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Artificial intelligence and unemployment in high-tech developed countries: New insights from dynamic panel data model

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ABSTRACT

This study examines the effect of artificial intelligence on unemployment in high-tech developed countries. While artificial intelligence is more discussed in futuristic aspects, comprehensive empirical studies are limited in the literature. Therefore, this study uses the dataset, which includes 24 high-tech developed countries from 2005 to 2021 and examines the relationship between a country's Google Trend Index related to AI and the unemployment rate. In the empirical approach, we control the dynamic effect of unemployment by using dynamic panel data and GMM-system estimation to determine the effect of AI on unemployment. The main results show that artificial intelligence decreases the level of unemployment, and the 'displacement effect' of AI is validated.

1. Introduction

In the past decades, the evolution and widespread diffusion of artificial intelligence (AI) and automation have led to considerable inspiration and significant transformation in different industries, from medical diagnosis and autopilot transportation to advanced manufacturing. Francis Gurry notes that "artificial intelligence is a new digital frontier that will have a profound impact on the world, transforming the way we live and work." (WIPO, 2019) The exponential growth in digitalized data and breakthrough computational power (Moore's Law) have enabled artificial intelligence to generate a revolutionary influence (Moore, 2006). Modern information technologies and the advent of cognitive machines powered by artificial intelligence (AI) have powerfully transformed people's lives and work. While artificial intelligence can amplify productivity in some industries, there are instances where it can take over human work and revolutionize occupations. Machine learning, computer vision, neural networks, and others related to AI have simplified daily tasks and even shaped humans' regular practice. On the other hand, a core component of the next generation of AI is natural language understanding (NLU), and a breakthrough in its core technology is of great scientific significance and industrial value. Language modeling includes performing abstract and mathematical modeling of natural language using computers, which is one of the principal scientific challenges of NLU. In the era of deep learning, pre-trained language models (represented by ELMo, BERT, and GPT) have profoundly impacted the field of natural language processing (NLP) and are regarded as a milestone in NLP (Chowdhary & Chowdhary, 2020). The most common example of this today is Generative Pre-trained Transformer 4 (GPT-4), a multimodal large language model created by OpenAI (Taecharungroj, 2023). The emergence of GPT-4-based applications in recent days has made artificial intelligence a phenomenon and has also created a broad debate about the role of humans in the job market. Hence, advances in artificial intelligence technologies have sparked discussions about the future of jobs and, more importantly, whether humans will have any jobs in the future.

The impact of AI on employment has aroused widespread interest (Goos et al., 2009; David, 2017; Oschinski & Wyonch, 2017; Acemoglu et al., 2022). These discussions are not new, and they have always existed in the fluctuations of work automation (Jenkins & Sherman, 1979). However, despite all the fluctuations, most job losses did not happen (Whitley & Wilson, 1982). However, the present day is different because artificial intelligence, linked with increased data accessibility and managing power, allows supercomputers to operate on much more assignments than the previous effects of digitalization (Brynjolfsson & McAfee, 2014). "Future strategic advantage depends on the ability to leverage artificial intelligence, such as machine learning, computer vision, and autonomous systems, and integrate it with the workforce to create symbiotic human–machine teams," according to Rahwan et al. (2019). On the other hand, the relationship between AI and unemployment is simple in economic theory, and it is referred to as a "pass-

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through" to labor productivity. According to Stevenson (2019), AI improves GDP growth by increasing productivity and future earnings. In this respect, AI is like other new technologies, similarly increasing productivity and economic growth and decreasing unemployment. Separate phases of structural unemployment can be recorded, but they are only temporary because they disappear once the labor market returns to stability.

In the literature, descriptive and comparative analyses are used while examining the relationships between artificial intelligence and unemployment, and no comprehensive econometric model is suggested to determine this relationship. One of the main reasons for this is the need for systematic data to measure the use of artificial intelligence. Hence, alternative data sources such as Google Trends (trends.google.com) can improve unemployment modeling. The Google Trends Index (GTI) tracks word or phrase patterns entered by the Google search engine. Attempts to integrate GTIs into the predictive model have been successful up to the present (Nagao et al., 2019; Mihaela, 2020; Simionescu & Cifuentes-Faura, 2022). From this perspective, this study uses GTIs related to AI in 24 high-tech developed countries to determine the relationship between AI and the unemployment rate. First, this study proposes a comprehensive analysis focusing on 24 high-tech developed countries compared to current studies. Second, this study is one of the first to use a dynamic panel data estimation method to examine the impact of artificial intelligence on unemployment.

