IJERMT

International Journal of Engineering Research & Management Technology
(Peer-Reviewed, Open Access, Fully Refereed International Journal) ISSN: 2348-4039
Volume 11, Issue-2 March-April- 2024 Impact Factor: 7.09

Email: editor@ijermt.org www.ijermt.org

ARTIFICIAL INTELLIGENCE AND UNEMPLOYMENT

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Abstract

In order to investigate the impact that artificial intelligence has on unemployment rates in the most technologically advanced and industrialized nations, this study employs a theoretical model that is supported by empirical evidence. Panel threshold and GMM-system estimations fall within the category of nonlinear approaches, which are utilized by empirical methods. A total of twenty-three countries spanning the years 1998–2016 are included in the document. According to the major findings, the impact of artificial intelligence (AI) on unemployment shows a nonlinear relationship; more specifically, when inflation is low, faster adoption of AI results in lower unemployment rates. One cannot find any indication that there is a "switch effect" between the two phrases in this instance. The influence of artificial intelligence on unemployment is insignificant in every other aspect.

Key words: artificial intelligence; unemployment; implications; high-tech countries

Introduction

Many people are concerned about the future of employment opportunities as a result of the rapid development and widespread application of artificial intelligence technologies. While those who are against artificial intelligence argue that it will lead to an increase in productivity and the creation of new job prospects, others who are in favor of the technology argue that it would result in significant job losses and technical unemployment. Numerous scholars, lawmakers, and members of the general public have shown a great deal of interest in this debate due to the fact that artificial intelligence (AI) will have far-reaching and difficult ramifications for the future of labor. In the intricate relationship that exists between the implementation of artificial intelligence and the rate of employee unemployment, there are a great deal of economic, social, and technological factors at play. Even though there has been a lot of research done on the topic, there has to be consensus over the overall impact that artificial intelligence will have on jobs. Additionally, it is challenging to generalize the findings due to the fact that the existing body of literature typically concentrates on certain companies or regions. The purpose of this literature review is to provide a comprehensive understanding of the impact that an adoption of artificial intelligence has on employee unemployment by analyzing the research that has already been conducted and identifying significant outcomes, limitations, and gaps in the existing body of knowledge. The purpose of this review is to, with any luck, help throw light on the complex web that is the association between artificial intelligence and joblessness, pave the way for further research and policy decisions, and synthesise the information that is now available.

The literature review may be broken down into seven major sections. The subsequent section, titled "Historical" Perspective on Automation and Employment, provides a chronological account of the evolution of these ideas over the course of time, with a particular emphasis on important occasions and foundational research. The portion of the report labeled "Theoretical Frameworks" dives into the most popular hypotheses that have been utilized to investigate the impact that artificial intelligence would have on the marketplace for workers. These ideas include concepts such as job polarization, skill-biased technological transformation, and technical unemployment all of which are examples of technological unemployment.

The section titled "Previous Research Findings" includes a summary of the previous research that has been conducted. This research is categorized into studies that support negative impact, studies that imply neutral or positive impacts, and studies that challenge the existing body of literature. The section under "Emerging Trends and Debates" covers a variety of topics, including talks concerning emerging concepts and movements, such as the gig economy and the moral repercussions of artificial intelligence in the workplace. The research article titled "The Multifaceted Relationship between AI Adoption and Employee Unemployment" offers a full summary of the research and digs into the intricate nature of the connection between the two. The conclusion brings the study to a close by including a summary of its most important aspects, a description of any gaps in our understanding, and a discussion of the consequences of the study for both policy and practice.

This concept was initially put up in 1956 during a symposium that was held at Dartmouth College's artificial intelligence session. However, its roots can be traced back to the early 1900s, during the time of the First World War. Nilsson makes the observation that this process results in the creation of a "new category of machines," which are computers that are capable of performing tasks that were previously reserved for humans and required people to use their reasoning, judgment, and perception. Both the continuation and the culmination of automation processes, the current state of artificial intelligence (AI) has far-reaching ramifications for the employment market. There are also far-reaching consequences for the job market. Stevenson contends that artificial intelligence bolsters economic growth because it leads to higher levels of productivity, which in turn leads to higher levels of future income. It is demonstrated by him that this positive effect is valid so long as the benefits of artificial intelligence are sufficient to compensate for the incomes that are lost by the workers who are affected.

