ARTIFICIAL INTELLIGENCE AND SERVICE, INDUSTRIAL, AND AGRICULTURAL EMPLOYMENT: COMPREHENSIVE INTERNATIONAL MACROECONOMIC EVIDENCE[1]

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ABSTRACT

Recent advancements in artificial intelligence (AI) technology have revived concerns about technological unemployment. Regarding the issue, this study examines the impact of AI on employment rates across 17 leading AI countries from 1998 to 2017 using two panel econometric techniques, DOLS and FMOLS, to ensure robust results. For the first time, as far as is known, the effect of AI on employment in distinct sectors is analyzed separately. By uniquely combining different countries and sectors within a macroeconomic framework, this study provides a more comprehensive understanding through a total of eight estimates. The findings indicate that, according to both DOLS and FMOLS techniques, increased AI innovation may raise employment rates in the overall economy and in the service sector, while reducing employment rates in the industrial and agricultural sectors. Consequently, while AI positively impacts overall employment, considering industrial and agricultural sectors, employment policies should be adjusted to meet evolving needs in the AI era.

Keywords: *Artificial intelligence, technological unemployment, patent, employment policy*
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[1] Compliance with the ethical rules of the relevant study has been declared.

YAPAY ZEKA VE HİZMET, SANAYİ VE TARIM İSTİHDAMI: KAPSAMLI ULUSLARARASI MAKROİKTİSADİ ANALİZ

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ÖZ | Yapay zeka (YZ) alanındaki son gelişmeler teknolojik işsizlik konusu tekrardan gündeme getirmiştir. Bununla bağlantılı olarak, bu çalışmada YZ'nin istihdam oranları üzerindeki etkisi, YZ teknolojisinde öncü olan 17 ülkenin 1998 ve 2017 yılları verileri kullanılarak ve sonuçların güvenirliliğini güçlendirilmesi adına DOLS ve FMOLS olmak üzere iki farklı teknikle analiz edilmiştir. Dahası, bilindiği kadarıyla literatürde ilk defa YZ'nin farklı sektörlerdeki etkisinin makroekonomik olarak ölçülebilmesi adına dört farklı model ve iki farklı yöntemle sekiz farklı analiz yapılmıştır. Bulgulara göre, hem DOLS hem de FMOLS tekniği için, YZ alanında inovasyon arttıkça, hem ekonominin bütünündeki, hem de sadece hizmetler sektöründeki istihdam oranları artmaktayken, sanayi ve tarım sektörlerinde istihdam oranları düşmektedir. Sonuç olarak, her ne kadar YZ'nin ekonominin bütününde pozitif bir istihdam etkisi yaratabileceği görülse de, sanayi ve tarım sektöründeki olumsuz etkileri göz önüne alınarak, istihdam politikalarının YZ çağındaki değişen ihtiyaçlara göre yeniden dizayn edilmesi tavsiye edilmektedir.

Anahtar Kelimeler: *Yapay zeka, teknolojik işsizlik, patent, istihdam politikaları*
JEL Kodları: *C23, J21, O33*

Alan: *İktisat*
Türü: *Araştırma*

1. INTRODUCTION

Recent advancements in Artificial Intelligence (AI) and related technologies, such as Machine Learning (ML), the Internet of Things (IoT), neural networks, Big Data (BD), and robotics, have accelerated digitalization and mechanization across nearly all economic sectors. Given that AI technology is still in its early stages, it is expected to significantly transform various aspects of human life. According to Moore’s Law, named after Gordon Moore of Intel, as chip sizes decrease, processor power typically doubles approximately every two years (Rowland, Delehanty, Dwyer & Medintz, 2017). However, the most significant impact of computing advances often comes from rapidly evolving algorithms rather than just improvements in chip technology. For example, from 1988 to 2003, standard optimization problems improved by a factor of 1,000 due to chip advancements, while improvements in algorithms and programming led to a 30,000-fold increase, enabling computers to solve problems previously considered unsolvable (Fallows, 2011).

The ongoing increase in both hardware and software computing power suggests that AI technologies may soon achieve levels currently beyond our foreseeable capabilities. This advancement could positively impact humanity in various ways, such as improving medical diagnosis, enabling error-free surgical procedures, enhancing logistics through autonomous vehicles, increasing energy efficiency, and strengthening cybersecurity.

Despite the numerous claimed benefits of AI, its impact on the labor market remains controversial. This is not surprising given the limited data sources and the relatively few academic studies available, which means there is insufficient empirical evidence to draw definitive conclusions on this emerging topic (Acemoglu, Autor, Hazell & Restrepo, 2022). Most existing studies do not directly address the relationship between AI and unemployment, but rather focus on the broader impacts of technological development, automation, and robotization on unemployment. The implications of these studies vary and are inconclusive. Some argue that technological development and automation may exacerbate unemployment, a phenomenon known as the "replacement effect." Conversely, others believe that AI advancements could create more job opportunities in the future, referred to as the "displacement effect."

