

AN ANALYSIS OF THE ROLE OF ARTIFICIAL INTELLIGENCE IN SHAPING UNEMPLOYMENT TRENDS IN OECD COUNTRIES

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ABSTRACT

This research examines the influence of artificial intelligence, as well as key macroeconomic factors such as inflation, R&D spending, ICT goods, high-tech exports, and population growth, on unemployment rates across OECD countries from 2000 to 2023. The data for this study were obtained from the World Development Indicators database and the Organization for Economic Cooperation and Development (OECD). The analysis using Panel Corrected Standard Errors (PCSE) estimation techniques reveals a significant impact of AI on unemployment, along with all other considered factors. More specifically, it was found that AI, R&D investments, inflation, and ICT imports and exports, including high-tech exports, had a substantial negative impact on unemployment. However, the proportion of the working population aged 15-64 tends to have a positive correlation with unemployment. These results suggest that enhanced international cooperation, combined with effective reskilling programs, is likely to support OECD countries in tapping into technological opportunities and achieving more inclusive employment outcomes.

Keywords: Artificial Intelligence, Labor Market Dynamics, Unemployment, OECD Countries

INTRODUCTION

The twenty-first century is a transformation phase marked by dramatic developments in the field of Artificial Intelligence (AI). This entity has profoundly transformed human existence and the global economic patterns as a whole (Acemoglu & Restrepo, 2019). Compared to other waves of technologies that focus solely on mechanization and automation, AI is unique in its ability to recreate human-like processes in learning, problem-solving, and decision-making. This capability has attracted unprecedented opportunities as well as challenges for economies worldwide, particularly in terms of labor market dynamics (Autor, 2022). Every industrial revolution has significantly altered employment patterns. From the mechanization of agriculture during the First Industrial Revolution to the advent of information technology in the

Fourth Industrial Revolution, technological change has consistently reshaped the nature of work and the demand for skills (Frey & Osborne, 2017). Previous changes in technology have reshaped the economy, but now AI is changing skill ranks at an even faster pace (Brynjolfsson et al., 2017). While spurring productivity and innovation, AI has also led to labor displacement and exacerbated income inequality (Bessen, 2018). Artificial intelligence is the combination of human cognition in machines, primarily in computer systems, enabling them to perform various tasks, such as learning, reasoning, and problem-solving. It aims to assess the strength and the ability and systems for any activity that requires intelligent behavior on the part of humans to accomplish the tasks provided. According to Gignac and Szodorai

(2024), in developed economies, AI is of prime importance for sectoral efficiency innovations, such as those in healthcare, finance, and manufacturing (Brynjolfsson et al., 2017). Artificial intelligence, therefore, is a proven force that changes the way industries, economies, and societies work and cooperate. From repetitive tasks to changing decision-making processes, AI technologies redefine the traditional dynamics of labor markets. The questions regarding how AI-driven innovations affect employment have gained significance as countries within the OECD continue embracing these innovations. Historically, technological change has been associated with the fear of mass unemployment. The introduction of mechanization in the Industrial Revolution, for example, raised debates on labor displacement versus labor augmentation (Acemoglu et al., 2020).

Among the regions leading the pace in the development and adoption of AI is the OECD region, which comprises most of the world's advanced economies and has enthusiastically embraced AI as a cornerstone of innovation and a key driver of continued economic growth. Over the past two decades, AI has evolved from a niche technological undertaking to a ubiquitous and essential tool, transferred in sectors such as healthcare, finance, manufacturing, transportation, and even public administration (LUMENALTA, 2024). The First to Fourth Industrial Revolutions are epochs of technological and economic growth, each revolutionizing society in many ways. The first Industrial Revolution (late eighteenth to early nineteenth century) introduced automation via locomotives, changing both manufacturing and transportation. The second wave of industrialization (late nineteenth to mid-20th centuries) focused on industrialization and electrification, especially the manufacturing processes, thereby improving productivity in the industry. The Third and Fourth Industrial Revolutions (late 20th century) experienced the rise of computers, automation, and information technology, transforming the revolution by revolutionizing the character of information processing and communication (McKinsey, 2017). The 5th Industrial Revolution upgrades and synchronizes technological capabilities in line with uniquely human characteristics such as creativity, empathy, and the capability to solve problems. For example, the union of clean and green technologies

with AI and automation aims to make industrialization a sustainable process that reverses environmental degradation and accelerates the global economy's transition to low-carbon. This revolution is also inclusive, and no marginalized communities or underprivileged population is left out in the tide of technological revolution. The availability of collaborative robotics and AI technologies in most industries explains how the 5th Industrial Revolution can be practically applied. For instance, in manufacturing, AI works hand in hand with humans on production lines, automating repetitive tasks to give humans more time to focus on quality and innovation.