2. Literature review

In the most recent few years, the literature on the topic of the effect of AI on unemployment has notably expanded (Ernst et al., 2019; Martens & Tolan, 2018), while various contributions consider AI as a component of a more complicated automation procedure (Wang & Siau, 2019). Generally, two-fold approaches can be discovered. The initial part of the scholars supports a 'replacement effect' of jobs by AI, and the next part of the scholars supports a 'displacement effect' of jobs.

The first part of the literature validates the ''replacement effect'', which consists of various aspects. In this part, the application of artificial intelligence negatively impacts the labor market, causing unemployment because of being without a job as an outcome of replacement. Some of the first academic studies about the negative impact of AI on employment belong to Leontief (1983). He highlights that nearly the entire workforce would be replaced by AI in future decades, expanding unemployment as an outcome. Ngo et al. (2014) discovered that 48% of specialists in the technology field believe robots may possibly perform the most standardized and automated labor. Consequently, in the age of AI, except for a few highly skilled employees in related industries, traditional jobs will be at risk of unemployment. Susskind and Susskind (2016) consider that in the age of artificial intelligence, high-tech unemployment will be additionally increased, and the work in traditional industries will be processed into routine labor, which technologies will replace. Frey and Osborne (2017) constructed a model, and the study found that 47% of 700 occupations are at risk of being replaced in the next two decades. David (2017) pointed out that the jobs with high substitution risk and no gender difference are as high as 55% with AI. Graetz and Michaels (2018) discovered that robots decreased responsibilities more for low-skilled labor than for medium-skilled and high-skilled labor. In addition, Felten et al. (2018) and Fossen and Sorgner (2019) found that a high computerization risk is associated with an increasing likelihood of changing occupations or being unemployed. Acemoglu and Restrepo (2020) used a task-based theoretical framework to analyze the effect of robot density on local labor markets in the US, and they found that one additional robot per thousand workers is associated with a drop of 0.2 percent in the employment-to-population ratio and it decreases in wages of 0.37 percent. They also emphasized the heterogeneity of the effects by showing that the lower the workers' level of education, the stronger the negative impact on jobs and hourly wages. Georgieff and Milanez (2021) analyze whether jobs considered at high risk of automation in 2012 experienced a net loss of workers seven years later. They found that these occupations saw weaker employment growth than other jobs and even sometimes a modest decline in employment levels. Ma et al. (2022) show that the development of artificial intelligence will significantly affect the structure of employment skills, and regional innovation has a significant mediating effect. With the improvement of innovation, industrial upgrading, and technological progress, the influence of artificial intelligence on middle-skill employment has gradually weakened. Under the influence of an innovative environment and technological progress, high-skilled employment shows a U-shaped change.

The second part of the literature proposes the ''displacement effect''. In this respect, AI positively impacts the labor market, decreasing the unemployment level because of its job-creating effect. Scholars believe that although artificial intelligence will have an impact on the job market in the short term, due to the substantial increase in production efficiency, the expansion of production will create more jobs and employment opportunities in the long term. Boden (1987), the Nobel Prize winner in economics, claims that AI development is replicable. According to him, "there will be all sorts of problems in the transition period, but finally, there will be many more jobs created—different perhaps, but many more jobs than there were before—so we do not need to worry about the unemployment issue in the long term''. According to the McKinsey Global Institute Research (2016) study group, which strengthens this theory, there will be a demand for 250,000 data scientists by 2024. Along the same lines, Dauth et al. (2018) looked at the effects of robot adoption on the German labor market and found that it has changed the job distribution across industries without decreasing the aggregate level of employment. On the other hand, Gries and Naudé (2018) integrate artificial intelligence into an economic growth model with limitations on total demand. They claimed that artificial intelligence did not directly lead to an increase in unemployment. Acemoglu and Restrepo (2018), who investigate the relationship between artificial intelligence, automation, and work, have come to some interesting results. AI and automation, they claim, improve productivity, which is then supported by additional capital accumulation. By way of additional capital, current work will be technically advanced using a more skilled worker, which creates new jobs. Chang-jun et al. (2019) believe that universities are more effective in improving professional skills and guiding good personality characteristics, which can help graduates reduce the risk of being replaced by artificial intelligence. Webb (2019), who found that jobs with high exposure to automation technologies experienced a decline in employment and wages, Aghion et al. (2020) used French data and found that automation positively impacts employment at the firm and industry levels. Koch et al. (2021) analyzed a panel of Spanish manufacturing firms. They pointed out that robot adoption led to a net increase in jobs of 10%, while firms that did not invest in robots suffered job losses over the period.