Although many studies have explored the relationship between mechanization, robotization, and unemployment, as explained briefly above, the impact of AI on the labor market may differ from previous disruptions caused by the industrial revolution. The context of AI presents unique challenges compared to earlier technological shifts. For example, 20th-century advancements in computer technology automated many data processing tasks, but a significant amount of work still required human involvement (Korinek & Stiglitz, 2018). Additionally, earlier developments in information technology and robotization focused on automating routine and repetitive tasks, whereas AI has the potential to automate both cognitive and non-routine tasks (Georgieff & Hyee, 2022).

To understand the specific relationship between AI and unemployment, as opposed to general technological development, more rigorous scientific analyses are required to make accurate predictions and propose effective policies. However, there is a lack of comprehensive studies in the existing literature. Some studies are purely theoretical, with no empirical analyses, while others focus on narrow geographical areas, examining only a single country or region. Additionally, some research investigates the impact of AI on unemployment in specific sectors or professions, such as its use in medical diagnostics and procedures.

However, different countries and sectors may exhibit varying relationships between AI and employment due to structural differences. Each of these studies offers valuable insights, but this study uniquely combines different countries and sectors within a macroeconomic framework to provide a more comprehensive understanding of the relationship between AI and employment. This approach represents a significant and original contribution to the literature, as studies in the existing literature are either based on microeconomic data, specific sectors, or individual regions, and therefore may not yield generalizable conclusions.

Therefore, this study examines 17 leading countries in AI patent applications from 1998 to 2017. Two empirical methods, Dynamic Ordinary Least Squares (DOLS) and Fully Modified Ordinary Least Squares (FMOLS), are used to ensure the robustness of the results. To explore variations in the relationship between AI and employment, four different estimations are conducted. Using these two methods and four models, a total of eight different estimations are conducted to analyze the impact of AI on employment in the overall economy, as well as in the industrial, service, and agricultural sectors. This approach allows for the differentiation of AI's effects on various sectors.

Thus, this study represents a significant contribution to the literature. Since, due to variations in capital or labor intensity and other structural differences, the impact of AI on different sectors may vary significantly. The remainder of the study is organized as follows: Section 2 reviews the relevant literature briefly. Section 3 describes the data used and the empirical methods employed. Section 4 discusses the findings from the empirical analysis. Finally, Section 5 presents the conclusions drawn from the analysis and discusses policy implications.

2. LITERATURE REVIEW

The concern that machines and automation might replace human labor is a longstanding issue that has been debated by academics and the public for centuries. This concern is discussed in the literature under the term "technological unemployment," which dates back to the late 18th century, during the Industrial Revolution in the U.K. One of the earliest classical thinkers to address this topic directly was David Ricardo. In the revised third edition of his book On the Principles of Political Economy and Taxation, Ricardo, in the chapter "On Machinery," argued that emerging machines could render some workers obsolete and increase unemployment, contrary to his earlier views (Kurz, 2010). John Maynard Keynes was among the first to explicitly define and name the issue as technological unemployment, although he acknowledged this problem as a short-term challenge, he believed that technological development would ultimately benefit the labor force by reducing working hours in the long term (Floridi, 2014).

Since Keynes, technological unemployment has remained a topic of intense discussion, especially with the rapid development of computer and internet technologies. The advent of AI and Machine Learning in the last decade has renewed public and academic interest in technological unemployment. While AI technologies might seem similar to previous machine and robotic technologies in their impact on the labor market, there are crucial differences. Historically, the introduction of machinery, such as in the textile industry, replaced repetitive tasks with large and expensive machines, posing a limited threat to labor within specific sectors. In contrast, AI has the potential to affect all industries due to its broad applicability. Additionally, the cost of implementing AI technologies is relatively lower and more accessible compared to the large, expensive machinery of the past. Moreover, as explained earlier in the introduction section, AI has the potential to automate many more tasks and duties, which may affect a much broader range of labor domains than earlier periods.

Therefore, the issue of technological unemployment should be investigated separately from previous developments, such as those observed with robotics technologies. However, since AI and ML technologies are relatively new, academic inquiries in this area are quite limited. Most studies have examined the effects of technological development and robotization or mechanization in general, rather than focusing specifically on the impact of AI on employment. Additionally, some studies have been case studies related to a single sector or specific professions, yielding mixed findings. For example, in the medical sector, research has compared AI-based optical image interpretation with radiologists, assessing its potential impact on unemployment in the profession (Pesapane, Codari & Sardanelli, 2018; Castagno & Khalifa, 2020; Tajaldeen &

Alghamdi, 2020; Botwe, Antwi, Arkoh & Akudjedu, 2021; Murugesan, Patel, Viswanathan, Bhargava & Faraji 2023). Similar investigations have been conducted in other sectors such as the legal sector, tourism, banking, finance, and various others (McGinnis & Pearce, 2013; Remus & Levy, 2017; Kong et al., 2021; Koo, Curtis & Ryan, 2021; Batiz-Lazo, Efthymiou & Davies, 2022; Campbell, 2023). Some studies (Rifkin, 1995; Ford, 2015) are based on philosophical or theoretical discussions without robust empirical investigation. Consequently, most research relies on microdata studies based on questionnaires (Kong et al., 2021; Kambur & Akar, 2022; Yakar, Ongena, Kwee & Haan, M. 2022), time series studies covering very narrow geographical regions, or purely theoretical discussions, as already reviewed previously. However, very few studies have examined the issue from a macroeconomic perspective using a comprehensive cross-country panel database.