Objective

RESEARCH METHODOLOGY

An econometric technique is chosen in this part in order to investigate the relationship between artificial intelligence and unemployment. When calculating the unemployment rate, which is the percentage of the labor force that is now unemployed, it is possible to utilize data from a number of different time periods, such as a month, a quarter, or an entire year. This particular indicator of the current state of the labor market reflects the amount of people who are looking for work but are unable to find any at a certain moment in time. It is essential to take into consideration the dynamic lag effect when doing research on unemployment.

This is due to the fact that shifts in the economy and the policies of the government can have a slow but significant impact on the job market. To provide an example of this, it may take a few months for a government stimulus program to become operational and for its impacts to become apparent in terms of the number of jobs that are created or maintained. A recession may not have an immediate impact on the unemployment rate for some time, just as businesses may first try to prevent layoffs by reducing the number of hours they work or the wages they pay their employees.

Furthermore, 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 levels that were before to the crisis. Specifically, this is owing to the fact that it may take some time for individuals to return to the labor after being out for a period of time as a result of the recession or just being demoralized by the process of looking for work. By taking into consideration the dynamic effect when researching changes in the labor market, it is possible to gain a better understanding of the factors that contribute to unemployment as well as the dynamics of the phenomenon. Therefore, in order to zero down on the ever-changing impact of unemployment, we have decided to adopt a model that is based on dynamic panel data (DPD). Several different econometric methodologies have been proposed as potential methods for estimating DPD models.

When developing the DPD model, it is important to take into account both the endogeneity of the factors that explain the phenomenon and the fact that the impacts of the country are both unobservable and time-invariant. Arellano and Bond (1991) initially presented the difference generalized method of moments (difference GMM) as a solution to manage the issue of endogeneity with explanatory factors. This method was developed by using instrumental variables to derive the GMM of corresponding moment conditions.

After taking the first difference of the regression equation, the basic idea behind this strategy is to use the lagged variable as an instrumental variable for endogenous variables in the difference equation. This is done in order to eliminate individual fixed effects. It is not particularly exact and has the problem of "weak instruments" when working with restricted samples, despite the fact that it performs a decent job of decreasing the influence of endogeneity due to the fact that it is a good method. Therefore, in order to utilize the system GMM estimate approach for the purpose of analyzing dynamic panel data, this work is carrying out. There is a possibility that System GMM will produce beneficial results; but, before putting your faith in them, you should verify that the instruments are authentic and that the first-differenced residuals do not exhibit any second-order serial correlation.

Your level of consistency with the estimation will be determined by this. According to the tests developed by Sargan and Hansen, instrumental variables are considered to be valid if and only if there is no correlation between the error term and the instruments. An additional benefit of Arellano-Bond tests is that they ensure the existence of second-order serial correlation. There are two different variants of system GMM, which are known as one-step and two-step estimation methods, and these versions are accessible depending on whether the weight matrix is homoscedastic or heteroscedastic. Two-step estimators are frequently thought to be more efficient than other methods, particularly when working with small samples. This is due to the fact that this method reduces the bias produced by the standard errors of the estimation values. In spite of this, the system GMM has the ability to produce a greater number of instrumental variables as the number of periods increases. Consequently, this can result in the model being overfit, as well as their being insufficient model definition. A one-step system GMM is more suitable for models that have a small number of countries and a longer period of time, whereas a two-step system GMM is better suited for models that have a large number of countries and a shorter period of time. In light of the fact that our research is based on data collected from twenty-four technologically advanced countries over the course of seventeen years, we discovered that the two-step GMM method produced more dependable results than the one-step method.

