Research Article

The Effect of Artificial Intelligence Investments on Economıc Development: Panel Data Analysıs

Muhammed Inal, Gokhan Karhan, Mucahit Cayin

***Abstract*— In the 21st century, the relationship between economic development and technological innovation is becoming increasingly complex. In recent years, with the emergence of artificial intelligence as a pioneer and leader in technological innovation and its increasing use in many fields, unemployment is rising on the one hand, while on the other hand, unit costs are decreasing due to increased productivity. This dilemma has become a question that needs to be explored, especially for countries with technologies that make intensive use of artificial intelligence. To this end, this study examined the effects of artificial intelligence (AI) investments on economic development in Germany, the United States, China, France, South Korea, India, Italy, and Japan for the period 2012-2023 using panel data methods. The Human Development Index (HDI) is used as an indicator of economic development in the models developed for the analysis, while AI investments are treated as the main independent variable. Per capita income (PCI), inflation (INF), and foreign direct investment (FDI) are included in the model as control variables. Second-generation panel methods, such as the Pesaran–Yamagata homogeneity test, Pesaran CD tests, and the CIPS unit root test, are applied in the study, and long- and short-term relationships are analyzed using the CS-ARDL model. The research indicates that investments in AI have a beneficial and substantial effect on HDI over time. However, INF was found to have a negative impact on the HDI. It has been observed that the FDI variable has negative effects contrary to expectations. The heterogeneity of the variables' parameters suggests that the impact of AI investments on development varies across countries. In conclusion, AI investments appear to be a supportive element for economic development, but the appropriate macroeconomic and institutional framework must be provided for the sustainability of this impact.**

Index Terms—**Artificial intelligence investments, Economic development, Human Development Index, Panel data analysis**

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I. INTRODUCTION

THE SUBJECT of artificial intelligence (AI) has recently been intensely discussed in many disciplines with its positive and negative aspects. Indeed, since its rise to global prominence, AI has become a research topic in nearly every field, from health and education to law and sociology, and from agriculture to technology. AI is also a subject of intense economic research, particularly in the context of unemployment, production, total factor productivity, and welfare. For example, Researchers such as [1-5] have investigated the issue of AI in the context of its impact on unemployment. In addition, there are also studies examining the issue of AI in terms of firms' total factor productivity [6-10].

In their study Aghion et al. [11], modeled AI and made predictions about the relationship between AI and economic growth and revealed the possible effects of AI on the economic growth process. In another study conducted by Aghion et al. [12], the effects of AI on employment and EG were examined. In the study, it was emphasized that AI can support growth by replacing labor with capital in both the production of ideas and the production of goods and services, but it can hinder growth when combined with inappropriate competition policies. On the other hand, empirical findings from the French example revealed that artificial intelligence reduced total employment and that educated workers were less affected than uneducated workers. Furthermore, the researchers emphasized that despite extensive theoretical and empirical research on AI, it is still too early to fully understand its impact on social welfare. However, they pointed out that AI's impact on employment and EG is largely determined by institutions and policies.

This situation, highlighted by Aghion et al. [12], where it is still early to understand the effects of AI on well-being, reveals the need for further research on artificial intelligence. Therefore, it was thought that further research was needed on the possible social and economic effects of AI on issues such as income distribution and general quality of life, and this research was carried out.

In this study, the impacts of AI investments on the HDI which is an indicator of economic development, are empirically examined in the case of Germany, the USA, China, France, South Korea, India, Italy and Japan, which are the leading countries in the field of artificial intelligence. Separate models were created for the study using data from 2012 to 2023, and the models were estimated using panel data techniques. The study will first examine some previous studies within the scope of the literature review. Applications will then be presented, and the application findings will be discussed. The study will conclude with an overview of the findings and policy implications.

II. LITERATURE REVIEW

With the increasing use of AI in production processes in recent years, the relationship between AI and economic development has become a hotly debated topic. Although studies have been conducted on a country/countries basis, literature lacks the desired level of research. In this regard, an empirical study on the impact of AI was conducted by He [13] for the USA (United States of America). The study investigated the effect of AI on macroeconomic indicators such as imports, exports, FDI, GDP, employment, and real income using data from 2010Q1-2017Q4. Using the Phillips-Perron test and Canonical cointegration regression methods, the study found that AI negatively affected imports while positively affecting other macroeconomic indicators. In another study conducted for the USA, [14] focused on the relationship between AI and growth and subjective well-being, underlining that the share of AI jobs in total job postings is increasing, but this is not distributed homogeneously among all cities in the USA. Cities with a high increase in AI job postings have experienced higher growth, gaining advantages in terms of EG. Due to the positive relationship between AI jobs and EG, there has also been an improvement in subjective well-being. In summary, although the research is still early, it suggests that AI-powered EG will lead to more professional or modern services, which could improve overall and social well-being.