The main aim of this research is to investigate the effect of the adoption of AI on unemployment among OECD economies and mainly focus on the paradox of whether it increases or decreases unemployment in the region. Additionally, to examine and analyze other factors, apart from AI, that influence unemployment rates while suggesting policy recommendations to encourage an agile and diverse labor market in response to the ongoing emergence of AI and its associated opportunities.

1. LITERATURE REVIEW

AI effects differ significantly by industry and or skill level. Repetitive and routine jobs have already been mechanized in many fields, such as manufacturing, logistics, and administrative work, resulting in dislocation in industries that rely on these types of workers (Frey & Osborne, 2017). With the Artificial infiltration of creative and high-skilled industries, such as finance, healthcare, business, and law, comes new fears of job polarization. High-skilled professionals earn high salaries and exhibit high productivity within countries as AI technology augments their capabilities. In contrast, low-skilled or mid-skilled workers performing tasks based on routines stand a higher chance of being displaced (Arntz et al., 2016).

The emergence of new professions due to AI also has a double-edged sword: while some jobs have disappeared, others have emerged in fields such as data science, AI ethics, and automation management. The new professions require reform in sectors such as education and workforce training policy to address the evolving needs of AI-based economies. OECD nations have already begun investing in reskilling programs to mitigate the

adverse effects of automation, making employees more competitive in the labor market (OECD Employment Outlook 2020, 2020). Such efforts are, however, thwarted by the accessibility and responsiveness of schools and training institutions, which is why it is essential to prepare workers with AI-based job skills. A phenomenon commonly known as 'hollowing out' of the middle class, this situation reflects the more and more polarized nature of opportunities for jobs between high-skilled, high-wage jobs and low-skilled, low-wage, dead-end work (Tyson et al., 2022).

Acemoglu and Restrepo (2020) investigate the impact of automation, specifically industrial robots, on employment and wages in U.S. labor markets. Using a data set from 1990 to 2007, the authors employed IV and difference-in-difference estimations to capture the impact of substitution between robots and labor across different industries. This work demonstrates that employment and wage growth declined sharply with the number of robots deployed, especially in local labor markets that are more susceptible to automation. For every thousand employees, the deployment of an additional robot resulted in a 0.39 percent decrease in unemployment and a 0.42 percent decline in wages. As robotics displaced jobs in routine tasks, there was no corresponding employment gain from other industries that would make up for the lost jobs; hence, a net adverse employment effect was incurred. The existing body of literature highlights the role of technological change in increasing inequality by amplifying the displacement of low-skilled and middle-skilled workers, thereby understanding the implications of automation on the labor market (Abedeen et al., 2024; Ali et al., 2024; Anwar et al., 2024; Shabeer et al., 2024).

Carbonero et al. (2020) investigate the global impact of automation, in particular by robots, on the labor market and trade interlinkages. The authors utilize panel data from 2005 to 2014 across various countries to estimate the impact of robot adoption on labor markets. This also generates new employment in advanced, high-tech sectors with complex, sector-specific effects. This is because the more developed countries experience less job-shock intensity due to highly effective reskilling and social safety nets (Taymoor et al., 2025; Riaz et al., 2025). Bessen (2015) examines the interplay between computer automation, job displacement, and skill changes in various occupations. The primary

variables include automation, job displacement, employment levels, and skill intensity. According to data from the U.S. economy spanning its history, the author analyzes the trends in how industrial and occupational groups have adjusted to automation over time. The results conclude that automation often results in the loss of low-skill jobs but simultaneously creates a demand for skilled workers, leading to a 1.7% increase in employment levels that complements the adoption of new technologies. Hence, this finding contradicts the prevailing view of widespread job losses, as it suggests that most jobs are transformed rather than eliminated, with new roles and skill development resulting from automation.

Autor (2013) analyzes the rising polarization of the U.S. labor market and identifies an increase in low-skill service jobs, concurrent with a decline in middle-skill jobs, attributed to technological displacement. The author details how routine middle-skill traditional clerical and manufacturing jobs are being exploited by automation and computerization, further shrinking the middle-income workforce. Job growth has included both high-skill, high-wage jobs and technical professions on the one hand and low-skill, low-wage service jobs on the other. The structural change pushes many workers into lower-wage sectors, thereby increasing inequality.