DATA ANALYSIS

Dataset, Variables, and descriptive statistics

Over the course of seventeen years, this empirical study was carried out by a total of twenty-four developed and high-tech nations. These nations included the United States of America, Canada, China, Germany, Denmark, Finland, Iceland, Japan, the Korea Republic, Luxembourg, Malta, the Netherlands, Norway, New Zealand, Sweden, and Singapore. There are two factors that must be met in order for this to be true: the advanced level of the countries and the complexity of their economies. In the second place, each of these countries achieved the top spot in the Global Innovation 2022 rankings, which is a clear indication of the great innovation potential they possess. That is to say, it spans the years in which people all around the world "exploded" with curiosity about artificial intelligence. The dependent variable, which is the unemployment rate, is a representation of the proportion of the labor force that is currently without a job and is actively exploring employment opportunities.

An additional control variable that is expressed as a percentage of GDP is the amount of money spent by the government. Specifically, this includes monetary payments made for operational operations related to the provision of products and services. However, fiscal policies have the potential to increase both the supply of workers and the unemployment rate, even when output is growing. On the other hand, if reductions in government spending lead to higher output and productivity in the private sector, then the Gross Domestic Product (GDP) could grow despite an increase in the unemployment rate. This lack of clarity is seen in investigations that were conducted more recently: There are a lot of empirical studies that demonstrate that excessive government spending will most surely increase unemployment. These findings contrast the conclusions that were reached by Monacelli et al. (2010), Auerbach and Gorodnichenko (2012), and Ramey (2012), who all found that higher government purchases lower unemployment. According to the findings of Abrams (1999), Christopoulos et al. (2005), Feldmann (2006), Bruckner and Pappa (2012), and Holden and Sparrman (2018), an increase in the amount of money spent by the government is linked to an increase in the rate of unemployment.

In light of this, Table 1 provides a description of the variables and the signs that are anticipated to be associated with them based on the economic literature and empirical studies. There is a growing interest in artificial intelligence, machine learning, and data science, and we are investigating this. Figure 1 depicts the Google trajectory Index for twenty-four developed countries that are wealthy in technology over the years 2005 to 2021. The line illustrates the progression of GTI volumes for the fields of data science, machine learning, and artificial intelligence in different countries. Machine learning and data science, on the other hand, show an upward trend until 2018, followed by a slight decrease trend after that.

Artificial intelligence (AI) exhibits an upward trend from 2005 to 2019, followed by a slight decreasing trend. According to GTI volumes, the primary emphasis of research and development in high-tech developed countries is often machine learning. individuals have been searching for artificial intelligence and data science at a higher rate since 2014, and since 2012, more individuals have been searching for machine learning. In addition, Figure 2 illustrates the percentage of gross domestic product (GDP) that may be attributed to data science, machine learning, and artificial intelligence (GTI) in technologically sophisticated nations from the years 2015 to 2021.

According to Fig. 2(a), which illustrates the volume of GTI for Artificial Intelligence in the 24 high-tech developed countries from 2015 to 2021, the countries with the highest percentage of GTI for AI are Japan (8.4%), Canada (9.3%), the United Kingdom (9.2%), and Australia (11.2%). The United States of America is responsible for 12.7% of the overall volume of Data Science GTI, as shown in Figure 2(b). This is followed by Australia, which accounts for 11.5%, the United Kingdom, which accounts for 10%, Canada, which accounts for 8.8%, and Switzerland, which accounts for 6.3%. In addition to this, the Machine Learning Global Trade Index rates the top five countries as follows: Japan, with 10.5%, the United States of America, with 7.9%, China, with 7.6%, Canada, with 7.2%, and Switzerland, with 6.9%. The heat maps of the correlations between all of the parameters are presented in Figure 3.

