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Artificial Intelligence, Inequality, and Economic Performance: An Empirical Investigation across Europe, USA, and China

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Abstract. *In today's fast-changing digital world, Artificial Intelligence (AI) is playing a key role in driving economic growth, boosting innovation, and reshaping global competitiveness. This paper analyzes the influence of Artificial Intelligence readiness on economic performance, proxied by GDP, for 36 countries: 34 European nations, the United States, and China. In this study, we explore through a regression model and correlation analysis how government preparation, technological infrastructure, data availability, and unemployment rates impact economic outcomes regarding AI deployment in 2024. The findings indicate that technological readiness has a favorable impact on GDP, however data and infrastructure present obstacles that could impede economic progress. The study examines the relationship between AI and income inequality, indicating a possibility for AI to mitigate inequality, however its effect on employment is ambiguous. The results highlight the significance of strategic investments in AI and technical infrastructure to promote inclusive economic growth and enhance economic performance.*

Keywords: Artificial Intelligence, GDP, Economic Performance, Technology, Data Infrastructure, Economic Growth, AI Readiness, Income Inequality.

Introduction

Artificial Intelligence (AI) is now a historic force of the digital age that is transforming industries, markets, and economic systems of exchange. As machine learning, automation, and information management are progressing at a faster rate day by day, AI has shifted from just being a facilitator of technological change to being a root driver of economic and social change. There are attempts worldwide to embed AI in their economy, understanding how it can upgrade productivity, efficacy, and competitive positioning on a global scale.

While the deployment of AI has picked up speed at a breakneck pace, its economic consequences have come under the radar of researchers, policymakers, and business leaders. While some nations have managed to emerge as leaders in AI by having sophisticated digital infrastructure, a skilled workforce, and open regulatory policies, there are others who are struggling to keep pace with this technological change, and are facing challenges of governance, labor change, and digital inclusion.

In such a dynamic configuration, understanding why the interplay of AI readiness and economic performance is important is imperative. While AI is full of potential, its realization is not equitably distributed, and how much each nation can maximize its use of such potential depends on other policy and structural drivers. Dismantling such processes can yield significant insights into the future of AI-based economies and the strategies needed to maximize its positive effects and minimize associated risks.

As technology related to artificial intelligence advances, huge economic progress is expected- it is even estimated that by 2030, AI might add as high as $13 trillion to GDP (Baldwin, 2019). However, significant concerns about labor replacement remain, and up to 375 million jobs are believed to be threatened by automation in various sectors of the economy. The potential of AI

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to replace human workers, especially those with low skills, has triggered debates about the technology increasing income inequality, especially in developed countries where its impact will be higher (Goldman Sachs Group, 2023).

This matter is most relevant from the perspective of economic growth and inequality within the contexts of the developed economies of Europe, the USA, and China. Artificial intelligence can spur growth by substituting abundant capital for labor; however, the differential nature of the impact depends upon the regional economic model and existing policies in place (Aghion, Jones, & Jones, 2017). The current shift to automation and an increase in AI applications across most industries do, however, constitute a very unique challenge for the labor market in general and specific sectors relying heavily on repetitive manual work. For instance, though AI poses a lesser risk in job loss or immediate occupational peril for very professionally accomplished persons involved in certain types of specialized, highly educated activities, including care, for low-paid employees it diminishes options in various locations, like warehouses.

The impact of AI on the economy also includes its potential influence on reshaping the division of wealth and power in society. As much as AI is instrumental in improving productivity and raising the prosperity level, benefits emanating from this technological development could be highly unequal and thus exacerbate growing inequalities in both income and opportunities. Low-skilled workers face salaries and reduced employment opportunities compared to higher-skilled workers, partly because of the presence of AI. A recent study indicates this trend might get worse as AI continues, according to Goldman Sachs Group (2023). It is, however, still remarkable that AI-caused inequities might indicate a more severe need for regulation to blunt such negative effects and mitigate those presented in domains with rapid AI use without protections of vulnerable individuals.

The aim of this paper is to discuss, from an empirical perspective, the way in which AI shapes economic performance and inequality in the three most powerful economies in the world: Europe, the United States, and China. Emphasis will be placed on the AI Readiness Index and its relationship with certain important economic measures such as GDP, unemployment, and inequality. The present research evaluates the various impacts that the adoption of AI exerts on the labor market, technical innovation, and productivity development, reflecting upon related risks like job displacement and deepening socio-economic inequality.

Artificial intelligence may positively and negatively impact economic performance. Whereas AI might improve productivity and, subsequently, the rate of growth, the infusion of AI into different industries could elicit structural shifts in the labor market, raising red flags about potential job losses and skills shortages. While the association between AI adoption and economic growth, in particular, GDP, is a niche of growing importance for large economies like Europe, the USA, and China, this study aims to analyze the effect of AI adoption on GDP across countries. This includes emphasizing the economic performance outcomes associated with varying degrees of AI readiness, infrastructure, and workforce transformation. This study analyzes the effects of AI on different economic dimensions to shed light on its capacity for transforming world economies and to propose policy measures that are capable of leveraging the advantages while alleviating the challenges presented by technological disruption.