The outputs of studies investigating the effect of technological development or mechanization are generally categorized into two perspectives: pessimistic and optimistic. The pessimistic view, which involves the replacement effect, predicts that unemployment will rise in the future. The optimistic view suggests that unemployment will decline or remain relatively unchanged.

In the pessimistic camp, Ford (2015) argues that this era might differ from the Industrial Revolution, which created job opportunities and increased workers' welfare. He claims that while machines were once seen as tools to boost worker productivity, AI machines are now becoming new workers themselves. Brynjolfsson and McAfee (2011) also note that following the 2008 global crisis, American companies resumed economic growth by investing in new machines rather than rehiring people, suggesting that if this trend continues, unemployment could worsen. Frey and Osborne (2017) found that nearly half of the jobs in the United States are at risk of computerization, based on their analysis of over 700 occupations. Webb (2019) concluded that, unlike robots and software, AI technologies pose more significant risks to high-skilled jobs. Additionally, Acemoglu and Restrepo (2017) estimated that for each new robot introduced per thousand workers, the employment ratio in US labor markets decreases by between 0.18 and 0.34.

On the other side, counterarguments based on the displacement effect suggest that technological development or automation may increase employment opportunities rather than reduce them. For instance, Gregory, Salomons, and Zierahn (2018), in their analysis of Europe, found that while routine-replacing technological change had a displacement effect from 1999 to 2010, it also created new employment opportunities by increasing the demand for goods, potentially resulting in a net positive employment effect. Similarly, Jacobs and Karen (2019), using U.S. labor market data from 1870 to 2015, concluded that a significant wave of future unemployment, as predicted by pessimists, is unlikely. They argue that new technologies can reduce costs, increase demand, and create new sectors and jobs.

Similar to studies that have investigated technological unemployment from a broader perspective, those examining the effect of AI using cross-country empirical data have yielded mixed results. Some studies have concluded that advancements in AI technology may reduce future employment opportunities, while others suggest the opposite—that AI may boost employment opportunities. For example, Guliyev (2023), using panel GMM system estimation with data from 24 high-tech developed countries between 2005 and 2021, estimated the effect of AI on unemployment and concluded that AI might reduce unemployment levels.

Guliyev, Huseynov and Nuriyev (2023) investigated the relationship between AI and big data technologies in G7 countries from 2005 to 2020. They concluded that there may be a negative relationship between AI, big data, and unemployment. Bordot (2022), using panel data analysis on 33 OECD countries, found that both robotics and AI technologies tend to increase unemployment, although the results for AI are statistically less significant compared to robotics. Keskin and Kasri (2023) examined 26 countries over an 8-year period using dynamic panel SGMM estimation and found no statistically significant relationship between AI and unemployment rates. Finally, Mutascu (2021) studied the issue from a nonlinear perspective and concluded that AI increases employment levels at low inflation rates, but has no effect at higher inflation levels. Conversely, Nguyen and Vo (2022) found that AI increases unemployment up to a certain inflation threshold, after which this effect decreases.

3. METHODOLOGY

Although the effect of technological development on unemployment has a long history dating back to the 19th century, the impact of the relatively new and emerging technology of AI on unemployment is still a novel and underexplored issue. In this section, two methodological approaches used to ensure the robustness of the results are described. The first method is DOLS and the second is FMOLS panel cointegration technique, which estimates long-term coefficients. The dataset covers the period from 1998 to 2017 and includes 17 developed countries: Austria, Australia, Belgium, Canada, Finland, France, Germany, Ireland, Israel, Italy, the Republic of Korea, the Netherlands, Spain, Sweden, Switzerland, the United States, and the United Kingdom. These countries are selected because, given the relatively recent emergence of AI technology, there are limited nations with extensive records of AI patents. To ensure the robustness of the estimations, only countries with sufficiently long histories of AI patent activity are included. All variables, except those already in percentage form or with negative values, are transformed and used in their natural logarithm form. Variables like employment rates, which are already in percentage form, have a normal scale dispersion and are used in nominal form. Similarly, inflation, which is in percentage form and has negative values, is also used in nominal form. However, data for explanatory variables like the total population and the total number of AI-related patents show wide dispersion and are therefore transformed using natural logarithms. Descriptive statistics and details about the datasets are provided in Table 1 below.

Table 1: Descriptive Statistic and Databases

Var.	Mean	Std. Dev.	Min	Max	Database
Emp	56.3	5.8	41.5	66.1	WDI, Employment to population ratio, 15+, total (%), ILO Est.
Ser	72.7	5.1	59.9	81.6	WDI, Employment in services. (% of total emp.), ILO Estimate
Agr	3.5	1.9	1.0	12	WDI, Employment in agriculture(% of total emp.), ILO Estimate
Ind	23.6	3.9	16.2	34.3	WDI, Employment in industry (% of total employment), ILO Estimate
Gdp	1.9	3.6	0.1	18.9	WDI, Gross Domestic Product (constant 2015 US$billion)
Inf	1.8	1.3	-4.4	7.5	WDI, Inflation, consumer prices (annual %)
Pop	46.2	68.6	3.7	325.1	WDI, Population, Total(million)
Cap	22.8	3.4	15.7	35.8	WDI, Gross fixed capital formation (% of GDP)
Ai	70.6	156.1	0.8	1315.1	OECD, AI Patents, IP5, based on inventors country of residence