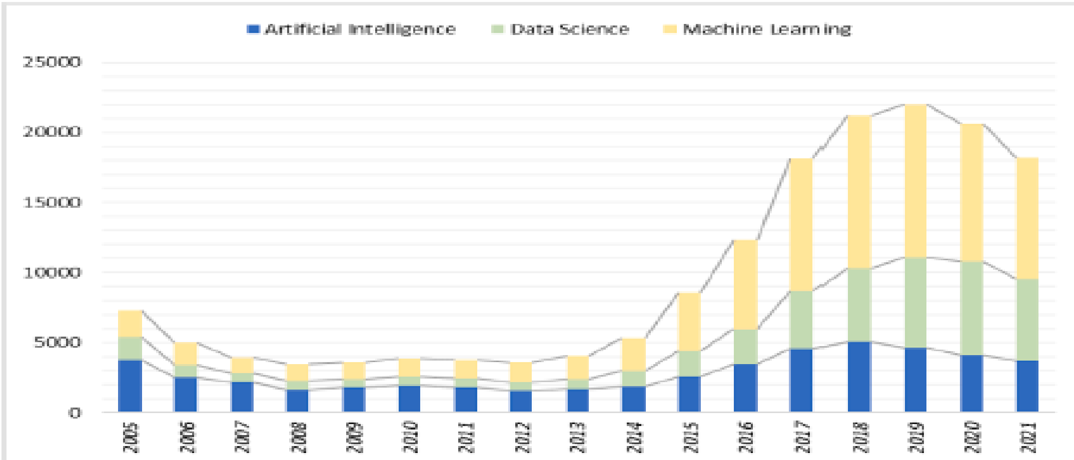
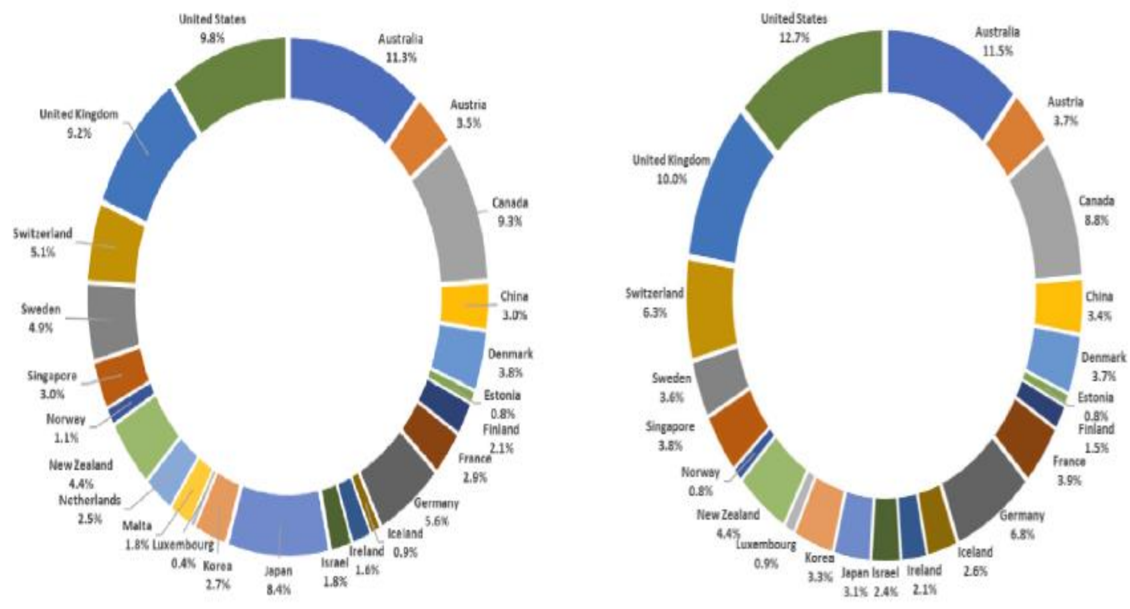
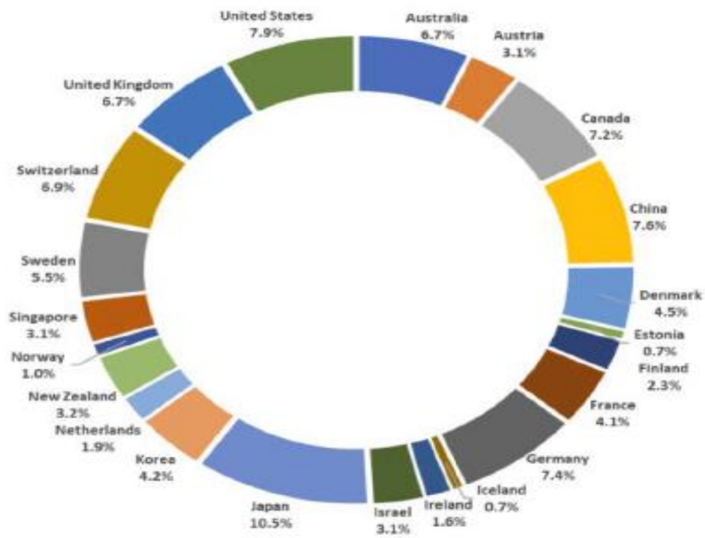