The purpose of this study is to empirically investigate how AI readiness-government, technology sector, and data infrastructure-is driving economic performance proxied by GDP in Europe, the USA, and China, while controlling for exogenous factors like GDP itself and the unemployment rate. The paper seeks to examine the role that the adoption of artificial intelligence has played in influencing economic development.

To ensure analytical clarity, the main research questions for this study are as follows:

- How does AI readiness, informed by government AI readiness, technological infrastructure, and data availability, impact GDP?
- Does AI adoption contribute to economic inequality?

From these research questions, the following main hypotheses are derived:

- H1: Increased AI readiness is associated with increased GDP growth.
- H2: Adoption of AI affects economic inequality, which could intensify income disparities.

The rest of the paper is structured as follows:Literature review, Methodology, Results and discussions.

Literature review

Impact of Artificial Intelligence on the Economy

At the macro level, AI has the potential to change the fundamentals of economic growth, productivity, and income distribution. Artificial intelligence can accelerate innovation, enable new product and service development, and increase efficiency in production and service delivery. Artificial intelligence in manufacturing can reduce operating costs and boost production, since machines can independently learn and optimize operations (Machlup, 2020). Further, with extensive data collection and predictive analytics that AI allows, governments and corporations are better able to generate more precise economic projections to inform better resource allocation and evidence-based decision-making for sustainable economic outcomes (Mashunin, 2023).

From a microeconomic perspective, AI shapes the operations of firms and the decisions of consumers in a very focused and personalized way. Organizations can use AI to gain insight into consumer behavior, optimize supply chains, and build dynamic pricing models that would automatically change as market conditions fluctuated minute by minute (May et al., 2022). The use of AI in the personalization of goods and services adds value to the consumer and can enhance brand loyalty. Moreover, these technologies empower enterprises of all scales to enhance competitiveness, scrutinize market trends, and forecast demand with increased accuracy, thereby significantly influencing the management and success of business operations (Mayer et al., 2023).

However, AI's influence on the economy is not without its challenges. At the macro level, the main question is how the benefits arising from AI are divided, whether new technologies will increase the gap in income and wealth or lead to a more even distribution of the same (Mökander & Axente, 2021). Concerns regarding "technological unemployment," wherein automation supplants jobs, necessitate policies that promote reeducation and skill enhancement, research into employment opportunities in emerging sectors, and redistribution strategies to alleviate income inequality (Morgan et al., 2022).

At the micro level, the adaptation to AI technology requires great investment in capital and human capability development. The small and medium-sized enterprises can hardly access advanced technologies or relevant knowledge to implement AI in their businesses, creating new barriers to entry and reinforcing market concentration among larger, more capable organizations (Omerali & Kaya, 2023). On the other hand, if this leads to increasingly privacy-sensitive consumers, they might avoid products or services relying on intrusive data analysis, making businesses find a balance between personalization and privacy. The impact of AI on the microeconomy cannot be confined only to the technological side but has to do with social and ethical dimensions, given that an enterprise must innovate in both its product offerings and business approaches, along with customer relations (Orlova, 2022).

The long-term possibility of AI to change both the macro and micro economy is very huge. It ushers in a new frontier of efficiency, customization, and innovation. A supportive policy and regulatory environment is required in ensuring that these benefits are widely and equitably shared across different sections of society (Pirrone et al., 2021). This may include, at the macro level, the design of fiscal and monetary policies that incentivize investment in AI technology while having checks on undue wealth concentration. At the same time, government policies that focus on education and skill development would prepare the labor force to meet the changing dynamics in the job market brought about by AI (Pitkäranta & Pitkäranta, 2024).

In conclusion, AI has the potential to disrupt whole macro and microeconomies, offering unparalleled opportunities for economic growth and quality of life. Realization of the full potential of AI would require responsibility and cooperation amongst key stakeholders in various sectors. The urgent need for cooperation by the government, industry, academia, and society through creation of a framework propitious to innovation and mitigating the risk and uncertainty. It is through an inclusive approach to the development and integration of AI that we will create a technology that leads toward an inclusive, equitable, and sustainable future for all.

Artificial Intelligence Integration Barriers in the Economy

The integration of AI into the economy raises a great number of pressing issues that need to be addressed in order to ensure its effective and ethical use. One major concern arises in the realm of data privacy and security. In today's information-based digital age, many uses of AI rely on large datasets to analyze and learn from (Lane et al., 2023). This calls for access to sensitive personal and financial information of persons and enterprises, raising concerns about privacy violations and possible data exploitation. Inadequate security and privacy measures while collecting, processing, and storing data have severe repercussions, including identity theft and loss of public confidence in institutions (Latypova, 2023).

A second concern is that AI algorithms inherently have bias and unfairness. While AI makes decision-making processes more objective, algorithms can, unconsciously or otherwise, preserve existing biases due to defective data used in their training. A credit or loan decision-making AI model, having been trained with past data, may retain or exacerbate discriminatory practices against subpopulations (Lestari et al., 2024). Resolving this issue necessitates continuous efforts to create transparent and equitable algorithms, together with strong audit procedures to oversee and rectify developing biases (Limsiritong et al., 2021).