On the other hand, the authors point out that, at the aggregate level, automation does not result in net job destruction and creation. Felten et al. (2019) proposed an "AI Occupational Impact" measure and found that, while artificial intelligence has a small positive effect on wages, it has no impact on employment. Acemoglu and Restrepo (2020) used data on online vacancies and found no correlation between AI exposure and employment or wages.

Although artificial intelligence and unemployment are discussed in various aspects in the literature, empirical studies are limited. Hence, this study fills the three most important research gaps. The first is associated with the lack of empirical papers concentrating on artificial intelligence and unemployment. While previous research has discussed AI's futuristic aspects, this study develops an empirical econometric model. The second gap is associated with the lack of large datasets. In addition to previous studies, this study uses a 17-year (2005–2021) dataset covering panel data from 24 high-tech developed countries. This increases the validity and reliability of the model results. The third gap is the lack of a systematic dataset of AI used for discovering the

relationship between AI and unemployment. Therefore, this study uses GTI, which will be a proxy variable for the use of AI.

3. Methodology

This section decides on the econometric method to investigate the relationship between AI and unemployment. Unemployment measures the number of people currently without a job over a particular period, such as a month, quarter, or year. It is a measure of the current state of the labor market and reflects the number of people who are actively seeking employment but are unable to find work at a given point in time. The dynamic lag effect is essential for unemployment because economic conditions and policies may take some time to impact the labor market. For example, a government stimulus program may take several months to be implemented and for its effects to be felt in terms of job creation or retention. Similarly, a recession may take some time to affect the unemployment rate, as businesses may initially try to avoid layoffs by reducing hours or wages. In addition, even after the economy has recovered from a recession, it may take some time for the labor market to fully recover and for the unemployment rate to return to pre-recession levels. This is because some workers may have left the labor force or become discouraged from seeking employment during the recession and may take some time to re-enter the labor market. Overall, considering the dynamic effect when analyzing changes in the labor market can provide a more accurate and comprehensive understanding of the dynamics of unemployment and the factors that contribute to it. As a result, we use a dynamic panel data (DPD) model to focus on the dynamic effect of unemployment in this study.

Several different econometric methods have been proposed to estimate DPD models. The DPD model allows for the endogeneity of explanatory variables and accounts for unobservable, time-invariant country effects (Baek, 2016; Yerdelen Tatoğlu, 2018). To address the concern of endogeneity with explanatory variables, Arellano and Bond (1991) first suggested using the difference generalized method of moments (difference GMM), whereby instrumental variables are used for deriving the GMM of corresponding moment conditions. The basic principle is that this method takes the first difference of the regression equation to eliminate the individual fixed effects and then uses the lagged variable as the instrumental variable of endogenous variables in the difference equation. While it is an effective method for mitigating the endogeneity issue, it suffers from the concern of "weak instruments" in the case of finite samples and results in low precision (Bond et al., 2001). A solution to this problem is proposed by Arellano and Bover (1995) and Blundell and Bond (1998), who suggested using the system GMM estimator that employs lagged variables as instruments in both the difference and the level equations.

$$y_{it} = \sum_{j=1}^{p} \alpha_j y_{i,t-j} + x_{it}\beta_1 + w_{it}\beta_2 + \nu_i + \in_{it} \; i = 1, \ldots, N \; t = 1, \ldots, T \qquad (1)$$

Where the α_j are p parameters to be estimated, x_{it} is a $1 \times k_1$ vector of strictly exogenous covariates, β_1 is a $k_1 \times 1$ vector of parameters to be estimated,w_{it} is a $1 \times k_2$ vector of predetermined or endogenous covariates,β_2 is a $k_2 \times 1$ vector of parameters to be estimated, ν_i are the panel-level effects (which may be correlated with the covariates), and $\in_{it}$ are *i.i.d.* over the whole sample with variance $\sigma_{\in}^2$. The ν_i and the $\in_{it}$ are assumed to be independent for each i overall t.