Lu [15] investigating the effects of AI on growth and welfare, he developed an endogenous growth model with three sectors. Accordingly, AI can increase EG along the transition dynamics path and households' short-term benefits due to increased productivity in AI or goods sectors. However, the increased use of AI to replace human labor may negatively impact households' short-term utility. AI may not always be beneficial for household welfare in the long run. Another study empirically examined the impact of AI on green energy efficiency in China using data from 2006 to 2019. Using a nonlinear dynamic panel regression model, the study found that AI affects green total factor productivity in a "U"-shaped fashion, initially decreasing and then increasing total factor productivity. It also demonstrated that enhanced AI can increase green total factor productivity in resource-rich regions and overcome the "resource curse" [16].

Goyal and Aneja [17] stated that while the development of automation and robots has led to higher EG and productivity in recent years, unemployment has nevertheless increased. According to the researchers, the rapid advancement of automation and robotization has reduced employment and worsened income distribution. Although not directly related to technology, income inequality can result from the interaction between technological changes and employee positions. Automation and robotization not only reduce low and medium-skilled jobs but also increase unemployment rates and widen the income gap between high and medium-skilled jobs. Furthermore, developing countries have higher Gini coefficients than developed countries, which reveals that income inequality is greater in developing countries. Similarly, in a descriptive study, Trabelsi [18] considers AI as an engine of productivity and growth. Accordingly, AI's analysis of large data sets can increase productivity while also improving decision-making processes. However, he emphasizes that despite these advantages , AI also carries some serious risks. For example, he states that it carries risks such as polarization in the labor market, structural unemployment, deepening income inequality, and the replacement of traditional sectors with new and uncertain industries.

On the other hand, Mhlanga [19] examines the impact of AI on some Sustainable Development Goals (SDGs) and shows that AI plays a strong role in reducing poverty in developing countries, improving transportation infrastructure, and supporting EG and development. Accordingly, AI can reduce poverty by improving the collection of poverty data, It is effective in transforming the financial sector and agricultural education through financial inclusion. Furthermore, through its impact on education and finance, it is enabling marginalized individuals to participate in the economy. However, Vinuesa et al. [20] examined the effects of AI on SDGs in a broader context and concluded that AI could help achieve 134 targets under 17 goals but could hinder 59 targets.

In their study Filippucci et al. [21] examining the impact of AI on social and economic welfare, emphasize its capacity to accelerate innovation and revitalize declining productivity growth in various sectors. However, researchers highlight uncertainties regarding the long-term impact of AI, noting that AI development is concentrated in large technology companies, adoption rates are uneven, and this could lead to social problems such as inequality, discrimination, and security. Therefore, researchers emphasize the need for more beneficial and careful development and dissemination of AI. In this context, they emphasized the need for policies that increase competition, facilitate access, and address income inequality and job loss. Similarly, in the study conducted by Capraro et al. [22], they pointed out that AI has the potential to worsen socioeconomic inequalities as well as improve them. In other words, it was stated that while AI offers advantages in sectors such as business, education, and healthcare, it also has disadvantages. The study also emphasized the importance of interdisciplinary collaborations to unravel the complex structure of AI.