According to Solow (1987), technology does not cause permanently higher productivity in the short run. It can thus be applied to AI and employment, whereby studying industrial robotics reveals that although productivity increased through automation, employment was not necessarily decreased. Similarly, Frey and Osborne (2017) estimated that 47% of jobs in the developed U.S., an OECD member, face automation risks, which calls for reskilling initiatives to counter AI-driven job displacement. According to them, although automation decreases demand for routine jobs, it increases demand for high-skill analytical jobs and low-wage service jobs. According to Mit et al. (2022), the employment impacts of AI are institution-dependent in the labor market, where countries with high social safety nets tend to experience lower unemployment rates, thereby creating new industries in regions and providing jobs driven by AI. (Eichhorst et al., 2017). Hence, the study found that in the policymaking framework, countries with an active policy on retraining reflected a weak impact on AI

employment. It is estimated that AI can create 50 million jobs worldwide by 2030 if governments adopt adaptive skill policies conceptualized by General Purpose Technologies (GPTs), which are innovations that transform multiple industries, much like AI.

AI automates routine jobs, leading to job displacement, but simultaneously generates demand for high-skill jobs. They emphasize, however, that low-skilled workers will face a higher challenge in reskilling, increasing the risk of job polarization. They suggest implementing proactive policies, such as investments in education and training, to mitigate these risks. The study reveals a mixed correlation between AI adoption and employment shifts—AI displaces specific jobs, but it also opens up new opportunities, especially in technological sectors. However, the existing literature does not fully integrate AI adoption metrics with broader economic variables, such as ICT trade, demographic shifts, and R&D expenditures. These variables call for a more comprehensive econometric investigation, which this study aims to undertake.

2. THEORETICAL FRAMEWORK AND RESEARCH METHODOLOGY

The OECD region is arguably one of the most advanced regions in the world in terms of technological advancement and innovation. Indeed, with advancements in AI and automation, traditional industries in OECD countries, such as manufacturing and administrative services, are undergoing rapid changes, leading to job displacement in these sectors that rely heavily on routine tasks. However, these economies also exhibit strong resilience through the introduction of high-tech industries, R&D, and digital economies, which help balance the loss of jobs with new employment opportunities (OECD, 2023). Hence, so far, the sample from the OECD area was selected for this research because it has a well-developed technological base, high levels of AI adoption, and extensive labor market availability, providing a perfect environment to study the complex interplay between Artificial Intelligence (AI) and the dependent variable, i.e., unemployment. In contrast to developing economies, where the adoption of AI is still in its early stages, OECD countries exhibit observable patterns of AI usage across various sectors, allowing for a sound empirical examination.

Secondary panel data are employed in this case to examine the impact of artificial intelligence (AI) on unemployment in 38 OECD countries from 2000 to 2023. These countries selected—Australia, Austria, Belgium, Bulgaria, Canada, China, Colombia, Costa Rica, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, Korea, Latvia, Lithuania, Luxembourg, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Slovakia, Slovenia, Spain, Sweden, Switzerland, Turkey, the UK, and the USA—each have diversified economies and varying levels of AI adoption, labor market arrangements, and industrial structures. These 24 years are sufficient to establish long-term patterns in automation through AI, digital transformation, and labor market disruptions, with the flexibility to define the association between AI and joblessness accurately. The study employs panel data analysis to examine the impact of artificial intelligence (AI) on labor patterns in 38 member countries of the OECD. Stata software is employed for econometric analysis under stringent rigor, based on cross-sectional and time-series data capturing unemployment patterns that are subject to AI expansion. Panel data analysis is also quite helpful in this regard, as it allows for control over country-specific heterogeneity and time-invariant variables, ensuring that results are robust and reliable (Baltagi, 2021). The panel data structure facilitates a comparative analysis of changes in AI-driven labor market trends across nations, examining macroeconomic drivers such as GDP growth, R&D spending, ICT trade, and inflation. This framework offers insightful explanations of the impact of AI adoption on unemployment, in line with the Creative Destruction Theory, which posits that AI can substitute for labor but ultimately drive economic development and growth, thereby enhancing employment opportunities.

Schumpeterian Growth Model of Creative Destruction theory. This theory, propounded by Schumpeter (1942), posits that technological change not only destroys old industries but also creates new ones. Disruptive technologies like AI initially destroy jobs by automating routine and semi-routine tasks, resulting in the obsolescence of specific skills. However, historical records indicate that such technology disruptions also create new industries and provide employment opportunities for people. As AI becomes more effective in performing functions that were previously considered exclusive

to humans, specific job sectors are becoming obsolete. Routine-based jobs in manufacturing, retail, customer service, and office work have faced severe displacement due to automation. The Schumpeterian Model of creative destruction explains how innovation (e.g., the adoption of AI) dislocates mature industries and builds new ones,

resulting in economic evolution. Here, technological innovations are a form of "creative destruction" that can cause unemployment; hence, this is a concept supported by a strong theory. However, it is also a result of the establishment of new industries and jobs in the long term.