This method involves a system of two equations: an equation for differences with lagged levels as instrumental variables and an equation for levels with lagged differences as instrumental variables. In addition to addressing the endogeneity concern, system GMM can take care of omitted variable bias, multicollinearity concerns, unobserved country heterogeneity issues, and measurement errors that are common in pooled ordinary least squares and fixed effect regression methods (Bond et al., 2001). It can also give better results than the different GMM estimators, which may generate biased and imprecise estimates (Arellano & Bover, 1995; Blundell & Bond, 1998). Therefore, this study relies on the system GMM estimation method for the dynamic panel data analysis. Although system GMM results are considered advantageous, it is vital to assess the consistency of its estimation, which is determined by the validity of the instruments and the absence of second-order serial correlation in the first-differenced residuals. Instrumental variables are considered valid when there is no correlation between the error term and the instruments, as tested by Sargan and Hansen tests (Akay, 2015; Baek, 2016; Yerdelen Tatoğlu, 2018). And the second-order serial correlation is tested by Arellano-Bond tests (Teixeira & Queirós, 2016). There are two variants of system GMM, namely, one-step and two-step estimation methods, depending on whether the weight matrix is homoscedastic or heteroscedastic. Two-step estimators are widely acknowledged to be more efficient because, with limited samples, this method reduces bias from the standard errors of the estimation values (Bond et al., 2001). However, system GMM may produce many instrumental variables as the number of periods increases, which, in turn, can overfit the model and result in low model specification (Roodman, 2009). Hence, using a one-step system GMM is recommended for a model with a small number of countries and a more extended period of time, and a two-step system GMM is encouraged for a model with a large number of countries and a shorter period (Teixeira & Queirós, 2016). Therefore, given that our analysis involves data from 24 high-tech developed countries over 17 years, we preferred the findings of the two-step system GMM over the one-step system GMM.

4. Empirical findings

4.1. Dataset, Variables, and descriptive statistics

This empirical study is conducted using panel data from 24 high-tech and developed countries (i.e., Austria, Australia, Canada, Switzerland, China, Germany, Denmark, Estonia, Finland, France, the United Kingdom, Ireland, Israel, Iceland, Japan, the Korea Republic, Luxembourg, Malta, the Netherlands, Norway, New Zealand, Sweden, Singapore, and the United States) and 17 years (i.e., 2005–2021). This follows two essential criteria: first, the countries are developed ones, having complex economies; and second, all of them occupied the first part of the Global Innovation 2022 rankings (Dutta et al., 2022), exhibiting outstanding performances in innovation. The time period covers precisely the years when interest in artificial intelligence "blew up" worldwide.

The ***dependent variable*** as a percentage of the total labor force represents the unemployment rate, which denotes the unemployed labor force that is available for and seeking work.

The ***interest variables*** capture the volume of the Google Trend Index related to artificial intelligence, machine learning, and data science. Although the literature on measuring artificial intelligence is limited, GTIs could be considered a proxy for AI use. Hence, we investigate the three most popular search terms for artificial intelligence: artificial intelligence, machine learning, and data science. We estimate the model in three different scenarios because of the multicollinearity between these search terms: Scenario 1 - Artificial Intelligence and Unemployment; Scenario 2 - Machine Learning and Unemployment; and Scenario 3 - Data Science and Unemployment.

A set of ***control variables*** is considered to isolate the effects of interest variables. They are inspired by both the theoretical model and the literature: the inflation rate, economic growth, and government spending. The economy's annual proportion of price fluctuations is reflected in the inflation rate, calculated using the consumer price index. In the theoretical literature, a negative relationship was found between inflation and unemployment (Phillips, 1958). The Phillips curve upholds stable relations for inflation and unemployment dynamics and asserts that inflation growth creates more jobs and decreases unemployment (Wulandari et al., 2019).

The next control variable is GDP growth. Economic growth and the

unemployment rate are the key indicators that are simultaneously monitored by both policymakers and the public, as they create a clear picture of the economic development of a country. Moreover, the linkage between the unemployment rate and economic growth as a relevant macroeconomic issue covers a wide area of theoretical and empirical research. It is a widely accepted view in economics that a higher growth rate of the GDP of an economy increases employment and reduces unemployment. This theoretical proposition relating output and unemployment is known as "Okun's Law." This relationship is among the most prominent in macroeconomic theory and is held for several countries and regions, mainly in developed countries (Lee, 2000; Farsio & Quade, 2003).