In the study conducted by Saba and Ngepah [23], the impact of artificial intelligence investments on EG and employment was examined in the case of BRICS countries and the impact of governance indicators was also taken into account. Data between 2012 and 2022 were analyzed using the Cross-Sectional Augmented Autoregressive Distributed Lag (CS-ARDL) technique and causality testing. The study revealed a long-term relationship between AI, governance quality, employment, and EG, demonstrating that all variables interact with each other. The causality test findings showed that there is a one-way causality relationship from EG to AI and from artificial intelligence to employment. The study, which obtained different findings in the coefficient estimates, emphasized that BRICS countries need to ensure the integration of AI into their governance systems to support EG and increase employment in both the short and long term. In other words, it is argued that these countries should develop AI-friendly governance policies. Analyzing data from the G-7 countries (USA, Germany, France, UK, Italy, Japan, and Canada) for the period 2012-2022, the study also emphasized the importance of governance indicators. In other words, researchers emphasized that both improvements in governance indicators and AI initiatives should be prioritized to ensure that AI's impact on human welfare is positive. In summary, these studies reviewed in the literature demonstrate that the economic impacts of AI are complex. These studies include both positive and negative assessments and findings. The studies also indicate that certain conditions must be met for AI to produce positive impacts, or at least avoid negative ones, and therefore, policy sets are needed. While this situation demonstrates the need to be careful about the effects of artificial intelligence, it also demonstrates the need for further research on the subject.

III. METHODOLOGY

The complexity of the economic impacts of artificial intelligence and the need for further research on the subject motivated this study. In this context, it was anticipated that examining the effects of AI investments on EG using a different sample and method would make a significant contribution to literature, and the study was designed for this purpose. In the studies conducted by [24, 25], robot installation numbers obtained from the International Federation of Robotics (IFR) data were used as an indicator of AI. Based on the use of robot installation numbers as an indicator of artificial intelligence, it was decided to conduct the study on countries that stand out in terms of robot installation numbers. Thus, using data from eight countries (N=8, T=12) that are prominent in robot numbers, namely AI, for the period 2012–2023 , namely Germany, the United States (US), China, France, South Korea, India, Italy, and Japan, The impact of AI investments on economic development was investigated using panel data analysis. According to IFR data, these countries are among the fifteen largest markets in terms of annual industrial robot installations in 2023 [26]. The study selected eight countries among the fifteen, but with data spanning a longer period, thus expanding the time span of the dataset used in the analysis.

On the other hand, the study conducted by [27] examined HDI, which represents human well-being, and AI investments, which represent artificial intelligence. Inspired by this study, the Human Development Index (HDI) was considered as the dependent variable representing economic development. AI investments (VC investments in AI, USD million) were included in the model as the main independent variable representing artificial intelligence investments. The study also considered control variables that could affect economic development. In this context, gross domestic product per capita (PCI) was used as a proxy for EG (GDP per capita, constant 2015 US$), inflation rate representing price stability (INF, consumer Prices, annual %) and foreign direct investment (FDI, net inflows of GDP) representing openness to the outside world were used as control variables (Table I).

In this context, the models created with control variables are listed below:

- Model 1:

$$log(HDI_{it}) = \alpha_i + \beta_1 log(AI_{it}) + \beta_2 log(PCI_{it}) + \beta_3 log(INF_{it}) + \varepsilon_{it}$$

- Model 2:

$$log(HDI_{it}) = \alpha_i + \beta_1 log(AI_{it}) + \beta_2 log(PCI_{it}) + \beta_3 log(FDI_{it}) + \varepsilon_{it}$$

- Model 3:

$$log(HDI_{it}) = \alpha_i + \beta_1 log(AI_{it}) + \beta_2 log(FDI_{it}) + \beta_3 log(INF_{it}) + \varepsilon_{it}$$

In the models, i represents the country size, t represents time, α_i represents effects of countries, and ε_{it} is the error term.

Pesaran–Yamagata (2008) homogeneity test was applied to reveal whether the relationship between variables is heterogeneous or has the same coefficients for different countries in panel data [28]. The test was calculated separately for three different models. This test tests whether the parameters are the same across countries and reveals the heterogeneous structure of the panel data model. Another critical step in panel data analysis is testing the existence of cross-sectional dependence (CSD) between the series. For this purpose, the CD test by Pesaran (2015, 2021) and the CDw + test developed by Fan et al. (2015) were applied [29-31]. To determine the degree of stationarity of the variables in the study, the CIPS panel unit root test, developed by Pesaran (2007), which takes cross-sectional dependence into account, was used [32]. Subsequently, due to the fact that some variables are stationary at the level and some are stationary at the first difference and there is CSD, the CS-ARDL method developed by [33] was preferred. This method allows the examination of dynamic relationships on independent variables that show weak exogeneity by including the lagged values of the dependent variable in the model. In addition, the CS-ARDL approach shaped within the framework of the error correction model (ECM) reduces bias problems arising from cross-sectional dependence in both the short and long term and ensures reliable estimations [34].