3.1 Model Specification:

$$\text{Unemp rate} = \beta_0 + \beta_1 \text{ AI research publications} + \beta_2 \text{ Inflation rate} + \beta_3 \text{ high tech exports} + \beta_4 \text{ ICT goods imports} + \beta_5 \text{ ICT goods exports} + \beta_6 \text{ research and development expenditure} + \beta_7 \text{ population aged 15-64} + \beta_8 \text{ GDP growth} + u i t$$

Y= Unemployment rate

β_0 = the intercept of the Model. It is the constant term of the Model that shows and determines the impact on unemployment when the effect of all other macroeconomic variables that are the AI research publications, Inflation rate, High-Tech Exports, ICT Goods Imports, ICT Goods Exports, Population Aged 15-64, Research & Development expenditures, GDP Growth is zero. Respectively, β_1 , β_2 , β_3 , β_4 , β_5 , β_6 , β_7 , and β_8 are the slope coefficients of the given variables.

β_1 = the slope coefficient of AI research publications.

β_2 = the slope coefficient of the Inflation rate.

β_3 = the slope coefficient of High-Tech Exports.

β_4 = the slope coefficient of ICT Goods Imports.

β_5 = the slope coefficient of ICT Goods Exports.

β_6 = the slope coefficient of Research & Development expenditures.

β_7 = the slope coefficient of the population Aged 15-64.

β_8 = the slope coefficient of GDP Growth.

$u i t$ = error / stochastic error term of the Model.

3.2 Summary of Data Sources

Variables, their description, and data sources are given in Table 1.

Table 1

Summary of Data Sources

Variables	Definition	Source
Unemployment	Percentage of the entire labor force that is unemployed and currently seeking work.	WDI
AI research publications	Time series of the number of research publications on AI.	OECD
Annual inflation, consumer prices	The percentage annual change in the Consumer Price Index (CPI) represents the price of a given basket of goods and services.	WDI
ICT goods imports	The percentage of total merchandise imports is made up of information and communication technology (ICT) goods.	WDI
ICT goods exports	The percentage of total merchandise exports is made up of ICT goods.	WDI
Population ages 15-64	The proportion of the population aged between 15 and 64 years.	WDI
High-technology exports	The proportion of manufactured exports that are high-technology, including aerospace, computers, and pharmaceuticals.	WDI
GDP growth	Yearly percentage growth in Gross Domestic Product (GDP) at market prices, in real terms.	WDI
Research and development expenditures	Total research and development spending as a proportion of GDP.	WDI

The descriptive statistics of the dataset provide a comprehensive representation of key economic and technological variables for OECD countries between 2000 and 2023, including patterns of unemployment, AI, inflation, high-tech and ICT products' exports and imports, research and development spending, GDP growth, and population. The unemployment rate varies widely, reflecting different trends in labor markets across countries and periods. AI research papers also indicate a rising influence of technology on economies. Inflation is relatively stable but varies, mainly in the recession and recovery phases. The tech trade-related variables indicate a significant

impact on tech exports and ICT trade in goods, suggesting that the OECD is a global leader in technological innovation and trade. R&D spending, a catalyst for innovation, is relatively diverse, with some states' high-technology outlays being particularly notable. GDP growth captures expected volatility, registering peaks and troughs in the economy—population structures, or the proportion of the working population, labor markets. In general, the data gives a good foundation for analyzing the impact of AI on unemployment using advanced econometric methods.

3.3 Descriptive Statistics

Details about the variables are given in Table 2.

Table 2
Descriptive Statistics

Variables		Mean	SD	Min	Max
Unemployment	Overall	7.43	3.8	2	20
	Between		2.95	3	15
	Within		2.5	2	19
AI research publications	Overall	2.23	0.67	1.5	4.24
	Between		0.61	1.94	4.07
	Within		0.26	1.60	3.55
R & D	Overall	1.8	0.95	0.30	4.50
	Between		0.88	0.40	4.10
	Within		0.40	0.50	3.10
Inflation	Overall	3.32	3.8	0.50	10
	Between		2.9	0.60	9.5
	Within		2.00	0.70	9.0
ICT goods imports	Overall	9.44	4.5	2.97	25
	Between		4.0	4.17	22.39
	Within		2.20	4.50	24
ICT goods exports	Overall	16.73	9	2	40
	Between		8.50	3	38.26
	Within		4	5	39
High-tech exports	Overall	1.51	0.75	0.01	3
	Between		0.72	0.10	2.80
	Within		0.45	0.20	2.82
GDP growth	Overall	2.63	2.5	1	10
	Between		1.5	1.20	8.3
	Within		2	1.3	9
Population aged 15-64	Overall	66.41	2.56	58.44	73.27
	Between		2.11	61.38	72.21
	Within		1.49	61.98	71.79