Government spending, which is another control variable expressed as a percentage of GDP, is cash payments for operating activities in supplying goods and services. Fiscal actions can increase labor supply and unemployment, even if output grows. Alternatively, if cuts in government purchases induce higher private-sector output and higher productivity in the private sector, GDP may grow even if unemployment increases. This ambiguity is reflected in recent research: While Monacelli et al. (2010), Auerbach and Gorodnichenko (2012), Ramey (2012), Holden and Sparrman (2018) conclude that an increase in government purchases leads to lower unemployment, a string of empirical studies indicates that enormous government spending will likely increase unemployment. Abrams (1999), Christopoulos et al. (2005), Feldmann (2006), Brückner and Pappa (2012) find that increased government purchases lead to higher unemployment. As a result, the variables and their predicted signs are described in Table 1 based on empirical studies and economic literature.

We investigate the rise of the Data Science, Machine Learning, and Artificial Intelligence Google Trend Index in 24 high-tech developed countries in Fig. 1.

Fig. 1 represents the trendline of GTI volumes for Data Science, Machine Learning, and AI in high-tech developed countries between 2005 and 2021. AI has an upward trend through 2018 and a slight descending trend after that, while machine learning and data science are rising from 2005 to 2019 and a slight down after that. According to GTI volumes, Machine Learning generally takes the most attention in high-tech developed countries. Artificial Intelligence and Data Science have received more searches since 2014; Machine Learning since 2012. In addition, Fig. 2 shows the share of Data Science, Machine Learning, and AI GTI in high-tech developed countries in 2005–2021.

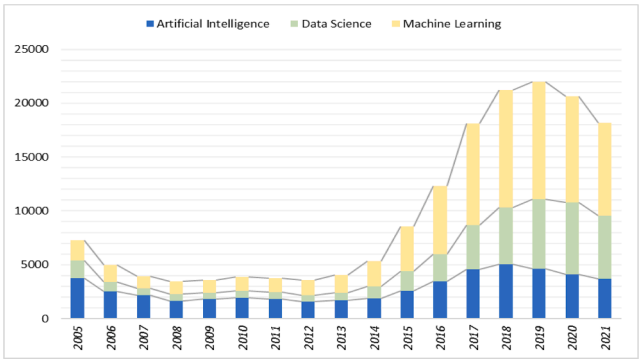


Fig. 1. Trendline of Data Science, Machine Learning, and AI GTIs in high-tech developed countries.

Fig. 2(a) shows that in the 24 high-tech developed countries in 2005–2021, the volume of GTI for Artificial Intelligence is highest in Australia (11.2%), the US (9.8%), Canada (9.3%), the UK (9.2%), and Japan (8.4%). Fig. 2(b) shows that the volume of Data Science GTI volume is highest in the US (12.7%), Australia (11.5%), the UK (10.0%), Canada (8.8%), and Switzerland (6.3 %). In addition, according to the Machine Learning GTI, the top 5 countries are Japan (10.5%), the US (7.9%), China (7.6%), Canada (7.2%), and Switzerland (6.9%). Fig. 3 shows the correlation heatmap between all variables.

Fig. 3 calculates Pearson's correlation coefficients between variables and visualizes the correlation heatmap. Especially the first column shows correlation coefficients among the dependent variable (UN), control, and interest variables. However, the other columns indicate correlation coefficients between control and interest variables. Fig. 3 shows that unemployment (UN) has a negative correlation with Inflation Rate (IR), Economic Growth (GDPGW), and the GTI volume of Artificial Intelligence (AI), Data Science (DS), and Machine Learning(ML). Conversely, unemployment has a positive correlation with Government Size (GS). Generally, correlation heatmap indicates that the correlation between the control variables is weak, but the correlation between the GTIs is high. Hence, to improve the quality of the model and avoid multicollinearity, we include each AI, DS, and ML GTIs in the model as different scenarios, not in the same model (Güriş & Çağlayan, 2018; Yerdelen Tatoğlu, 2020).

Table 1
Variable Descriptions and their expected signs.