Finally, there might be an impact of AI on jobs and labor market structure. While AI might improve productivity and create new economic opportunities, the resulting automation may replace human jobs with those automatized and thus cause unemployment and economic instability at an unprecedented level (Liu & Tang, 2021). In such a labor market, changing with AI, proactive adaptation measures are needed re-re-education and retraining of workers, but also social policy aimed at overcoming income inequality and making sure strong social safety nets are in place. Addressing these difficulties necessitates a multidisciplinary strategy that harmonizes efforts among diverse stakeholders, including governmental bodies, the commercial sector, and the academic community, to facilitate an equitable and inclusive transition to an AI-enhanced economy (Liu et al., 2024).

Impact of Artificial intelligence on Economic Growth

Numerous pertinent studies highlight that AI possesses the capacity to profoundly influence economic growth through multiple avenues. Nonetheless, it is important to recognize that the influence of AI on economic growth varies across different sectors and locations. Certain industries may undergo more pronounced transformations and expansion, whilst others may have difficulties or disruptions. Furthermore, the effective adoption and integration of AI technologies require sufficient infrastructure, data accessibility, and conducive legislation, which may differ among various economies. In its 2017 study, the British consulting firm PricewaterhouseCoopers (PwC) projected that AI would contribute $15.7 trillion to global GDP from 2018 to 2030, or a 14% rise. Value generation is expected to be greater in Asia Pacific (26%) and North America (14.5%) compared to Europe (9.9% to 11.5%) and underdeveloped nations. The primary outcomes will be productivity gains (55%) and a resurgence in consumption (45%) until 2030; however, this ratio is expected to invert beyond these benchmarks due to an optimal productivity threshold.

The Stanford University report, "2023 AI Index Report," indicates that the United States invested the most in AI from 2013 to 2022, totaling $248.9 billion, followed by China at $95.1 billion. In 2022, the most significant investments in artificial intelligence were in the fields of medicine and healthcare, totaling $6.1 billion, as reported.

Conversely, a recent study by the International Federation of Robotics indicates that the operational robots in the Chinese manufacturing sector attained a ratio of 322 units per 10,000 people in 2021, while the American industry recorded 274 units per 10,000 employees. China currently occupies the fifth position globally, trailing South Korea (1,000 per 10,000 employees), Singapore (670), Japan (399), and Germany (397). The global average is 141 units per 10,000 employees. Accenture (2017) posits that AI has the potential to quadruple the growth rates of twelve prominent Western nations by 2035. This is elucidated by the assertion that automation, utilizing AI, enhances productivity.

Methodology

To explore the relationship between AI readiness and economic performance, this study adopts a quantitative approach using a regression model. The goal is to understand how different aspects of AI readiness—government policies, technological advancements, and data infrastructure—affect Gross Domestic Product (GDP) across a diverse set of countries.

Sample and Data Sources

The study focuses on **36 countries**, including **34 European nations, the USA, and China**. These countries were selected because of their varying levels of AI adoption and economic development, allowing for a broad and meaningful analysis. The participation of European countries guarantees an extensive examination of AI uptake within a continent which has been very much involved in the development of AI legislation. Because they lead in AI development and have considerable impact on the world economy, the USA and China were also included. Instead of focusing on one particular economic bloc or continent, the examination of this union of developing and developed economies by the study reflects more on the AI readiness-economic performance relationship. Data is gathered from reputable sources such as the **Government AI Readiness Index (Oxford Insights**), **World Bank**, and **Statista** to ensure accuracy and reliability.

The data used in this study is cross-sectional, focusing on a snapshot of AI readiness and economic performance for the year 2024.

Econometric Framework

To assess the impact of AI readiness on GDP, the study employs a **multiple regression model**. The equation is as follows:

$$GDP_i = \beta_0 + \beta_1 GovAI_i + \beta_2 TechAI_i + \beta_3 DataInfra_i + \beta_4 Unemployment_i + \beta_5 Gini_i + \beta_5 GDP(-1)_i + \varepsilon_i$$

where:

- **GDP (GDP_i)**: The dependent variable, representing the economic output of each country (World Bank).
- **Government AI Readiness ($GovAI$)**: Reflects how well governments support AI development through policies, regulations, and investments (Oxford Insights).
- **Technology Sector AI Readiness ($TechAI_i$)**: Captures the strength of AI-driven industries, innovation ecosystems, and research capabilities (Oxford Insights).
- **Data & Infrastructure Readiness ($DataInfra_i$)**: Measures the availability of digital infrastructure, computing power, and accessibility of data—key enablers of AI-driven growth (Oxford Insights).
- **Unemployment Rate ($Unemployment_i$)**: Serves as a control variable, accounting for labor market conditions that may influence GDP (World Bank).
- $\boldsymbol{Gini_i}$: A measure of income inequality within a country (Statista).
- $\boldsymbol{GDP(-1)_i}$**:** lag to capture any carryover effects from previous economic conditions.
- $\boldsymbol{\varepsilon_i}$: The error term captures unobserved factors.

The study will estimate this model using Least Squares regression, supplemented by diagnostic tests for heteroskedasticity, multicollinearity, and model specification errors to ensure the robustness of the results.