The employment variables are categorized into four groups: overall economy, services, agriculture, and industry, based on data from the World Bank World Development Indicators. Since AI is a very new technology, there are limited options to measure its utilization. This lack of measurement tools is a primary reason for the scarcity of macroeconomic studies examining the relationship between AI and employment. Consequently, most studies in this area rely on microeconomic approaches using questionnaires. Some research, such as Guliyev (2023), employs Google Trend Index data to gauge AI utilization. However, a high frequency of searches for the term "artificial intelligence" in a particular country does not necessarily indicate substantial production and utilization of AI technology in national economies.

However, it is reasonable to assume that countries with significant patent creation and innovation in AI technology are more likely to utilize these technologies effectively in their industries. Since, while patents are often considered output indicators, they are also widely used as input indicators because they can serve as valuable information sources for other entrepreneurs and inventors (OECD). Additionally, some studies use proxies such as robot's usage (Acemoglu & Restrepo, 2017) to represent technological development, expecting a similar relationship between these proxies and unemployment as with AI. However, as previously discussed, AI may present different future implications for unemployment compared to earlier technological advancements. Therefore, in the context of AI data, patents related to AI are the most relevant choice for use as an independent variable. In this context, following the method used by Mutascu (2021), Nguyen and Vo (2022), Bordot (2022), and several other researchers, patents related to AI are used as a proxy for AI-related technological capabilities of countries to estimate the relationship between AI and employment rates.

However, there are various patent offices globally that receive and issue patents to choose from. To obtain most comprehensive patent data, this study uses patents from IP5 patent families, sourced from the OECD Patents by Technology database. IP5 patent families include patents protected in at least two patent offices worldwide, one of which must be within the Five IP offices (IP5): the Korean Intellectual Property Office (KIPO), the Japan Patent Office (JPO), the European Patent Office (EPO), the United States Patent and Trademark Office (USPTO), and the China National Intellectual Property Administration (CNIPA). Fractional counts in AI patent data arise from patents with multiple inventors or applicants. To avoid multiple counting, the contributions of each country are considered.

This study examines the effect of technological development, specifically innovations in AI, on employment across three sectoral categories and one general category for overall employment rates. To achieve this, four different models are analyzed using two techniques, DOLS and FMOLS, resulting in a total of eight estimations. The equations for the different models are listed below, with variable definitions provided in Table 1. Control variables, including GDP, population, fixed capital formation, and inflation, are selected based on a literature review and are commonly used and available variables.

Model 1: $Emp_{it} = \beta_0 + \beta_1 \ln Gdp_{it} + \beta_2 \ln Ai_{it} + \beta_3 Inf_{it} + \beta_4 \ln Pop_{it} + \beta_5 LnCap_{it} + u_{it}$ **(1)**

Model 2: $Ind_{it} = \beta_0 + \beta_1 \ln Gdp_{it} + \beta_2 \ln Ai_{it} + \beta_3 Inf_{it} + \beta_4 \ln Pop_{it} + \beta_5 LnCap_{it} + u_{it}$ **(2)**

Model 3: $Ser_{it} = \beta_0 + \beta_1 \ln Gdp_{it} + \beta_2 \ln Ai_{it} + \beta_3 Inf_{it} + \beta_4 \ln Pop_{it} + \beta_5 LnCap_{it} + u_{it}$ **(3)**

Model4: $Agr_{it} = \beta_0 + \beta_1 \ln Gdp_{it} + \beta_2 \ln Ai_{it} + \beta_3 Inf_{it} + \beta_4 \ln Pop_{it} + \beta_5 LnCap_{it} + u_{it}$ **(4)**

The four different models are employed to investigate the varying effects of AI on employment across different sectors and to compare the results, which can offer important policy implications. Before performing these estimations, several preliminary tests and methodological steps must be conducted to select and apply the most appropriate estimation technique, ensuring the most reliable results based on the data characteristics. These methodological steps are outlined in Figure 1 below.

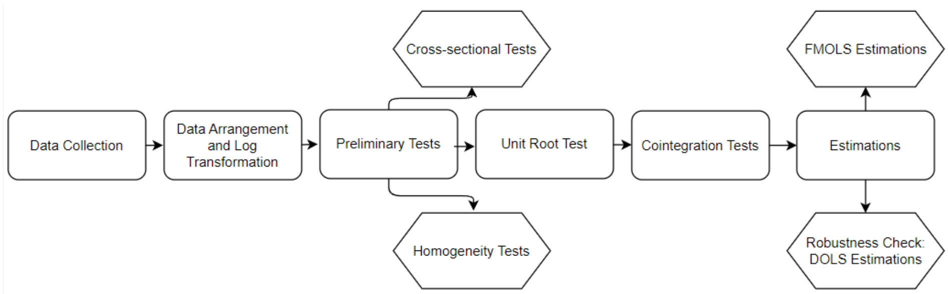

Figure 1: Methodological Procedure

One of the initial important preliminary tests in panel econometrics involves assessing homogeneity and cross-sectional dependence. Slope heterogeneity can lead to biased estimation results if it is present in the data. Since datasets often exhibit heterogeneous slope characteristics, they should be analyzed using specific econometric techniques designed to account for this heterogeneity. To test for slope heterogeneity, the Pesaran and Yamagata (2008) test, also known as the Delta test, is employed. The null hypothesis of the Delta test posits that slope coefficients are homogeneous across different cross-sectional units, meaning the slope coefficients are identical for all units. The Delta test is implemented using the "xthst" command in Stata, developed by Bersvendsen and Ditzen (2020).