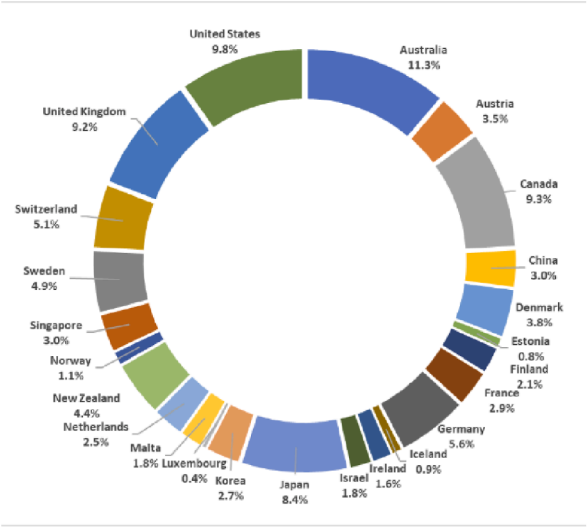
Variables (Short Name)	Data Descriptions - Unit	Data Source	Expected Signs
Response Variable:			
Unemployment rate (UN)	Unemployment rate as a percentage of the workforce - %	WDI	
Interest Variables:			
Scenario 1 - Artificial Intelligence (AI) Scenario 2- Machine Learning (ML) Scenario 3- Data Science (DS)	Search keywords in Google Google Trend Index	Data obtained with "gtrendsR" R package by Massicotte et al. (2016)	+/ -
Control Variables:			
Inflation rate (IR)	Annual percentage change in the cost to the average consumer of goods and services basket - %	WDI	–
Economic Growth (GDPGW)	Annual percentage change in GDP constant 2015 $ - %	WDI	–
Government Spending (GS)	Expenses are cash payments for the government's operating activities in providing goods and services as a share of GDP- %	WDI	+/ -

4.2. Econometric model and estimation

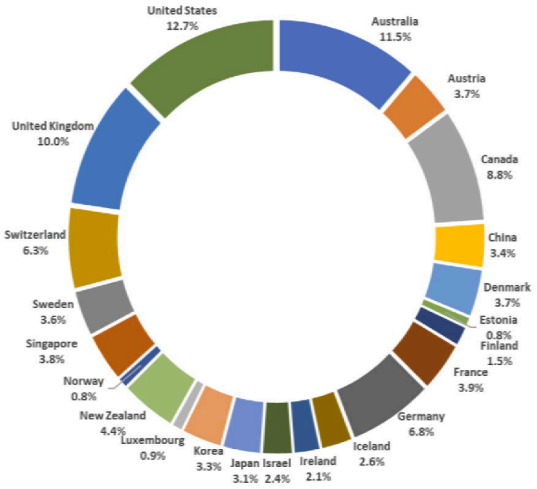
The present study investigates the artificial intelligence-unemployment nexus in high-tech developed countries. To address the research question, the dynamic panel data model is developed as in Equation (2):

$$UN_{i,t} = \alpha_i + \beta_1 UN_{i,t-1} + \beta_2 IR_{i,t} + \beta_3 GDPGW_{i,t} + \beta_4 GS_{i,t} + \beta_5 GTI_{i,t} + \varepsilon_{i,t} \quad (2)$$

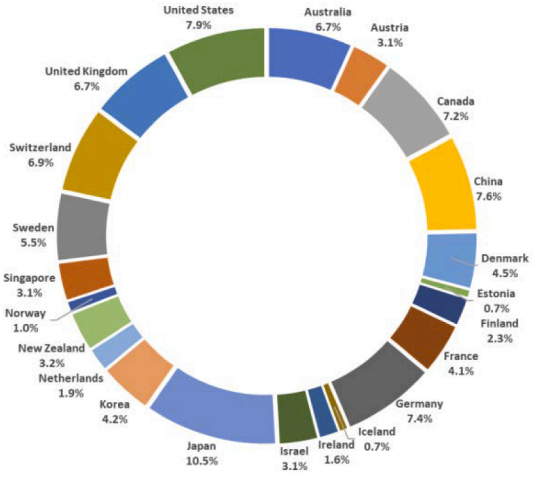
Where $UN_{i,t}$ is the unemployment rate, $UN_{i,t-1}$ is the unemployment rate for the previous year. $IR_{i,t}$, $GDPGW_{i,t}$, and $GS_{i,t}$ are control variables, and the $GTI_{i,t}$ is Google Trend Index with different scenarios such as Scenario 1-Artificial Intelligence, Scenario 2- Machine Learning (ML) and Scenario 3- Data Science (DS). Furthermore, 24 high-tech developed countries denote (i), 2005–2021 years denotes (t), constant (α_i) is heterogenous across countries, coefficients (β_1 to β_5) and error term ($\varepsilon_{i,t}$). We adapt our econometric framework keeping in view the goal of the study and the type of data that is accessible. We use a dynamic panel model because the unemployment variable is more affected by its historical values, and we estimate the model using Blundell–Bond's (1998)