This will, therefore, enable this study to bring forth a clear, data-driven understanding of how AI readiness contributes to various economic performances within Europe, the USA, and China by applying this methodology.

The Government AI Readiness Index 2024 by Country

In its 7th edition, the Government AI Readiness Index has quickly established itself as a go-to benchmark among policymakers worldwide. At the request of national governments, UNESCO, and the G20, among others, it provides unparalleled insight into how to maximize AI for the benefit of the public interest (Fuentes Nettel et al., 2024).

The 2024 edition assesses the AI readiness of 188 countries at a time of growing complexity, where governments face evolving citizen needs and pressing challenges like economic uncertainty, climate risks, and rising inequalities. Addressing these issues effectively requires stronger, more innovative public sector capabilities, and AI has an important role to play. While most of the global debate focuses on the regulation of AI, another and equally important question is how governments can harness AI to enhance their performance. In the capacity of responsible and effective adoption, AI can enhance the delivery of service, optimize operations, and enable better targeting and addressing of societal challenges (Fuentes Nettel et al., 2024).

The 2024 index examines this readiness across three core pillars: Government, Technology Sector, and Data & Infrastructure. It highlights progress, identifies gaps, and provides actionable insights for policymakers working to integrate AI into public services. At its core, the index seeks to answer a fundamental question: How prepared are governments to implement AI in service delivery? By offering a practical, evidence-based tool, it supports decision-making and helps unlock AI's potential to better serve citizens worldwide (Fuentes Nettel l et al., 2024).

One important theory of change has been developed that outlines key factors that will enable countries to best prepare for and adopt AI. Within the framework of this theory, 10 dimensions have been identified, organized around three foundational pillars including Government, Technology Sector, and Data & Infrastructure. These pillars play a crucial role in shaping a country's ability to integrate AI into public services (Fuentes Nettel et al., 2024).

1. **Government**
   A well-prepared government requires a clear strategic vision for AI development and governance, supported by robust regulations and a strong focus on ethical considerations. Effective AI adoption also depends on internal digital capacity—the skills, structures, and adaptability needed to implement and manage emerging technologies successfully.
2. **Technology Sector**
   Governments rely on a capable technology sector to supply AI tools and innovations. A mature AI ecosystem requires strong innovation capacity, supported by a business environment that fosters entrepreneurship and sustained R&D investment. Of equal importance is the skilled workforce that further develops AI solutions with respect to public sector needs.
3. **Data & Infrastructure**
   AI systems rely on good quality, representative data to carry out their work and function without biases. The availability and inclusiveness of data are important factors in achieving the goal of trustworthy AI applications. In addition, infrastructure is crucial to effectively deal with data and deliver AI solutions to the citizens.

The Index scores a country against those parameters to appraise how well prepared the countries are with respect to the integration of AI into governance and public service delivery (Fuentes Nettel et al., 2024).

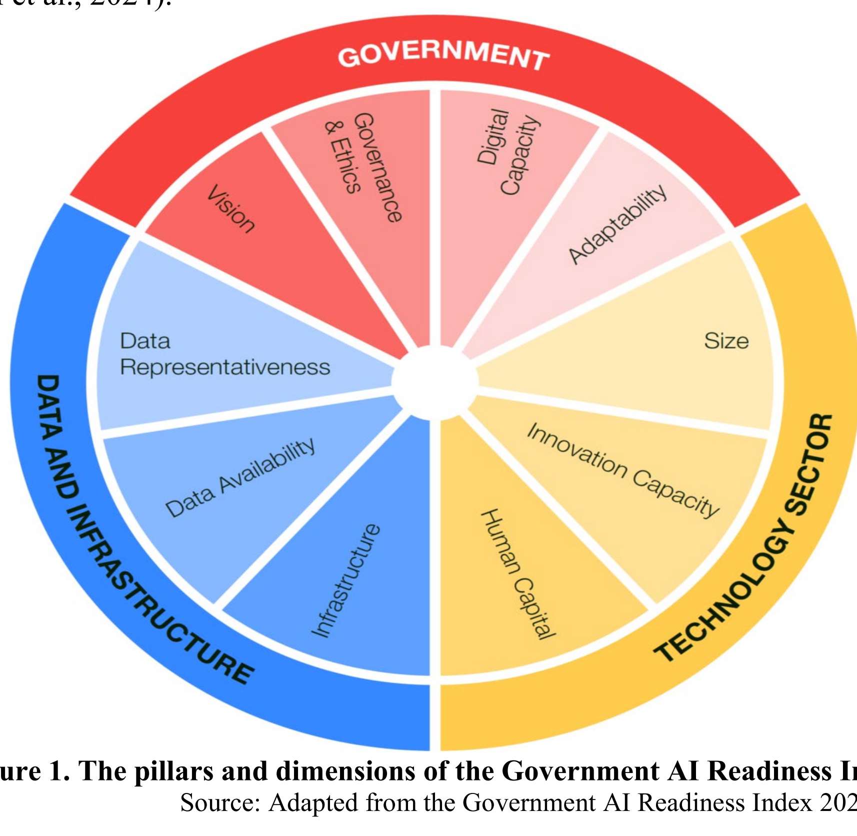

Figure 1. The pillars and dimensions of the Government AI Readiness Index
Source: Adapted from the Government AI Readiness Index 2024, Oxford Insights.