The next step is to examine the potential presence of cross-sectional dependence among different units. This is important because, when the assumption of cross-sectional independence is violated, a shock affecting one country or unit may also impact other units. This issue is common due to the highly interconnected nature of the global economy in the 21st century. Therefore, testing for cross-sectional dependence is a crucial step. To address this problem, various unit root and econometric tests have been developed. In this study, potential cross-sectional dependence is assessed using the Breusch & Pagan (1980) LM test, the Pesaran (2004) CD test, and the Pesaran, Ullah, and Yamagata (2008) bias-adjusted LM test.

Understanding the homogeneity and cross-sectional dependency characteristics of the data is crucial for assessing its stationarity. Unit root tests are divided into first-generation and second-generation tests, with second-generation tests being more robust for analyzing cross-sectional dependency when present. Given the characteristics of the dataset, this study employs the Multivariate Augmented Dickey-Fuller (MADF) panel unit root test. The MADF test is preferred for two reasons: first, it is based on a higher-order autoregressive equation rather than a first-order, and second, it can accommodate different autoregressive coefficients (Taylor & Sarno, 1998; Furuoka, 2012). MADF statistic is akin to the Wald statistic, as shown in Equation 5 (Adalı, Toygar, Karataş & Yıldırım, 2024). Additionally, the test is applicable when T > N (Tatoğlu, 2020), which is suitable for this study.

$$MADF = \frac{(1-\varphi\hat{\beta})\{\varphi[Z(\hat{\Lambda}^{-1}\otimes 1_T)Z]^{-1}\varphi'\}(1-\varphi\hat{\beta})N(T-k-1)}{(Y-Z\hat{B})'(\hat{\Lambda}^{-1}\otimes 1_T)(Y-Z\hat{\beta})} \quad \textbf{(5)}$$

To analyze the presence of long-term relationships among the series, the Westerlund (2005) panel cointegration method is employed. This method involves subtracting cross-sectional means from the averages in the series across the panel, as recommended by Levin et al. (2002), due to the data's cross-sectional dependence characteristics.

After completing all preliminary tests, including unit root and cointegration tests, the next step is to implement the coefficient estimation procedure. Two different econometric techniques are used to ensure the robustness of the results. FMOLS and DOLS methods, both suitable for heterogeneous data with cointegrated panels (Ghazali & Ali, 2019), are employed to determine the magnitude and direction of the independent variables' effects on employment variables. Both DOLS and FMOLS are robust against issues such as series correlation and small sample bias, which can affect traditional Ordinary Least Squares (OLS) estimators (Sulaiman, Abdul-Rahim & Ofozor 2020; Ngoma & Yang, 2024). Additionally, while standard OLS is not appropriate for estimating long-run coefficients when variables are cointegrated, DOLS and FMOLS are valid methods for this purpose (Rahman, Hosan, Karmaker, Chapman & Saha, 2021).

FMOLS estimator, initially developed by Phillips and Hansen (1990) and refined by Pedroni (2001), is considered highly effective for estimating cointegrating regressions in heterogeneous panels (Hamit-Haggar, 2012; Khan, Panigrahi & Almuniri, 2019). The FMOLS estimator is defined as shown in Equation 6 (Khan et al., 2019) below.

$$\beta_{NT}^{*} - \beta = \left(\sum_{i=1}^{N} L_{22i}^{-2} \sum_{i=1}^{T} (\chi_{it} - \bar{\chi}_{it})^{2}\right) \sum_{i=1}^{N} L_{11i}^{-1} L_{22i}^{-1} \left(\sum_{i=1}^{T} (\chi_{it} - \bar{\chi}_{i}) \mu_{it}^{*} - T\hat{\gamma}_{i}\right) \quad \textbf{(6)}$$

The DOLS estimator is used as a second technique to verify the consistency of the estimation results. An important benefit of DOLS methodology is its consideration of presence of a mix allowing the integration of the variables in the cointegrated perspective and by regressing one of the I(1) variables against other I(1) and I(0) variables by taking leads (p) and lags (-p) handles the potential minor sample bias and endogenous bias problems (Lustrilanang et al., 2023). Moreover, as detailed by Stock and Watson (1993) and Saikkonen (1992) DOLS technique is both effective tool in the case of autocorrelation problem and relatively simple to implement on the cointegrating vector parameters' as the utilization of the standard testing methodology is valid (Saikkonen, 1992; Stock & Watson, 1993; Modeste, 2016).

$$Y_t = \beta_0 + \vec{\beta} X + \sum_{j=-q}^{p} \vec{d} j \Delta X_{t-j} + \mu_t \quad \textbf{(7)}$$

The equation for DOLS methodology is defined in the equation 7, where $\vec{\beta}$ is a cointegrating vector, p and q is the lag and lead length which intended to ensure its stochastic error term independent of all past innovations in stochastic regressor (Lustrilanang et al., 2023).