(a) Artificial Intelligence GTI



(b) Data Science GTI



(c) Machine Learning GTI

Fig. 2. Share of AI, Machine Learning, and Data Science GTIs in high-tech developed countries in 2005–2021.

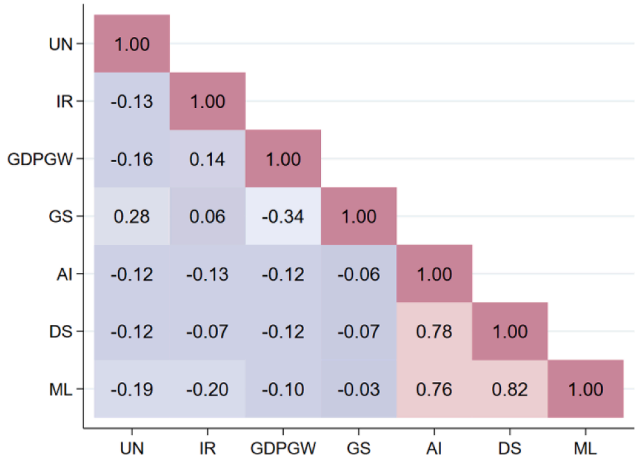


Fig. 3. Correlation Heatmap.

GMM-system two-step estimator in Table 2.

The last part of Table 2 shows diagnostic test results for the dynamic panel data model. The Sargan (1958) test of overidentifying restrictions p-values ($p > 0.10$) indicates that the instruments are well-identified, and overidentifying restrictions are valid in all scenarios. Arellano–Bond's (1991) test for autocorrelation in first-differenced AR(2) errors p-values ($p > 0.10$) indicate that the residuals have no autocorrelation in order 2. The results of the Xie and Pesaran (2022) CD* cross-sectional dependence test, which is robust in weak or strong forms of cross-sectional dependency and is valid for $N > T$ panel data, confirm that no cross-sectional dependence exists in all scenarios. As a result of diagnostic tests, all scenarios' models which use Blundell–Bond's (1998) two-step GMM-system estimator are valid.

In Table 2, we use Windmeijer's (2005) robust standard errors that resist finite sample correction for the variance of efficient linear two-step GMM estimators. The control and interest variables we include in the model are statistically significant, at least at the 5% level. In scenario 1, the 1% increase in unemployment in the previous year has an increasing effect on the current year's unemployment rate of 0.877%. On the other hand, a rise of 1% in the ratio of government expenditures to GDP is observed to increase unemployment by 0.08%. In contrast, a 1% increase in inflation and economic growth reduces unemployment by

Table 2
Blundell-Bond (1998) GMM system two-step estimation results.

Dependent Variable: Unemployment Rate	**Scenario 1 Artificial Intelligence**	**Scenario 2 Machine Learning**	**Scenario 3 Data Science**
Control Variables:			
$UN_{i,t-1}$	0.877***	0.788***	0.850***
	[0.053]	[0.035]	[0.038]
$IR_{i,t}$	−0.145***	−0.167***	−0.138***
	[0.042]	[0.051]	[0.039]
$GDPGW_{i,t}$	−0.159***	−0.148***	−0.156***
	[0.030]	[0.031]	[0.028]
$GS_{i,t}$	0.080***	0.114***	0.086***
	[0.024]	[0.024]	[0.020]
Interest Variables:			
$AI_{i,t}$	−0.003**	–	–
	[0.001]		
$ML_{i,t}$	–	−0.002**	–
		[0.001]	
$DS_{i,t}$	–	–	−0.002**
			[0.001]
Number of Observation N = 24 T = 16	384	384	384
Diagnostic Tests:			
Sargan Test	18.881	20.951	19.847
	p > 0.10	p > 0.10	p > 0.10
Arellano Bond test for AR (2) test	−1.619	−1.599	−1.559
	p > 0.10	p > 0.10	p > 0.10
Pesaran and Xie (2022) CD* test	0.67	0.87	0.17
	p > 0.10	p > 0.10	p > 0.10

Scenario 1 indicates a model in which Artificial Intelligence is an interest variable.
Scenario 2 indicates a model in which Machine Learning is an interest variable.
Scenario 3 indicates a model in which Data Science is an interest variable.
*, **, *** show significance at 10%, 5% and 1% level.
[…] denotes the robust standard error.