Oxford Insights' government AI readiness index has lately been used as an assessment tool for Fourth Industrial Revolution development. Oxford Insights' Government AI Readiness Index evaluates several factors to assist governments in effectively preparing for the implementation of AI services. The pillars identified are the government, the technological industry, and the data and infrastructure. Worldwide, governments are adopting AI to enhance public services and secure strategic economic benefits. To capitalize on this AI-driven shift, governments must possess the appropriate tools and operational framework (Fuentes Nettel et al., 2024).

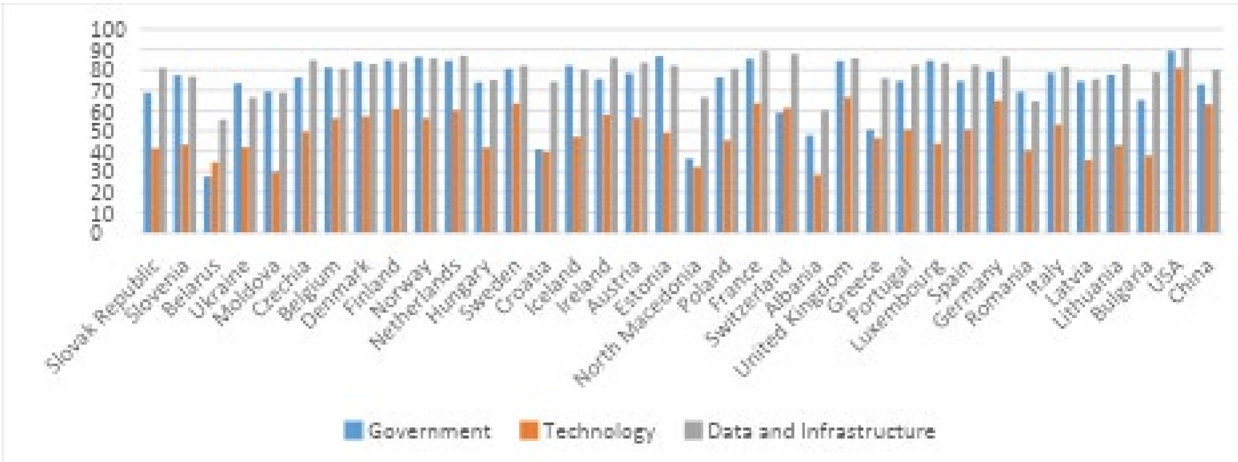

Figure 2 Key AI Readiness Developments in Europe, USA, and China

Source: Government AI Readiness Index 2024, Oxford Insights (By author).

Figure 2 shows the AI readiness scores of the 36 countries included here, divided between government AI readiness, technological infrastructure, and data and infrastructure. To give coverage to 34 countries across Europe and also the USA and China enables comparative analysis of AI take-up across economic and technological environments of different kinds. High AI preparedness among European nations such as Germany, France, the United Kingdom, and the Nordic countries also reflects in government regulations and data infrastructure. Next are the emerging economies of Eastern Europe, such as Romania, Bulgaria, and Slovakia, that have blended AI preparedness based on the varying levels of technology and policy maturation. Including the United States and China in the analysis more accurately represents the economic effects of AI since they are investing more in digitalization, and they have more developed AI ecosystems. It is trying to capture the overall effects of AI readiness on the performance of the economy and inequality by applying different AI adoption countries.

North America remains the top in the Government AI Readiness Index, with the United States at the top globally at 87.03. It does very well in all the pillars: Governance and Ethics at 91.14, Innovation Capacity at 92.48, and Tech-Sector Maturity at 83.8, reflecting its strong AI ecosystem. With superior policies, infrastructure, and innovation, the U.S. still dominates the globe in AI readiness. In 2024, it resumed leadership through high-level discussions on AI strategy, gathering big tech players to make sure their dominance in the field continued. In October, the White House issued its first-ever National Security Memorandum on AI, emphasizing the need for trustworthy AI development and international leadership in AI governance. These efforts highlight the United States' commitment to shaping the future of AI on the global stage.

Basically, Western Europe remains the leading region in getting ready for AI, with France topping regional positions with 79.36 points, trailed by the UK with 78.88, the Netherlands with

77.23, Germany with 76.90, and Finland with 76.48. The region beats the rest in the global top 10 because of its strong data infrastructure, mature governance frameworks, and robust AI innovation. With an average of 69.56 well above the global average of 47.59, Western Europe is performing especially well in Data & Infrastructure, which has a total of 81.91 points. In 2024, AI regulation and governance are taking center stage, with the EU launching an AI office to oversee its landmark AI Act, Spain establishing the region's first AI agency, and France appointing a Secretary of State for AI and Digitalization. Strategic planning is also advancing, with the UK, Netherlands, and Italy refining their national AI visions. Investments in AI infrastructure are ramping up, as France, Germany, and Poland form a political alliance to align their AI strategies, while the EU commits €1.5 billion to build AI factories, and the UK invests £300 million in advanced AI research computing. These developments reaffirm Western Europe's position as a global leader in AI readiness.