TABLE I
Description and Source of Variables

Variables	Description	Source
HDI	Human Development Index	World Bank
AI	VC investments in AI (USD millions)	OECD
PCI	GDP per capita (constant 2015 US$)	World Bank
INF	Inflation, consumer prices (annual %)	World Bank
FDI	Net inflows of Foreign Direct Investment (% of GDP)	World Bank

IV. FINDINGS AND DISCUSSION

In the first stage of the analysis, the homogeneity of the coefficients in the models was examined using the Pesaran–Yamagata (2008) test [28]. According to the findings, the Delta and adjusted Delta values calculated for Model 1 were found to be significant. This result demonstrates that the null hypothesis assuming homogeneity of the coefficients was rejected, and therefore, the effects of the variables in the model on the HDI differ across countries. The results of Model 2 similarly point to heterogeneity. The Delta (3.153; p=0.002) and adjusted Delta (4.128; p=0.000) values were found to be significant, indicating that the effects of artificial intelligence investments, per capita income, and FDI on the HDI differ across countries. According to the homogeneity test results performed for Model 3, the null hypothesis of homogeneity of the coefficients was rejected (Table II). The coefficients in all models exhibit heterogeneity. This result reveals that the relationship between AI investments and HDI varies from country to country.

According to the results of the CSD test, strong evidence of cross-sectional dependence was obtained for all variables (HDI, AI, PCI, INF, and FDI). The CD statistic for the HDI variable was 15.36 ($p<0.01$) and the CDw + value was 78.98 ($p<0.01$), indicating that the level of human development does not move independently across countries. Similarly, the relatively high CD and CDw + statistics for the AI and PCI variables indicate that these variables exhibit strong dependence across countries. The CD and CDw + values calculated for the INF variable were found to be significant, suggesting that inflation rates are affected by common shocks and do not move independently across countries. According to the CSD test statistics results of the FDI variable, it was concluded that there is a cross-sectional dependence.In general, these results show that the variables in the panel data set do not move independently of each other but rather are affected by common global and exogenous shocks.

TABLE II
Homogeneity Test

Equations	Δ	p- value	Δ adj.	p- value
Equation 1	3,408	0.001	4,462	0.000
Equation 2	3,153	0.002	4,128	0.000
Equation 3	2,091	0.037	2,737	0.006

According to the results of the CSD test (Table III), strong evidence of cross-sectional dependence was obtained for all variables (HDI, AI, PCI, INF, and FDI). The CD statistic for the HDI variable was 15.36 ($p<0.01$) and the CDw + value was 78.98 ($p<0.01$), indicating that the level of human development does not move independently across countries. Similarly, the relatively high CD and CDw + statistics for the AI and PCI variables indicate that these variables exhibit strong dependence across countries. The CD and CDw + values calculated for the INF variable were found to be significant, suggesting that inflation rates are affected by common shocks and do not move independently across countries. According to the CSD test statistics results of the FDI variable, it was concluded that there is a cross-sectional dependence.

TABLE III
Cross- sectional Dependency Test

Variables	CD	prob.	CDw +	prob.
HDI	15.36	0.000	78.98	0.000
AI	16.37	0.000	84.56	0.000
PCI	16.02	0.000	82.69	0.000
INF	5.49	0.000	20.03	0.000
FDI	1.97	0.049	39.55	0.000

In general, these results show that the variables in the panel data set do not move independently of each other but rather are affected by common global and exogenous shocks.

Due to the existence of CSD across countries, the CIPS test (2nd generation unit root test) that takes this characteristic into account, was applied. The test results indicate that there are differences in the degrees of integration of the variables (Table IV). Accordingly, the HDI variable became stationary in the first difference. PCI and FDI variables also followed a similar process. The AI and INF variables are found to be stationary at the level.

The findings reveal that some of the variables in the model are stationary at the level and some are stationary at the first difference. Therefore, the CS-ARDL method, which takes into account different degrees of integration, was used in the analysis. This approach, developed by Chudik and Pesaran (2015), allows for the simultaneous examination of short and long-term relationships in situations where variables have different degrees of integration [33].