4. EMPIRICAL FINDINGS

Contemporary econometric models exhibit a wide range of techniques, limitations, and perspectives. To ensure robust analysis and accurate estimation results, it is essential to first examine the nature of the data and then select the appropriate estimation model. One crucial step in this process is assessing the homogeneity of the data. Table 2 below presents the results of the Delta test (Pesaran & Yamagata, 2008). The results indicate that, at the 1% significance level, the null hypothesis of homogeneous slopes is rejected, suggesting the presence of slope heterogeneity across all four models.

Table 2: Homogeneity Tests Results

	Δ	**p-value**	Δ_{adj}	**p-value**
Model 1	9.64	0.00***	11.96	0.00***
Model 2	14.31	0.00***	17.75	0.00***
Model 3	13.84	0.00***	17.17	0.00***
Model 4	11.16	0.00***	13.84	0.00***

The next step is to test for cross-sectional dependency among the units. Table 3 below displays the results of three different cross-sectional dependence tests—LM, LM Adj., and LM CD—across the four models. The results indicate that cross-sectional dependency is present in all four models. This suggests that an external shock affecting one unit may also influence other units.

Table 3: Cross Sectional Dependence Tests Results

	LM Test		**LM Adj.**		**LM CD**	
	Statistic	P-value	Statistic	P-value	Statistic	P-value
Model 1	234.5	0.00***	8.20	0.00***	2.77	0.00***
Model 2	211.60	0.00***	5.50	0.00***	4.24	0.00***
Model 3	212.60	0.00***	5.63	0.00***	5.12	0.00***
Model 4	262.8	0.00***	11.47	0.00***	5.38	0.00***

To assess the stationarity of the variables, the Multivariate Augmented Dickey-Fuller (MADF) panel unit root test is conducted. The results for all variables are presented in Table 4 below. The null hypothesis of this test posits that all series are non-stationary. According to the results, all variables are stationary at the level, as the MADF test statistics exceed the critical values (C. V. 5%)

Table 4: Unit Root Tests Results

Variable	**MADF**	**C. V. 5%**	**Variable**	**MADF**	**C. V. 5%**
Emp	256.27	41.70	Inf	9932.49	41.70
Ser	2193.26	41.70	Pop	51369.70	41.70
Ind	361.58	41.70	Cap	960.85	41.70
Agr	5514.32	41.70	Ai	26306.76	41.70
Gdp	331.49	41.70			41.70

Before proceeding with coefficient estimations, it is crucial to verify the panel cointegration condition of the data to confirm the existence of a long-term relationship among the variables. The results of the Westerlund (2005) panel cointegration test for all four models are presented in Table 5 below. The findings indicate that, with the exception of Model 2, which pertains to the industrial sector, all models show statistically significant long-term relationships among the variables.

Table 5: Cointegration Tests

Model	Statistic	P value	Model	Statistic	P value
Model 1	1.59	0.05**	**Model 3**	2.09	0.01***
Model 2	1.12	0.13	**Model 4**	1.70	0.04**

Estimating the existence of a long-term relationship is a crucial step in assessing the robustness of a model. However, confirming only this relationship is not always sufficient. In econometric models, it is also important to determine the magnitude and direction of the relationship. Therefore, coefficient estimations are conducted for all four models. To ensure the robustness of the results, these estimations are repeated using two different econometric techniques, namely FMOLS and DOLS models.

In Table 6, the results for Model 1, which estimates the relationship between AI and general employment rates, are presented for both FMOLS and DOLS methods. For both models, the GDP variable indicates a positive relationship between the use of AI and general employment rates. In all four models, the dependent variable is in linear form, while some of the independent variables are linear and others are in natural logarithmic form. To interpret the coefficients of the logarithmically transformed variables, the coefficients are divided by 100.

Table 6: FMOLS and DOLS Estimation of Model1

Fmols Model1						
Emp	Coefficient	Standard Error	z	P> |z|	95% Coefficient Interval	
Gdp	10.37	1.54	6.70	0.00***	7.34	13.41
Inf	0.89	0.33	2.65	0.00***	0.23	1.55
Pop	-12.58	1.46	-8.57	0.00***	-15.45	-9.70
Cap	10.32	3.01	3.42	0.00***	4.40	16.23
AI	2.81	0.43	6.39	0.00***	1.94	3.67
Constant	-58.73	24.43	-2.40	0.01**	-106.62	-10.84
Dols Model1						
Emp	Coefficient	Rescaled Std. Error	z	P> |z|	95% Coefficient Interval	
Gdp	10.32	1.61	6.38	0.00***	7.15	13.49
Inf	1.40	0.53	2.74	0.00***	0.41	2.50
Pop	-12.86	1.56	-8.25	0.00***	-15.92	-9.81
Cap	10.09	3.35	3.01	0.00***	3.52	16.66
AI	3.04	0.47	6.35	0.00***	2.10	3.98
Constant	-53.60	25.73	-2.08	0.03**	-104.03	-3.17

For the AI variable specifically, ceteris paribus, a 1% increase in AI innovation is projected to raise the employment rate by 0.0281 and 0.0304 point in the FMOLS and DOLS models, respectively, with a significance level of 1%. These empirical findings are consistent with the optimistic perspective in the literature. For instance, Guliyev et al., (2023) examined the relationship between AI, big data, and unemployment for G7 countries using panel econometric techniques. They found that these technologies boost productivity and capital accumulation, leading to the creation of new jobs. The authors concluded that, despite some job displacement, the overall effect of these technologies is expected to be positive for employment.