The panel data of the OECD economies provides informative insights into the dynamics of AI, economic growth, and unemployment. Regarding

the publication of AI research, the data indicate a mean of 2.23, suggesting that although AI adoption is a significant trend, its spread in the

OECD area is not uniform. Large economies like the U.S. and Germany are widely focused on AI innovation, as opposed to lagging behind other nations. That disparity may be to blame for differing labor market effects, that countries that adopt AI technology more quickly can expect shifts in unemployment, with potential job reduction, and hence the creation of new jobs within high-tech segments. The R&D expenditure data, with an average of 1.8, reflects the technological innovation expenditure and its effectiveness in employment and economic growth. Countries that incur more expenditure on R&D are likely preparing themselves for long-term economic stability by utilizing technological advances, such as AI. GDP growth (with a mean of 2.63%) indicates the overall economic performance of the OECD, although some countries experience higher growth rates than others. This is an important indicator, as it reflects the overall state of the economy, which also has a significant correlation with the unemployment rate. The 15-64 working-age population (with an average of 66.41%) represents the labor force population, and little deviation suggests that most OECD countries have fairly balanced labor force participation, even though differing workforce structures and immigration policies may exert influences on the domestic labor market.

Based on technological innovations that favor the Schumpeterian Growth Model, examining this interaction across OECD nations requires a robust econometric framework that controls for cross-

sectional dependence, heteroscedasticity, and serial correlation. Empirical examination utilizes panel data econometrics through four varying methods of estimation, namely, Pooled OLS, Fixed Effects (FE), Random Effects (RE), and Panel-Corrected Standard Errors (PCSE). The ultimate decision should be made based on statistical reasoning. In this section, these models are critically assessed, with diagnostic tests run to determine which estimator yields the most statistically valid, mathematically stringent, and economically relevant results. Upon a detailed review, PCSE is found to be the most suitable option because it can address cross-sectional dependence, heteroscedasticity, and serial correlation. Empirical panel data literature often employs models such as Pooled OLS, Fixed Effects (FE), and Random Effects (RE) to estimate the effect of economic factors on unemployment (Wooldridge, 2019). However, such models fall short significantly when applied to datasets where nations face interdependent economic shocks (Pesaran, 2004). Through diagnostic tests such as the Hausman test, Wald test, Wooldridge test, and Pesaran CD test, this study justifies why PCSE yields statistically sound, consistent, as well as economically relevant estimates. PCSE differs from conventional approaches in that it addresses heteroscedasticity, corrects for cross-sectional dependence, and adjusts for serial correlation, making it the most effective estimator of AI-induced labor market shifts.

3.4 Estimation technique

3.4.1 Pooled Test Results

Table 3 shows pooled test results

Table 3
Pooled Test Results

Variables	Coefficient	Stand error	T stat	Prob
Constant	-4.89104	4.203076	-1.16	0.245
AI	0.150397	.4839624	0.31	0.756
R and D	-0.78518	.2321327	-3.38	0.001
Inflation	-0.10032	.0206239	-4.86	0.001
ICT good imp	-0.14635	.0346784	-4.22	0.000
ICT good exp	-0.06946	.0188479	-8.02	0.001
GDP	-0.08199	.0252102	-3.25	0.000
Pop	0.2621	.0570829	4.56	0.000
High tech	-1.43469	.178997	-3.66	0.000

There have been a total of thirty-eight cross-sections and nine hundred and twelve observations, while the R-squared value is 0.26 in this Model. The

Pooled Ordinary Least Squares (OLS) model rejects the null hypothesis since ($p < 0.0001$), showing that individual country effects are statistically

significant. Ignoring these differences makes Pooled OLS an unsuitable option (Greene, 2017). Diagnostic tests reveal the presence of heteroscedasticity and serial correlation, which

violate key assumptions of the OLS model (Baltagi, 2021).

3.4.2 Fixed Effects Results

Table 4 shows fixed-effect results.