Eastern Europe ranks fourth in the 2024 Government AI Readiness Index, with an average score of 57.88—well above the global average of 47.59. Estonia (72.62) leads the region and is the only Eastern European country in the global top 25. The region performs strongly in Data & Infrastructure (72.10), ranking third worldwide, and also shows solid governance (62.52). However, challenges remain in the Technology Sector, which scores 39.03, highlighting the need for greater investment in AI innovation. Despite this, Eastern Europe's strong governance frameworks and data infrastructure position it as a leader among emerging regions. In 2024, several countries are advancing their AI strategies—Moldova and Romania have introduced national plans, with Moldova focusing on public administration and Romania prioritizing economic competitiveness. Slovenia is enhancing AI transparency with a new public sector AI registry, while Poland is investing €232 million in developing domestic AI models, including a national large language model. With ongoing investments and strategic initiatives, Eastern Europe is steadily strengthening its AI readiness.

Results and discussions

The relevance of understanding the association between the readiness of AI and economic performance is high in the present times, when the digital economy is advancing every second. This section unfolds the empirical results of our regression analysis to show the effect of government AI policies, technological advancement, data infrastructure, inequality, and unemployment on GDP in 36 countries, including 34 European nations, the USA, and China.

The regression model shows some interesting insights on the facets of readiness to AI in contributing to economic performance. The high R-squared obtained is 0.89, indicating that the model is highly explanatory of the variation in GDP and confirming the relevance of the selected variables. These interpretations are done in both a statistical and real-life economic context in the discussion that follows, addressing implications for policy makers, businesses, and global competitiveness.

This regression model considers how AI readiness, combined with key macroeconomic variables, affects GDP. The estimates for the coefficients and their significance levels are shown below (table 1).

Table 1 Regression Model

Dependent Variable: GDP				
Method: Least Squares				
Included observations: 35 after adjustments				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
C	55066046	7148496.	7.703165	0.0000
GovAI	10534.23	34844.37	0.302322	0.7646
TechAI	287640.9	51866.76	5.545765	0.0000
DataInfra	-318192.1	84611.49	-3.760625	0.0008
Gini	-603716.6	63570.99	-9.496732	0.0000
Unemployment	-32103431	13304507	-2.412974	0.0226
GDP(-1)	-0.224662	0.101878	-2.205205	0.0358
R-squared	0.890094	**Mean dependent var**		2032951.
Adjusted R-squared	0.866543	**S.D. dependent var**		5532910.
S.E. of regression	2021273.	**Akaike info criterion**		32.05321
Sum squared resid	1.14E+14	**Schwarz criterion**		32.36428
Log likelihood	-553.9312	**Hannan-Quinn criter.**		32.16059
F-statistic	37.79381	**Durbin-Watson stat**		1.828118
Prob(F-statistic)	0.000000			

Source: Eviews (By Author).

Key findings and interpretation

The F-statistic here tests that at least one of the independent variables is significantly predicting up to GDP: We see a high F-statistic (37.79381) with an accompanying p-value of (0.000000), indicating that the model as a whole is statistically significant, which means the predictors are jointly having a strong effect on GDP.

AI readiness in technology has a great, positive effect on GDP with a coefficient: 287,640.9 | p-value: 0.0000 (Highly significant): statistically significant and very strong. The critical contributions of technological innovation, AI-driven industries, and digital transformation will drive economic growth. The fact that countries have more advanced ecosystems, such as Germany, the USA, or China, show evidence of higher productivity, efficiency, and global competitiveness.

Somewhat counterintuitively, the GDP is negatively influenced by the variable of data and infrastructure readiness with a coefficient: -318,192.1 | p-value: 0.0008 (Highly significant); it is not all about having the data and infrastructure, but it is about using them. While countries might invest a great deal in the infrastructure for AI, if either the regulatory environment, level of digital literacy, or cybersecurity measures are too weak, this might not eventually be translated into real economic benefits. Furthermore, this could show the short-term costs of the adoption of AI, whereby investments in infrastructure are not immediately translated into GDP growth.

The government AI readiness index has a negligible impact on GDP with a coefficient: 10,534.23 | p-value: 0.7646 (Not significant). Of course, good AI policy is instrumental, but this result would suggest that policy initiatives themselves will not yield economic growth. Whether or not AI policy is effective is a question of implementation, coordination with the private sector, and workforce adaptation. Countries like Estonia, which intertwines progressive AI strategies with strong execution, receive greater economic benefits, while others may fight off bureaucratic inefficiencies.

The negative and highly significant effect of income inequality on GDP points to a key economic challenge with a coefficient: - 603,716.6 | p-value: 0.0000 (highly significant): increasing inequality may be harmful to long-term growth. Economies with high levels of income inequality generally have lower consumer spending, weaker social cohesion, and reduced human capital development, all of which hurt economic performance. This finding supports international concerns that AI-driven automation may widen the income gap, benefiting high-skilled workers while displacing those in lower-skilled jobs.

A higher rate of unemployment drastically lowers GDP, establishing a strong relationship between labor market conditions and economic output with a coefficient: -32,103,431 | p-value: 0.0226 (Significant). More seriously, AI-based economies have challenges in automation and job displacement, particularly in traditional industries. This calls for policymakers to ensure reskilling programs, education reforms, and social safety nets as intervention policies that put a buffer on AI-induced job losses and sustain economic growth.