Fig. 1.Trend line of Data Science, Machine Learning, and AI GTIs in high-tech developed countries



(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 2015–2021.

Figure 3 presents the correlation heatmap as well as Pearson's correlation coefficients for the variables that are being studied. With particular attention paid to the first column, the coefficients of correlation between the variables of interest, control, and the dependent variable (UN) are presented. Nevertheless, the correlation coefficients between the control variables and the interest variables are shown in the columns that are not the control variables. As can be seen in Figure 3, the unemployment rate (UN) is negatively correlated with the inflation rate (IR), the growth of the gross domestic product (GDP), and the volume of data science (DS), machine learning (ML), and artificial intelligence (AI) in the business technology industry (GTI). On the other side, there is a positive correlation between the size of the government (GS) and the rate of unemployment. In contrast to the GTIs, which exhibit a significant correlation, the control variables have a weak link, as seen by the correlation heatmap. Therefore, in order to improve the quality of the model and avoid multicollinearity, we add AI, DS, and ML GTIs into the model as independent scenarios rather than incorporating them into the same model.

Fig. 3 Correlation Heatmap

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	+/ -
Control Variables: Inflation rate (IR)	Annual percentage change in the cost to the average consumer	WDI	–

	of goods and services basket - %		
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	+/ -

Table 1 Variable Descriptions and their expected signs

FINDING AND RESULT

Potential Job Losses

Numerous studies indicate that there is a risk of widespread employment losses as a consequence of the broad usage of artificial intelligence, particularly in fields and professions that are already heavily mechanized. According to the foundational study that Frey and Osborne conducted, 47 percent of jobs in the United States are extremely susceptible to becoming automated within the next twenty years. According to them, developments in mobile robotics and machine learning will make artificial intelligence systems capable of performing a wide range of cognitive and physical tasks. This could result in the loss of employment opportunities for millions of individuals everywhere.

In other research, similar estimates of the potential employment losses that could occur as a result of the implementation of AI have been provided. According to the McKinsey Global Institute, one example is the possibility that automation, including artificial intelligence technologies, would result in the loss of hundreds of millions of jobs around the world by the year 2030. They give the impression that less developed nations and industries will be more severely impacted by the effects of artificial intelligence on employment than more established economies and businesses that are dependent on human labor.

Many people believe that these studies overstate the number of jobs that have been lost as a result of automation. This is due to the fact that they disregard the social and legal obstacles that stand in the way of adoption and instead focus on the technological capabilities of the technology. In addition, the research does not take into account the new sectors and employment that have formed as a direct result of the development of artificial intelligence.

Job Creation and Productivity Gains

In spite of the fact that many people are concerned about losing their jobs in the event that artificial intelligence becomes extensively deployed, many who support the technology assert that it would boost productivity and create new employment prospects. Together with Rest rep, Acemoglu developed a paradigm with the purpose of distinguishing between the effects of artificial intelligence on production and displacement. They argue that artificial intelligence (AI) will ultimately have a beneficial impact on unemployment because it will increase productivity and develop new occupations that require human labor. This is despite the fact that it will temporarily eliminate certain jobs.

On the basis of the empirical information that is now available, the implementation of AI has the potential to both boost productivity and provide new job opportunities. As an illustration, artificial intelligence has the ability to increase productivity and develop new goods and services, which might result in a global economic boost of up to thirteen trillion dollars by the year 2030, as stated by Bughin et al. respectively. The argument that they are making is that while artificial intelligence may result in employment losses in certain industries, it will also result in net benefits in other fields, such as data analysis, digital marketing, and the development of AI.