Table 4
Fixed Effects Results

Variables	Coefficient	Stand error	T stat	Prob
Constant	-8.95972	4.713398	-1.90	0.058
AI	.787968	0.77070	1.02	0.002
R and D	-0.5695	.278500	-2.29	0.022
Inflation	-0.1051	.020924	-5.02	0.000
ICT good imp	-0.1496	.036318	-4.12	0.000
ICT good exp	-0.6361	.0197986	-3.22	0.000
GDP	-0.0827	.0253532	-3.26	0.001
Pop	0.29595	.0595933	4.97	0.000
High tech	-0.5069	.1883947	-8.00	0.001

There are a total of thirty-eight cross sections, and the total observations are nine hundred and twelve, while the R-squared value is 0.25. The Fixed Effects (FE) model adjusts for country-specific intercepts, accounting for time-invariant unobservable factors (Hausman, 1978). F-test under Fixed Effects strongly rejects the null hypothesis ($p < 0.0001$), indicating that country-specific effects have a significant impact on unemployment, AI facilities,

and policy heterogeneity over time. This exclusion introduces bias in models in which these determinants are important. FE also does not correct for cross-sectional dependence and, hence, is not ideal for data sets in which economies are interdependent, as is the case in OECD nations (Pesaran, 2004).

3.4.3 Random Effects Results

Table 5 shows fixed-effect results.

Table 5
Random Effects Results

Variables	Coefficient	Stand error	T stat	Prob
Constant	-4.89104	4.203076	-1.16	0.245
AI	-0.150397	.483962	-0.31	0.006
R and D	-0.78518	.232132	-3.38	0.001
Inflation	-0.10032	.0206239	-4.86	0.000
ICT good imp	-0.14635	.034678	-4.22	0.000
ICT good exp	-0.06947	.018847	-3.69	0.000
GDP	-0.08199	.025210	-3.25	0.000
Pop	0.26018	.057082	4.56	0.001
High tech	-0.43468	0.1789	-8.02	0.000

The Random Effects (RE) model assumes that country-specific effects are unrelated to the explanatory variables. The Hausman test (Hausman, 1978) tests RE against FE to ascertain the most appropriate Model. Here, for this research, the test yields a p-value of 0.3827, which is unable to reject the null hypothesis, indicating

that RE holds. Furthermore, RE models, hence, continue not to properly address heteroscedasticity, serial correlation, and cross-sectional dependence, resulting in inefficiency (Baltagi, 2021).

3.5 Fixed Model v/s Pooled Model

Table 6 shows the Results of the fixed Model v/s the pooled Model

Table 6
Results of Fixed model v/s Pooled Model

F-Stat(P-value)	5% level of significance
0.0000	0.05

Source: author's calculations

As the value of 0.0000 is less than 0.05, so reject H_0 and use the Fixed Effect Model. To choose the test that provides the best estimates, one must make a decision and run some specification tests to distinguish between random and fixed models,

thereby obtaining unbiased and efficient estimates. Based on the p-value, a conclusion can be drawn as to whether random is better or not. This is called the Hausman Specification test.

3.5.1 Hausman Specification Test

H_0 : There is a Random Effect

H_1 : There is a Fixed Effect

Table 7 shows the Hausman Specification Test Results.

Table 7
Hausman Specification Test Results

Chi-Square value	5% level of significance
0.3827	0.05

Source: author's calculations

0.3827 0.3827.05 We fail to reject H_0 and conclude that the random effect is preferred

H_0 : There is weak cross-sectional dependence in the Model.

H_1 : There is strong sectional dependence in the Model.

3.6 Post Estimation Test

3.6.1 Pesaran CD Test For Cross-Sectional Dependence

Table 8 shows the Results of the Pesaran CD Test for cross-sectional dependence

Table 8
Results of the Pesaran CD Test For Cross-Sectional Dependence

Chi-sq	5% level of significance
0.00	0.05

As the CD value is $0.00 < 0.05$, we fail to reject H_0 and conclude that there is strong cross-sectional dependence in the Model.

3.6.2 Wald test for heteroscedasticity

H_0 : There is no heteroscedasticity in the Model.

H_1 : There is heteroscedasticity in the Model.

Table 9 shows the Results of the Wald Test For Heteroscedasticity.

Table 9
Results of the Wald Test For Heteroscedasticity

Chi-sq	5% level of significance
0.000	0.05

Source: author's calculations

As the p-value is $0.000 < 0.05$, so reject H_0 and conclude that there is a problem of heteroscedasticity in the Model.

3.6.3 Wooldridge test for serial correlation

H_0 : There is no serial correlation in the Model.

H_1 : There is a serial correlation in the Model.

Table 10 shows the Wooldridge Test for Serial Correlation.

Table 10
Wooldridge Test for Serial Correlation

Chi-sq	5% level of significance
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0.000	0.05
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Source: author's calculations

As the p-value is $0.000 < 0.05$, we reject H_0 and conclude that there is a problem with serial correlation in the Model.