Though the model includes a lagged GDP variable, or GDP (-1), our study is cross-sectional for the year 2024, rather than time-series in nature. In this context, the negative and significant coefficient: -0.224662 | p-value: 0.0358 (Significant), might reflect structural economic differences among countries rather than temporal economic trends. This result would suggest that for very high levels of GDP, countries might actually grow more slowly due to the impacts of market saturation, lower marginal returns to capital investment, or economic maturity effects. At the same time, emerging economies could have larger scope for growth by catching up on more advanced economies. This finding implies that AI readiness and economic policies should be designed in concert with the current economic position of a country-for example, innovation-driven policies for advanced economies and AI adoption in labor-intensive sectors to spur growth in emerging economies.

Model Assumptions

1. Normality Test

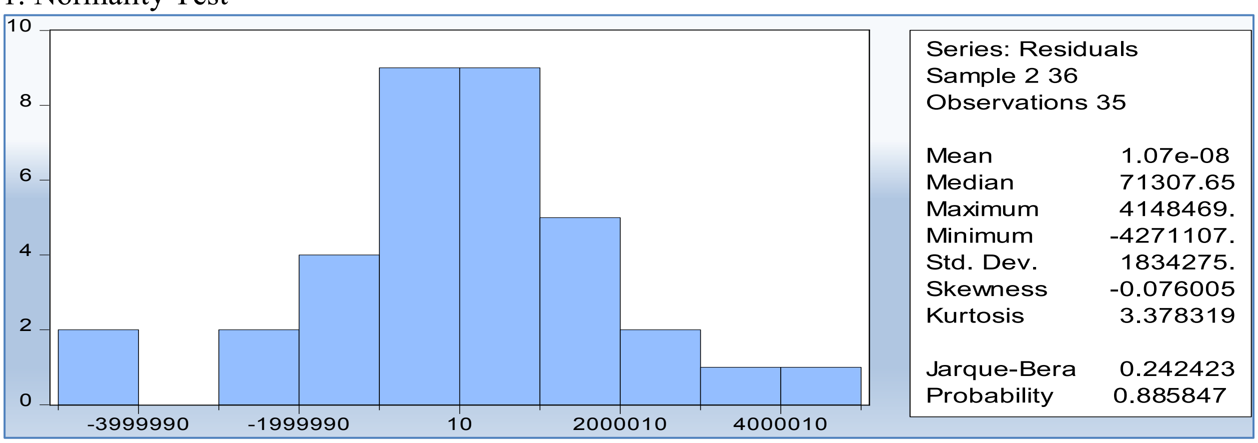

Figure 3 Model Assumption 1- Normality test

Source: Eviews (By Author).

The **Jarque-Bera test** p-value (0.885847) in figure 3 suggests that we fail to reject the null hypothesis of normality, implying the residuals are normally distributed.

2. Heteroskedasticity Test

Table 2 Model Assumption 2- Heteroskedasticity Test

Heteroskedasticity Test: ARCH			
F-statistic	1.253056	**Prob. F(1,32)**	0.2713
Obs*R-squared	1.281203	**Prob. Chi-Square(1)**	0.2577

Source: Eviews (By Author).

The high p-values in table 2 (greater than 0.05) indicate that we again fail to reject the null hypothesis of homoscedasticity. That is, the variance of the residuals is constant across observations, indicating no significant heteroskedasticity in the model.

4. Autocorrelation Test
5.

Table 3 Model Assumption 3- Autocorrelation Test

Breusch-Godfrey Serial Correlation LM Test:			
F-statistic	0.327211	**Prob. F(2,26)**	0.7239
Obs*R-squared	0.859324	**Prob. Chi-Square(2)**	0.6507

Source: Eviews (By Author)

Table 3 suggests that we cannot reject the hypothesis of no serial correlation, since both the p-value for the F-statistic and the Chi-square statistic are greater than 0.05. There is no significant evidence of serial correlation in the residuals of the model; this therefore goes down well with the validity of the assumptions taken up by the model.

4. Multicollinearity Test

Table 4 Model Assumption 4- Multicollinearity Test

Variance Inflation Factors			
Sample: 1 36			
Included observations: 35			
	Coefficient	**Uncentered**	**Centered**
Variable	**Variance**	**VIF**	**VIF**
C	5.11E+13	437.7714	NA
GovAI	1.21E+09	57.25756	2.281197
TechAI	2.69E+09	61.08291	3.198860
DataInfra	7.16E+09	388.4649	4.143586
Gini	4.04E+09	160.3604	2.085198
Unemployment	1.77E+14	6.312309	1.178902
GDP(-1)	0.010379	2.136641	1.934757

Source: Eviews (By Author).

The centered VIF values are below the threshold value of 5 for all the variables bar the constant, suggesting that generally, multicollinearity would not be an issue in this model. This normally implies that the coefficient estimates are reasonably dependable, and also the standard error does not include a very wide error due to multicollinearity.

Overall, the model seems to look good with regard to the multicollinearity assumptions.