0.145% and 0.159%, respectively. Scenarios 2 and 3 also yield the same outcomes with slight coefficient differences. Generally, results consider the unemployment process with "memory" of the unemployment ($UN_{i,t-1}$) and indicate that the process of unemployment adjustment is still rigid, with current unemployment being positively associated with the previous year's unemployment. Government Spending ($GS_{i,t}$) increases the unemployment rate in all scenarios, whereas inflation rate ($IR_{i,t}$) and economic growth ($GDPGW_{i,t}$) decrease unemployment in 24 high-tech developed countries. Hence, Phillips's (1958) curve and Okun's (1963) law are valid in 24 high-tech developed countries.

The main findings about interest variables indicate a significant negative relationship between artificial intelligence ($AI_{i,t}$), Machine Learning ($ML_{i,t}$), Data Science($DS_{i,t}$), and unemployment. The unemployment rate reduces by 0.003 percent as the search volume ($GTI_{i,t}$) related to artificial intelligence increases in 24 high-tech developed countries (Scenario 1). In addition, the unemployment rate decreases by 0.002% when the Machine Learning (Scenario 2) and Data Science (Scenario 3) GTIs are upward. As a result, all scenarios ultimately validate the 'displacement effect.' New technologies such as AI, DS, and ML do not increase unemployment. On the contrary, they create new job opportunities and decrease unemployment.

5. Conclusion

This study analyzes the effect of artificial intelligence on unemployment in the 24 high-tech developed countries in 2005–2021 using dynamic panel data estimation, which considers the dynamic lag effect of unemployment. The dynamic panel data model consists of control variables for unemployment, such as inflation, economic growth, and government spending, and interested variables, such as GTIs related to artificial intelligence, machine learning, and data science. This study tested the relationship between artificial intelligence and unemployment in three scenarios. Scenarios 1–3 involve GTIs associated with artificial intelligence, machine learning, and data science. We decided to use the Blundell-Bond (1998) system's two-step GMM estimator to test all scenarios, which gives robust results when the lag of the dependent variable is contained in the dynamic panel data model. All diagnostic tests prove that the econometric model is valid, and all variables involved in the model are statistically significant at a 5% level.

The negative effect of the inflation rate on unemployment is consistent with Phillips's (1958) curve in all scenarios. Okun's law also favors the inverse relationship between economic growth and unemployment in high-tech developed countries. In all scenarios, government spending is significant and negatively correlated with unemployment and results are all fully supported by Feldmann (2006), Brückner and Pappa (2012). Our most important findings suggest a negative relationship between AI, machine learning, data science, and unemployment. As a result, the "displacement effect" is validated for artificial intelligence. Hence, AI has the potential to revolutionize the workforce by creating new job roles, automating routine tasks, and increasing productivity. AI-enabled technologies can free employees to focus on more complex and creative work requiring human skills such as critical thinking, problem-solving, and innovation. This can lead to a more fulfilling work experience and increased job satisfaction. Furthermore, AI can help businesses make better decisions by providing data-driven business model insights and analytics, resulting in increased profitability and growth and it can lead to the creation of new job roles and the expansion of existing ones, resulting in job creation. Ultimately, the positive impact of AI on employment is creating a more efficient, productive, and fulfilling work environment with new jobs.

Regarding policy implications, if other developed and developing countries effectively provide for the application of artificial intelligence technologies and applications in economic procedures, they could decrease the unemployment rate. On the other hand, new jobs created due to AI will control the unemployment rate and help drive economic growth and competitiveness by improving efficiency.

Future research can examine the relationship between artificial intelligence and unemployment using GTIs in developing countries. In addition, new control variables such as interest rates and wage rates could be added to the model and alternative econometric frameworks could be used for estimation.

CRediT authorship contribution statement

Hasraddin Guliyev: Conceptualization, Methodology, Investigation, Writing – original draft, Visualization, Resources.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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