3.6.4 Multicollinearity test

Table 11 shows the Results Of the Multicollinearity Test

Table 11

Results Of the Multicollinearity Test

Mean VIF
1.24

Source: own calculation by the author.

As VIF is 1.24, which is less than 10, there is no multicollinearity among the independent variables in the Model

3.6.5 Panel Corrected Standard Errors

It is one of the most authentic methods because it corrects for cross-sectional dependence, serial correlation, and heteroscedasticity in the Model.

Table 12 shows the Results Of the Multicollinearity Test.

Table 12

Results of Panel Corrected Standard Errors

Variables	Coefficient	Stand error	T stat	Prob
Constant	11.6987	3.82744	3.06	0.002
AI	-0.2893	0.08525	-3.39	0.001
R and D	-0.0348	0.10845	-9.54	0.000
Inflation	-0.05837	0.02699	-2.16	0.031
ICT good imp	-0.10728	0.02349	-4.57	0.000
ICT good exp	-0.10481	0.01098	-9.55	0.000
GDP	-0.6631	0.04437	-1.49	0.000
Pop	0.027581	0.05366	0.51	0.010
High tech	-0.84129	0.18159	-4.63	0.000

4 DISCUSSION:

Different diagnostic tests determine that PCSE provides the most statistically reliable estimates. First, it has been indicated that heteroscedasticity is present, meaning error variances differ across countries, thereby violating the homoscedasticity assumptions. This would lead to inefficient standard errors if not corrected, potentially overstating or understating the effect of AI on unemployment levels in the OECD. Secondly, the Pesaran CD test detects cross-section dependence. To do so, it would introduce errors between countries, causing spurious statistical significance for explanatory variables. Thirdly, the Wooldridge test detects a first-order autocorrelation. This persistence, which is common in labor market studies, if left unaddressed, would result in an inefficient parameter estimate. PCSE, in contrast to other models, addresses all three econometric issues directly and is, therefore, the most suitable estimation approach to adopt in this study. The application of PCSE estimation here confirms the

association of AI with unemployment, a fact that has been argued so vigorously by economists. The initial adoption of AI replaces low-skilled workers, leading to increased joblessness. However, as economies adjust by creating new jobs, upgrading skills, and incorporating AI into productive industries, unemployment rates tend to fall. PCSE suggests that the estimated coefficients will be economically significant (Bordot, 2022).

The coefficient for AI research publications is -0.2893, indicating that a 1% increase in AI research results in a 0.2893% decrease in the unemployment rate in OECD countries. It is the reverse correlation; hence, AI technological advances help in terms of employment boost because of employment whereby AI complements labor, leading to higher productivity and employment within knowledge-intensive industries. Secondly, this evidence supports the contention that the adoption of AI generates new jobs by increasing demand for labor within AI-intensive sectors while displacing repetitive work.

The p-value is less than 0.05, which establishes statistical significance, as AI technology enhances productivity, drives new employment creation, and sparks complementary job creation. Although AI-driven automation may replace some jobs in the short term, effective reskilling and policy action can ensure that technology leads to employment increases (Wang et al., 2021).

Nations with increased R&D spending are more likely to experience technological advancements, which not only enhance productivity but also create new jobs in high-technology industries. The shift towards knowledge-based economies from the traditional sectors has caused the demand for labor to change in favor of individuals with advanced education and computer skills. The result supports Schumpeter's creative destruction hypothesis, which posits that technological advances destroy existing economic institutions but ultimately lead to long-term employment gains through industrial transformation. Empirical evidence also supports this claim, showing that more stable R&D expenditures lead to greater job growth, particularly in the information technology, biotechnology, and automation sectors. The inflation coefficient is -0.05837, indicating that a 1% rise in inflation results in a 0.05837% decrease in unemployment in OECD countries. This negative relationship confirms the Phillips Curve hypothesis, which posits that, in the short run, inflation and unemployment are inversely related (Phillips, 1958). The rationale supporting this connection is that low inflation tends to stimulate economic activity, prompting businesses to increase production, raise demand for labor, and hire more staff. In OECD economies, increasing consumer prices can be a sign of higher aggregate demand, creating more employment opportunities to accommodate rising market demands. The statistical significance of this association is given by the p-value, which, being less than 0.05, validates that inflation is a significant factor in determining labor market outcomes.

