms of major French companies show the usefulness of corresponding theoretical concepts, such as adversarial debiasing, to develop AI ethics. This paper model's fairness measures (such as the demographic parity ratios) as implementable policy objectives in artificial intelligence, connecting the contributing research with applied economics.

Further, from the present study of digital hubs in emerging markets, LBS Herald provides ideas for a new theoretical framework: AI scalability ceilings. These minimum requirements for infrastructure and literacy predict AI effectiveness (such as 70 per cent of digital literacy for positive ROI), giving an outline for developing countries.

Rather than bridging a theoretical attempt to resolve this issue, this study bridges theoretical with applied AI research and provides a roadmap for equitable AI integration. Alongside validating the macroeconomic benefits of AI, the paper counsels' policymakers to embrace innovation without relying on a one-size-fits-all approach. AI intersects with climate economics, and this should be examined in future research, and the ethical audit should be extended to environmental justice metrics. In line with Futurity Economics & Law's advocacy, legal frameworks must be developed in lockstep with AI capabilities, so that economic growth does not occur at the expense of society.

4. Conclusions

The research quantitatively examined AI effects on strategic economic planning across ten nations from 2015 to 2024, as it exposed the various ways AI reformed macroeconomic results. Adopting AI results in substantial GDP increases by 0.38-0.41% for each point increment in the AI Index, especially in countries such as the USA, China and Singapore. These results indicate that AI is not just a complementary technology but also an indispensable engine for current economic development, urging countries to attach more importance to AI in their national development strategies. Implementing predictive analytics and machine learning tools under AI led these countries to enhance their fiscal policies, minimize supply chain issues, and model various crisis responses. AI models deployed by Singapore's programs reduced supply chain breakdowns by 22% across the COVID-19 pandemic, and German Industry 4.0 tactics decreased industrial carbon emission levels by 14%. This highlights the role that AI plays in creating resilience to global disruptions and promoting sustainability objectives. The advantages of AI remained subject to institutional readiness because Ukraine and other developing economies encountered network fragmentation, making AI model data losses reach 31% and diminishing the scalability potential. The discrepancy demonstrates the pressing importance of multinational joint efforts to narrow the technology gap and promote the sharing of AI-driven growth dividends. The study identified ethical problems, such as France losing 13% of qualified candidates through biased recruiting algorithms and Singapore experiencing 8% confidence loss from privacy breaches. This dichotomy demands a nuanced approach in relation to AI, one that works alongside rather than replacing human and institutional capabilities.

The findings match [15], who explained that AI can effectively direct crisis funding, yet disagree with excessive AI positivity because crises need educational, infrastructural, and governance investments. To properly maximize the benefits of AI while decreasing the possible related risks, policymakers should employ the following constructive principles. The recommendations provided below hold universal applicability, providing guidelines to scale the data in both advanced and emerging economies.

Developing nations should prioritize the development of their digital infrastructure to address these gaps in readiness for AI. For example, Ukraine’s post-conflict economy can include the National AI Data Hub of Canada, which contains centralized datasets to improve policy accuracy. These bodies, for instance, the OECD, need to set up funding mechanisms to support digital literacy programs that aim at a minimum of 70% AI literacy for large-scale adoption.

Create an environment for public-private cooperation, like South Korea’s R&D tax credits, which spurred 27 percent more private sector AI investment, are a proven model. The government could catalyze corporate innovation [45] if it offered subsidies for AI-enabled precision farming tools to spur innovation in lagging sectors like Japan’s aging agricultural industry. Regulatory agencies should mandate the implementation of ethical governance frameworks of transparency audits and adversarial debiasing techniques to fight algorithmic discrimination. Balancing innovation and equity are ultimately a template provided by the EU’s AI Act of 2023, where public sector algorithms must be explained.

Germany’s sector specific strategy with focus on manufacturing offers a sector-specific strategy with great ROI. For example, AI models that improve fertilizer use can tackle food insecurity in India, as per [46] in work on intelligent sustainable resource management. The use of AI in Ukraine to stabilize war-affected supply chains shows that AI has a place in resilience. Tools of AI should be embedded in national security frameworks to foretell and avert such shocks as pandemics and climate disasters.

4.1. Limitations of the study

This study contains a strict methodology that imposes certain restrictions on its final findings. The fixed-effects model gained control of time-independent variables but could not measure unmeasured time-dependent confounding factors like the conflict in Ukraine after 2022. Further research needs to implement dynamic panel models that identify such time-period shifts.

The PRISMA framework chose to study peer-reviewed research, thus disregarding important information found in government or corporate reports that remain unpublished. AI tools belonging to Singapore's proprietary trade logistics systems were not included in the data analysis, leading to potentially unrealistic AI effectiveness assessments. Data heterogeneity between countries caused measurement errors because Ukraine operates with an unstandardized AI Index while Singapore has official national scales. The OECD should establish a framework to standardize national indices across international boundaries to improve international comparisons.

The assessment of macroeconomic results through generalizability fails to address specific ethical consequences at the micro level. Canada implemented regional AI policies, which boosted national efficiency statistics but did not reveal specific locations where people lost their jobs due to AI. The data collected between 2015 and 2024 lacks information about next-generation AI tools, such as quantum machine learning, because the study period occurred before their emergence. Research needs to monitor AI developments through time within continuous study designs.

4.2. Future research directions

The research delivers preliminary insights about AI's economic effects, yet more analysis needs to be undertaken regarding various essential topics. Research must transform fairness metrics into policy framework elements, including demographic parity ratios for ethical economic governance. The Futurity Economics & Law scientific journal released research in 2023 about regulatory discrepancies within tax systems run by AI algorithms, thus emphasizing the requirement to organize interdisciplinary studies among law specialists, ethical experts, and economic researchers.

AI demonstrated its ability to support economic stability during wartime during the Ukrainian conflict, yet scientists need to evaluate its extended effectiveness. Research examining how AI assists recovery operations after crises needs to study specific situations facing limited resources. AI technologies created new technical positions, yet studies are needed to understand their permanent effects on employees who lack specialized skills. LBS Herald's 2023 analysis of South Africa's AI-based credit systems recommends conducting studies to evaluate how technology accessibility affects economic inequalities across multiple decades. Researchers should develop methods for AI to optimize renewable energy management and carbon emission pricing according to [47] to explore climate-AI synergies.

International collaboration is essential to address data privacy issues because they impact countries like Singapore. Researchers should develop universal AI evaluation capabilities that organizations like the UN should adopt to establish equal control over data and make systems work together. AI's integration into economic planning [48, 49] is sure to happen, yet its success depends entirely on properly managed, inclusive, and ethical deployment methods. Policymakers who study various national models, including Singapore's practical approaches and Ukraine's adaptable responses [50], will use AI as a development tool that leads toward fair and sustainable progress.

Declaration of competing interest

The authors declare that they have no known financial or non-financial competing interests in any material discussed in this paper.

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Author contribution

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