For the GDP variable, ceteris paribus, a 1% increase in GDP is projected to raise the employment rate by 0.1037 and 0.1032 point in the FMOLS and DOLS models, respectively, at a 1% significance level. Similarly, ceteris paribus, a 1% increase in inflation is expected to increase the employment rate by 0.89% and 1.4% according to the FMOLS and DOLS models, respectively. Additionally, ceteris paribus, a 1% increase in gross fixed capital accumulation is anticipated to raise the employment rate by 0.1032 and 0.1009 point in the FMOLS and DOLS models, respectively.

These results align with expectations, as growth in GDP and gross fixed capital accumulation, along with rising inflation, generally lead to increased employment opportunities. However, both estimation methods indicate that an increase in population correlates with a decrease in the unemployment rate. Specifically, ceteris paribus, a 1% increase in population is expected to reduce the general employment rate by 0.1258 and 0.1286 point for the FMOLS and DOLS models, respectively. This may be attributed to the possibility that economic capacity might not keep pace with a rapidly growing population, potentially leading to a decline in overall employment rates in the long term.

Table 7: FMOLS and DOLS Estimation of Model2

Fmols Model2

Ind	Coefficient	Standard Error	z	P> |z|	95% Coefficient Interval	
Gdp	-3.71	1.79	-2.07	0.03**	-7.23	-0.19
Inf	0.07	0.39	0.20	0.84	-0.68	0.84
Pop	5.49	1.70	3.23	0.00***	2.15	8.83
Cap	5.88	3.50	1.68	0.09*	-0.98	12.74
AI	-1.49	0.51	-2.93	0.00***	-2.49	-0.49
Constant	18.94	28.36	0.67	0.50	-36.63	74.53

Dols Model2

Ind	Coefficient	Rescaled Std. Error	z	P> |z|	95% Coefficient Interval	
Gdp	-3.52	2.00	-1.76	0.07*	-7.46	0.40
Inf	0.09	0.66	0.15	0.88	-1.19	1.39
Pop	5.40	1.93	2.79	0.00***	1.61	9.20
Cap	5.92	4.15	1.42	0.15	-2.22	14.07
AI	-1.62	0.59	-2.74	0.00***	-2.79	-0.46
Constant	15.60	31.92	0.49	0.62	-46.96	78.16

In Model 2, which examines the relationship between AI innovation and employment rates in the industrial sector, the results for the FMOLS and DOLS models are presented in Table 7. These results reveal a divergence from those observed in the general employment rates. Specifically, for the industrial sector, an increase in AI adoption is associated with a decrease in the employment rate.

Similarly, GDP and population variables yield opposite results compared to those found in the general employment model. Although gross fixed capital formation shows results consistent with Model 1 in the FMOLS technique, it is not statistically significant in the DOLS technique. Additionally, the inflation variable is not statistically significant in either model. These findings should be interpreted with caution, as the earlier cointegration tests did not indicate a long-term relationship among the variables.

Table 8: FMOLS and DOLS Estimation of Model3

Fmols Model3

Ser	Coefficient	Standard Error	z	P> |z|	95% Coefficient Interval	
Gdp	6.28	2.27	2.77	0.00***	1.83	10.73
Inf	-0.04	0.49	-0.08	0.93	-1.01	0.92
Pop	-8.25	2.15	-3.83	0.00***	-12.47	-4.03
Cap	-12.71	4.42	-2.87	0.00***	-21.38	-4.04
AI	1.87	0.64	2.91	0.00***	0.61	3.13
Constant	73.30	35.82	2.05	0.04**	3.08	143.51

Dols Model3

Ser	Coefficient	Rescaled Std. Error	z	P> |z|	95% Coefficient Interval	
Gdp	5.73	2.60	2.20	0.02**	0.63	10.82
Inf	-0.10	0.85	-0.12	0.90	-1.78	1.57
Pop	-7.81	2.50	-3.11	0.00***	-12.72	-2.89
Cap	-12.37	5.38	-2.30	0.02**	-22.93	-1.81
AI	2.12	0.77	2.76	0.00***	0.61	3.63
Constant	79.43	41.35	1.92	0.05**	-1.62	160.49

In Model 3, which examines the relationship between AI innovation and employment rates in the service sector, similar results to those observed in Model 1 are noted. Specifically, ceteris paribus, a 1% increase in AI innovation is expected to raise the employment rate in the service sector by 0.018 and 0.021 point with 1% significance levels for the FMOLS and DOLS techniques, respectively. The findings for GDP and population variables in the service sector also align with those from Model 1. However, the results for gross fixed capital formation differ, likely due to the fact that increased fixed capital may replace human labor, particularly in a sector that is highly labor-intensive. Coefficient estimates for the inflation variable are not statistically significant in either technique.