Correlation Analysis

The variables at the center of the analysis for correlation, with key variables from the side of AI readiness-government, technology, and infrastructure-on the variable representing the level of inequality expressed through the Gini coefficient, can thus provide at least an interim indication of their possibly linked causes in a comprehensive overview of this matter, within AI and economic impacts. By investigating these relations, we will be able to identify any existing patterns or trends that could assist the more thorough econometric analysis in order for us to perceive the role that AI plays in shaping income inequality across the 36-country sample.

Table 5 Correlation Analysis for AI and Economic Inequality

	Gini
Gini	1
GovAI	-0.1254904814713568
TechAI	-0.3876397964715369
DataInfra	-0.2299049447589311

Source: Eviews (By Author)

We could notice the following from this correlation analysis:

Government AI Readiness and Inequality: A somewhat low negative value of the correlation coefficient between Government AI Readiness and Gini implies that though government efforts toward AI can contribute to reduced income inequality, it has not had much significant bearing on the results in 2024. That would perhaps imply that time and a wide range of policy measures must go in for AI to effectively shake up income distribution.

Technology for Reduction to Inequality: It is expected that technology, with its moderate negative relation to the Gini coefficient, could turn out to be a strong factor in reducing inequality. This is, therefore, promising: a relationship in which AI can provide new avenues for job opportunities, powered by innovation.

Impact of Data and Infrastructure on Inequality: These are negatively related, meaning data and infrastructure themselves have a weakened effect on changing inequality. In this case, it may simply be indicative of the fact that digital infrastructure needs supplementation with another policy, be it education, training programs, or something like that, as a way for it to affect inequality more tangibly.

Conclusion

The results of our regression study demonstrate that technology preparedness is a substantial positive determinant of GDP, indicating that nations with a robust technological infrastructure are likely to achieve superior economic performance. This corresponds with current literature that emphasizes the significance of digital infrastructure and technical progress in fostering economic growth. The positive coefficient of technology indicates that proliferation and integration of AI in the technology sector could lead to better resource allocation, innovation, and productivity gains, hence increasing GDP in the end.

However, data and infrastructure, though important in the development of AI, appear to have a dampening effect on GDP in our model. Indeed, this may have implications for infrastructural barriers or inefficiencies in the studied countries that could act as a damper on the expected positive contribution of AI towards economic growth. While some of these nations could be technologically capable, there could be drag factors in realizing the full potentials of AI for catalyzing economic growth in terms of speed or delays in data utilization in infrastructure adoption.

The correlation study of the Gini coefficient and the analyzed factors underscores the intricate relationship among AI, inequality, and economic performance. The inverse relationship between the Gini coefficient and technical readiness indicates that enhanced technology and improved infrastructure could potentially mitigate economic inequality, since the advantages of technological advancement may be more equitably disseminated throughout society. It aligns with those theories that AI will increase productivity across all sectors and, consequently, provide opportunities for all-inclusive growth. The low correlation with the unemployment rate is an indication that while the readiness for AI might affect the distribution of income, it doesn't affect the outcome in employment matters, putting into consideration the limitation of this study.

The examination of the Gini coefficient as a variable in our regression model reveals a substantial inverse correlation with GDP, suggesting that nations with less income inequality generally exhibit higher GDP. This discovery underscores the idea that mitigating inequality via policies designed to enhance AI adoption can foster a more affluent economy. The unemployment rate has a negative correlation with GDP, indicating that elevated unemployment may hinder economic progress, hence highlighting the necessity for measures that facilitate the labor market's adjustment to technological advancements.

This study enhances the existing literature regarding the influence of AI on economic and societal outcomes. Our findings highlight the significance of technical preparedness and AI infrastructure for economic success, while also acknowledging the intricacies of tackling inequality and unemployment in an AI-driven economy. The findings indicate that governments must invest in AI-related infrastructure and legislative frameworks to optimize the beneficial economic effects of AI, while guaranteeing equitable distribution of gains throughout society. Future research should further examine the dynamic interaction among these elements, particularly within the setting of a swiftly changing global technology environment.

To avail the maximum possible benefits of AI while mitigating its socio-economic issues, the governments must adopt a holistic strategy that reconciles technical progress with socially equitable development. AI-based vocational training is essential to train people in such skills that enable them to gain employment in AI-based industries and thereby minimize technological unemployment. Furthermore, progressive taxation systems or universal basic income schemes can be introduced by governments to minimize job loss and economic inequality caused by AI. Balancing the development of AI infrastructure across all industries in the economy will promote equitable distribution of AI benefits, mitigating regional and societal imbalances. In addition, industry-specific regulations to offset the special effect of AI on particular industries must be applied to overcome the various challenges from automation and incorporation of AI. By promoting collaboration between governments, enterprises, and schools, nations can create open systems that have the ability to release the overall potential of AI without economic exclusivity.

This study offers informative observations but is constrained by the cross-sectional approach employed, which cannot identify long-run trends in AI adoption. Long-term studies should include longitudinal data in a bid to examine AI readiness influencing the long-term performance of the economy. Additional insight into the impact of AI may also be obtained through sectoral analysis. By knowing potential limitations to data as well as assumptions in models enhances our lucidity and dependability of observations.

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