TABLE IV
Cross- sectional Dependency Test

Variables	I (0)	I (1)
HDI	-2,526	-4.736***
AI	-3,541	-
PCI	-1,981	-2.969**
INF	-3.033	-
FDI	-1,861	-2,794*

*, ** and *** represent 1%, %5 and 10% level of significance, respectively.

Examining the results of the CS-ARDL analysis (Table V), it is clear that the long-term effects of AI investments on the human development index (HDI) are largely positive. Specifically, the AI variable has a significant and positive coefficient in Models 1 and 3, indicating that increased AI investments promote human development. Conversely, in Model 1 per capita income (PCI) is positive and significant, confirming that EG is a fundamental component of human development. However, in Model 2 the AI coefficient is not statistically significant, indicating that the effects may be weakened depending on the variable selection. In Models 1 and 3, INF variable yields negative and significant results, indicating that price instability negatively affects human development. Furthermore, FDI is particularly negative and significant in Model 3.

TABLE V
CS-ARDL (Long Run) Findings

Equations	Variables	Coeff.	Standard Err.	t- Stat.	Probability
Equation 1	AI	0.206952	0.065532	3.158010	0.0032
	PCI	6.16E-05	2.72E-05	2.263163	0.0296
	INF	-0.280353	0.119295	-2.350088	0.0242
Equation 2	AI	0.170111	0.198586	0.856611	0.3972
	PCI	-7.80E-05	9.53E-05	-0.818641	0.4182
	FDI	-0.071651	0.089035	-0.804757	0.4261
Equation 3	AI	0.075324	0.001489	50.58667	0.0000
	INF	-0.331933	0.005535	-59.97004	0.0000
	FDI	-0.516240	0.008255	-62.53767	0.0000

The results show that in the long-term AI investments have a positive impact on HDI. This results is consistent with studies in literature emphasizing the positive effects of AI on productivity, innovation, and social welfare [14, 19, 21] is consistent. The negative impact of inflation demonstrates that price stability is a fundamental prerequisite for development. The negative impact of foreign direct investments is striking and highlights the decisive role of the nature of these investments and the sectors they target on development.

As a result, ensuring macroeconomic stability, directing foreign investments to strategic sectors, and implementing policies to encourage technology transfer are critical for the sustainable contribution of AI investments to development.

V. CONCLUSION

This study uses panel data to determine the impact of AI investments on HDI in G7 countries (Germany, the United States, China, France, South Korea, India, Italy, and Japan) between 2012 and 2023. The study analyzes the role of AI investments on HDI, a key indicator of economic development, and uses FDI, INF, and PCI as control variables in the model. The analysis results indicate that AI investments have a significant and positive impact on HDI in the long run. This finding shows that AI can contribute significantly not only to economic efficiency and innovation but also to social welfare. In particular, the significant coefficients obtained in Models 1 and 3 confirm that increases in AI investments are a factor supporting development. Conversely, the negative and significant impact of inflation demonstrates that price stability is a prerequisite for sustainable development. Conversely, the negative impact of FDI, contrary to expectations, points to the decisive role of the nature of these investments and the sectors they target on development.

The study also revealed heterogeneity in coefficients across countries. Findings of heterogeneity test suggests that the impact of AI investments on development varies depending on country characteristics, and therefore, uniform policies will not produce similar results across countries.These differences may be due to countries' economic structures, institutional capacities, and technological adoption processes.

In light of the findings, several important points emerge for policymakers to consider. First, developing financial and institutional mechanisms to encourage AI investments is a key element supporting the development process. However, given the negative impact of inflation on development, strengthening price stability policies is crucial. Furthermore, for FDI to achieve its expected contribution, these investments must be directed to strategic sectors and regulations must be implemented to support technology transfer. Finally, the varying impacts of AI investments on development across countries necessitate considering the institutional, economic, and technological characteristics of each country in policy design.

In conclusion, AI investments appear to have an impact on human development and, consequently, economic development. However, for this impact to be sustainable and inclusive, factors such as ensuring a favorable macroeconomic environment, the strategic importance of the sectors where investments are directed, and institutional quality must be carefully considered. Furthermore, future studies could examine this issue both country-specifically and using different analysis methods.

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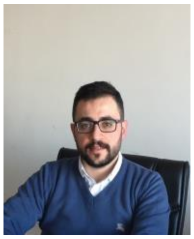
BIOGRAPHIES



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