Table 9: FMOLS and DOLS Estimation of Model 4

Fmols Model4						
Agr	Coefficient	Standard Error	z	P> |z|	95% Coefficient Interval	
Gdp	-2.46	0.43	-5.73	0.00***	-3.31	-1.62
Inf	0.04	0.09	0.51	0.61	-0.13	0.23
Pop	2.13	0.42	5.08	0.00***	1.31	2.96
Cap	6.07	0.85	7.11	0.00***	4.40	7.75
AI	-0.76	0.17	-4.35	0.00***	-1.10	-0.41
Constant	16.94	6.21	2.73	0.00***	4.76	29.12

Dols Model4						
Agr	Coefficient	Rescaled Std. Error	z	P> |z|	95% Coefficient Interval	
Gdp	-2.20	0.93	-2.36	0.01*	-4.03	-0.37
Inf	0.004	0.30	0.02	0.98	-0.59	0.60
Pop	2.40	0.90	2.67	0.00***	0.63	4.16
Cap	6.45	1.93	3.34	0.00***	2.66	10.24
AI	-0.50	0.27	-1.81	0.07*	-1.04	0.04
Constant	4.96	14.84	0.33	0.73	-24.12	34.04

In Model 4, which examines the impact of AI innovation on the agricultural sector, the results differ from those observed in the general and service sector cases. Specifically, ceteris paribus, a 1% increase in AI innovation is expected to reduce the employment rate in the agricultural sector by 0.0076 and 0.0050 point for FMOLS and DOLS techniques, respectively. These findings are consistent with expectations. In the early stages of economic development, the agricultural sector typically holds the largest share of the economy and is highly labor-intensive. As economic development progresses and technological advancements occur, the industrial sector's share of total production increases, leading to a shift of labor from agriculture to industry and services. Countries with high levels of AI innovation are usually more technologically advanced and economically developed, and their agricultural sectors are often capital-intensive with lower employment rates. Conversely, countries with lower AI adoption, such as many in Africa and the southern hemisphere, often have highly labor-intensive agricultural sectors. Thus, as technological development and AI innovation advance, a corresponding reduction in employment rates in the agricultural sector may be observed.

A similar pattern is observed for the GDP variable, where increases in GDP are associated with a decrease in employment rates within the agricultural sector. This phenomenon likely reflects the economic development processes previously discussed. Conversely, increases in both population and gross fixed capital formation are linked to higher employment rates in agriculture. However, there is no statistically significant relationship between inflation and employment in the agricultural sector.

5. CONCLUSION AND POLICY IMPLICATIONS

This study examines the relationship between AI and employment rates across 17 countries, including those with significant AI innovation. The analysis uses data from 1998 to 2017, the most recent available. Two panel data estimators, DOLS and FMOLS, are employed to ensure the robustness of the empirical findings. To explore potential sector-specific variations, four models are estimated, covering employment rates in the overall economy, industrial sectors, service sectors, and agricultural sectors. Each model is rerun using both estimation techniques, resulting in a total of eight models. This approach aims to identify how AI impacts employment rates across different sectors. By analyzing AI's effects on various labor markets within a macroeconomic, cross-country panel data framework, this study provides a significant contribution to the literature, as no other research has investigated AI's effects on employment in different sectors in such detail, as far its known.

The findings reveal that both the DOLS and FMOLS methodologies indicate an increase in employment rates across the overall economy with the rise in AI-related patents. Similarly, in the service sector, employment rates also increase with more AI-related patents, as shown by both methodologies. Conversely, in the industrial and agricultural sectors, an increase in AI-related patents is associated with a decrease in employment rates according to both DOLS and FMOLS techniques. This suggests that while AI development may pose a threat to jobs in the industrial and agricultural sectors, it generally benefits employment in the service sector. Consequently, job losses in the industrial and agricultural sectors are offset by gains in the service sector, leading to a net positive effect on overall employment. This outcome is expected, as service sector jobs have increasingly surpassed those in agriculture and industry since the latter half of the 20th century. For instance, in the EU, 73% of jobs were in the service sector in 2021 (Eurostat), a trend also observed globally.

Based on the empirical findings, which indicate that AI does not pose a threat to the overall labor market and may even increase employment rates, it is important to revise employment policies globally. While AI appears to generate new employment opportunities across various sectors, particularly in the service industry, there is a need to focus policy efforts on the industrial and agricultural sectors. To fully capitalize on the new job opportunities created by AI in these sectors, employment policies should be adjusted to align with the evolving skill demands. This can be achieved through targeted training and skill enhancement programs facilitated by educational institutions. Such measures are crucial to adapting to the rapidly changing global labor markets.

6. CONFLICT OF INTEREST STATEMENT

There is no conflict of interest between the authors.

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8. AUTHOR CONTRIBUTIONS

YA: Idea, Design, Supervision, Collecting and processing resources, Analysis and interpretation, Literature review, Writer, Critical Review

9. ETHICS COMMITTEE STATEMENT AND INTELLECTUAL PROPERTY COPYRIGHTS

Ethics committee approval is not required for the study.

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