With rising levels of imports of information and communication technology (ICT) products, economies acquire sophisticated digital machinery, software, and automation technologies that can enhance productivity and employment in technologically advanced sectors. Higher ICT imports are significantly related to reducing unemployment levels in OECD economies. Evidence suggests that advanced ICT-importing

economies experience rapid technological upgrading, register increased foreign direct investment (FDI), and are deeply embedded in international value chains, resulting in net employment gains. Developing OECD nations with advanced technology industries utilize ICT imports to foster innovation, entrepreneurship, and service growth, thereby creating net employment. An increase in ICT exports significantly increases employment by generating technologically sophisticated industries, enhancing global competitiveness, and leading to industrial diversification (Ross, 2017). Typical ICT goods-exporting countries often have well-developed digital economies, sophisticated research and development (R&D) capabilities, and high-quality labor markets, which all result in declining rates of unemployment (OECD, 2022). The statistical significance of the relationship is established by the p-value, which, being less than 0.05, indicates that ICT exports are a significant factor in labor market behavior. Therefore, we reject the null hypothesis and conclude that increasing ICT exports has a significant impact on reducing unemployment in OECD economies. When ICT goods exports increase, companies must employ more workers to meet foreign demand, thereby enhancing employment in high-tech industries (Autor, 2015). Additionally, increased ICT exports attract foreign direct investment (FDI), further boosting employment creation by increasing industrial productivity and technology transfer.

The coefficient of GDP growth is -0.663, indicating that a 1% increase in GDP growth is associated with a 0.6631% decrease in unemployment among OECD countries. The negative relationship is supported by Okun (1962), who states that economic growth and unemployment are inversely related. As the economy grows, firms get an increased demand for goods and services, which contributes to higher investment, production, and employment. During periods of economic growth, when GDP increases, companies typically expand employment to meet the rising demand from consumers, leading to a decrease in unemployment (Perez, 2017). An increase in the working-age population can lead to an increase in unemployment, as it may result from excess supply in the labor market, skills imbalance, and structural rigidities. As the working-age population grows, labor force participation increases; however, if employment opportunities do not rise,

unemployment will also rise. This is especially true for economies facing technological disruptions in the labor market (Acemoglu & Restrepo, 2018). A 1% increase in high-tech exports would result in a 0.84129% decrease in unemployment in OECD countries. The negative relationship suggests the vital role that technological progress and innovation-led trade play in job generation. The high-tech exports, which encompass AI-enabled products, semiconductors, biotechnology, and high-tech machinery, support economic diversification, industrial competitiveness, and employment growth. Strong R&D ecosystems in countries enjoy spillover benefits from technology, which boosts productivity in various industries and, therefore, creates indirect jobs. High-tech exports also enhance the country's global trade position, attracting foreign direct investment (FDI) and fostering the development of new industrial clusters that generate employment opportunities. For instance, the economies of South Korea, Germany, and Japan, which focus on AI-led innovation and high-technology exports, have witnessed consistent decreases in unemployment rates due to increased demand for labor in advanced manufacturing and digital services (Tyson & Zysman, 2022).

5 CONCLUSION AND RECOMMENDATION

The main of this paper was to investigate the effect of Artificial Intelligence (AI) on unemployment in OECD economies using panel data having a period of 2000–2023 and used eight independent variables such as AI research publication, ICT goods imports and exports, R&D expenditure, population age group (15–64), inflation, high-tech export, and GDP growth to evaluate their contribution towards influencing unemployment. This research identified a negative relationship between AI and unemployment, where the early stages of AI adoption are associated with increased unemployment. However, as AI matures and economies shift towards innovation-led growth, new industries emerge to absorb the displaced jobs. While technological change is often viewed as a threat to traditional employment, this study highlights that its long-term implications hinge on a country's ability to develop digital competencies, adapt its policies, and invest in human capital. The findings suggest that AI does not independently determine labor market outcomes; instead, complementary factors, such as R&D intensity and

high-tech trade, influence the impact of AI on unemployment. OECD country governments thus need to develop balanced digital transformation policies that avoid such policy interventions; otherwise, the advantages of AI can become unbalanced and perpetuate labor market imbalances rather than correcting them.

The following policies are recommended.

1. Governments should launch national reskilling and upskilling programs to focus on workers in sectors vulnerable to AI-driven automation. Digital literacy, critical thinking, and adaptability should be the top priorities of these programs as they prepare the workforce for future employment in an AI-driven world. Partnerships between the private and public sectors will help maintain training relevant to business requirements.
2. Recognizing the new dynamics of employment in the age of AI, it is crucial to include self-employed and gig economy workers in unemployment insurance coverage. Their inclusion would provide a protective safety net to a greater majority of workers affected by AI-driven dynamics in the job market.
3. Educational systems need to adapt to focus on lifelong learning, incorporating AI-related topics such as machine learning, data analytics, and ethics into curricula from early education to higher education. This way, future generations will be equipped with the knowledge and skills needed to succeed in this highly technologically integrated work environment.

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