Mixed and Context-Dependent Impact

In spite of the fact that some studies assert that artificial intelligence would have a detrimental impact on employment while others assert that it will have the opposite effect, an increasing quantity of research demonstrates that the relationship between AI and employment is multifaceted and reliant on the environment to which it is applied. It is projected that the impact of artificial intelligence (AI) on employment would vary from country to country, industry to industry, and profession to profession. This is due to factors such as the rate of technological improvement, the degree of labor competency, and the institutional and regulatory framework.

For example, according to the findings of Felten et al.'s investigation on the impact that AI has had on employment in the United States, the impact varies greatly from job to job. It is anticipated that artificial intelligence will enhance highly trained personnel in domains such as management and professional services, while simultaneously displacing less skilled labor in industries such as manufacturing and transportation. This is based on the findings of the researchers.

The impact that artificial intelligence has on employment varies from region to region, as stated by Muro et al. (2019), who also investigate the distribution of jobs related to AI in the United States. When it comes to enjoying the benefits of artificial intelligence, communities that are home to a large number of educated individuals and information technology enterprises have a higher chance of doing so. There is a possibility that employment losses will be more severe in rural areas with a lower population density and in locations where workers have lower levels of education.

Reskilling and Lifelong Learning

As the field of artificial intelligence (AI) continues to develop and shake up the labor market, workers will require systems that help them reskill and learn throughout their entire lives in order to aid them in adapting to new employment requirements. The funding of education and training programs is vital, according to many experts and lawmakers, in order to soften the impact that artificial intelligence (AI) is causing to jobs and to equip people to prosper in the era of AI.

Some examples of reskilling initiatives include training that is provided on the job, classes that are taken online, and specialized programs. Consider, for example, the program known as the Reskilling Revolution. This organization was established by the World Economic Forum (2020), and its primary objective is to enhance the educational possibilities, professional development, and employment prospects of one billion people by the year 2030. As part of the effort to give new opportunities for education and professional progress, partnerships are being formed not only between educational institutions but also between enterprises, governments, and educational institutions.

Conclusion

Using dynamic panel data estimation—which takes into account the dynamic lag effect of unemployment—this study examines the impact of AI on unemployment in the 24 high-tech developed nations from 2005 to 2021. Inflation, GDP growth, and government expenditure are examples of control factors for unemployment in the dynamic panel data model. On the other hand, variables of interest include GTIs associated with data science, artificial intelligence, and machine learning. Under three different conditions, this study examined the link between AI and joblessness. In scenarios 1-3, GTIs related to data science, artificial intelligence, and machine learning are included. We chose to evaluate all scenarios using the two-step GMM estimator from the Blundell-Bond (1998) method. This estimator produces robust findings when the dependent variable's lag is included in the dynamic panel data model. At the 5% level of significance, all model variables are statistically significant, and all diagnostic tests demonstrate that the econometric model is viable. Under all circumstances, Phillips's (1958) curve shows that inflation has a negative impact on unemployment. In industrialized nations with advanced technology, Okun's law also favors a negative correlation between joblessness and economic growth. Feldmann (2006), Brückner and Pappa (2012), and Holden and Sparrman (2018) all strongly support the idea that government spending has a significant and negative correlation with unemployment and results. A negative correlation between data science, artificial intelligence, machine learning, and unemployment appears to be our most significant finding. Consequently, AI support for the "displacement effect" is established. Therefore, AI may increase productivity, automate mundane jobs, and create whole new occupations, thereby transforming the workforce. AI-powered tools can liberate workers to engage in higher-level, more imaginative tasks that call for human abilities like creativity, critical thinking, and problem-solving. A more satisfying work experience and higher levels of job satisfaction may result from this. Artificial intelligence (AI) has the potential to provide new employment opportunities as well as to enhance current ones through the development of data-driven insights and analytics into business models. This, in turn, can enhance profitability and growth for enterprises. A more efficient, productive, and satisfying work environment, together with new job opportunities, is the ultimate goal of artificial intelligence (AI) in relation to employment.

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