The Rise of Artificial Intelligence and the Job Destruction View

Falih M. Alsaaty
Bowie State University

Augustin Ntembe
Bowie State University

Kavita Kapur
Bowie State University

Hussain Ahmad
University of Virginia

ABSTRACT

The employment impact of advancement in artificial intelligence (AI) has emerged in recent years as a key concern in national discussions in the United States. It is suggested in many circles that the rapid progress in robotics, machine learning, and other AI-enabled technology would trigger massive unemployment in the country. The study uses the Autoregressive and Distributed Lag Co-integration(ARDL) to investigate the relationship between patents - as a proxy for technological progress and, hence, AI and employment and gross domestic investments to show that invention and innovation in various sectors of the economy tend to induce increasing demand for the labor force in the country. Evidence from data from 1970-2019 shows the existence of significant short-run and long-run relationships between AI and labor demand. Undoubtedly, long-term society planning efforts are needed to meet AI growing demand for a qualified labor force. This paper concludes that the 'doom and gloom' view about AI is unrealistic for lack of evidence.

Keywords: Artificial Intelligence, Employment, Innovation

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INTRODUCTION

The focus of this paper is on two interrelated issues - AI and employment – because of their considerable impact on economic activities in the United States. Employment is a prime target of economic policy in the country as well as in many other countries around the world. Governments typically deploy different policy tools including fiscal and monetary policies to ensure the level of job creation reaches full employment while, at the same time, maintain price stability. Causes, consequences, and sources of employment have extensively been addressed in the literature (e.g., Pierce and Schott, 2016; Gray, et al. 2019).

For example, Majchrowska and Zólkiewski (2012) studied employment trends in Poland and realized that the country's minimum wage policy had an adverse impact on employment. Seyfried (2014), in a study about employment in several countries (e.g., Greece, Spain), found out that the degree of labor unionization was negatively correlated with employment intensity. Pierce and Schott (2016) determined that U.S. manufacturing employment experienced a sharp decline since 2000 as a result of easing trade restrictions on Chinese imports.

An array of domestic and international factors could influence sector or national aggregate employment level (job creation or job destruction). The factors include trade, automation, competition, foreign direct investment, and the county's overall business environment. Aside from creating goods and services along with other factors of production, employment generates wages, salaries, and fringe benefits that constitute (i) the bulk of consumption expenditures and (ii) the major portion of the gross national product (GDP). Indeed, employment plays a critical role in the nation's economic progress.

To illustrate, according to the U.S. Bureau of Economic Analysis, personal consumption expenditures in 2019 amounted to ($14,545 billion), or 68 percent of GDP, while employees' compensation ($11,432 billion) was 79 percent of personal consumption and 53 percent of GDP. In business settings, the cause-and-effect relationship between AI and employment is established by the deployment of AI-enabled technology of robotics, automation, machine learning, and other algorithms-induced applications that are designed to enhance productivity or replicate human efforts. Hernandez (2018) expressed the fear of technological advancement by saying that, as machines get smarter, there is a persistent fear in the minds of economists, policymakers, and, well, everybody: Millions of people will be left obsolete and jobless. The author added, however, the outcomes of artificial intelligence deployment are likely to be a lot more complex than that. Wilson and Daugherty (2018) indicated that AI is becoming good enough at performing human tasks and it's improving fast. The authors added that AI will also complement and augment human capabilities and not replacing them.

The purpose of this paper was to explore the effects of AI on aggregate employment in the United States. The study employs the Autoregressive Distributed Lag bound testing procedure proposed by Pesaran and Shin (1999), and Pesaran et al. (2001). Unlike the Johansen and Juselius (1990) conventional method of co-integration, the ARDL procedure does not restrict the variables in the regression to be integrated of the same order. The initial findings indicate that the 'doom and gloom' view about the devastating influence of AI on the national employment level is unrealistic for lack of evidence. Our analysis of patents - as a proxy for technological progress - shows that invention and innovation in various sectors of the economy tend to induce increasing demand for the labor force in the country. AI is the engine of overall job creation in the country. Society's long-term planning efforts are, nevertheless, needed to meet AI growing demand for a qualified, highly skilled labor force.

THE OPAQUE WORLD OF AI

In the *Possible Minds: Twenty-Five Ways of Looking at AI,* Brockman (2019, p. xv) introduced the book by saying that "Artificial intelligence is today's story" and that it is "good AI and bad AI". Kaplan (2016), in response to the question 'What is AI?', said it is a hard question to answer because of (i) lack of an agreement among experts about the meaning of intelligence, and (ii) it is difficult to believe that machine intelligence bears a relationship to human intelligence. Brooks (2019) declared that AI is terrifying, overhyped, hard to understand, and plain awesome. Iriondo (2018) indicated that the field of AI is complex and vast; it is about the science, engineering, and technology that attempt to make computers behave rationally, intellectually, and intelligently. *Futurism* (2019) regarded AI as the field of simulating human intelligence or teaching computers to perform tasks ordinary accomplished by human beings. Barbera (1987, p.17) defined AI as a "field of science and technology".

Moreover, Tseng and Ting (2013) divided AI into four types of technological fields: (i) problem reasoning and solving, (ii) machine learning, (iii) network structures, and (iv) knowledge processing systems. Sheil (1987), in expressing AI technology, asserted that rule-based systems can program behavior that is difficult to write in the form of conventional programs. Finally, Husain (2017, p.20) defined the term AI as "A broad field of study". The author observed that AI has explored different techniques that could be deployed in machines to enable them to learn, reason, and act intelligently. As the discussion in this section shows, AI is viewed from different angles, and perceived differently, by different writers. Disagreement also exists regarding its impact on society, applicability, and boundary. Whatever the case might be, the AI field is elusive, fascinating, and mystifying. As eluded to earlier, AI is viewed in this paper as an aggregation of invention and innovation in various sectors of the economy that could be represented by granted patents,

AI has in recent years become a growing field of research, innovations, and technology applications. An army of scientists, professionals, organizations, and others are thrusting the field into new frontiers and expanding its scope to replace especially ordinary, repetitive human tasks, and seek to explore the environment of land, ocean, and space. The applications of AI technology have in recent years become diverse and expanding to a variety of areas, including the following:

- Recruitment to assist organizations to hire the right employees (e.g., Daugherty, Wilson, and Chowdhury, 2019; Patrick van Esch, Black, and Ferolie, 2019);
- Imaging processes in agriculture to help farmers decide on when to plant, water, and harvest crops (e.g., Deaton, 2019);
- Transformation of personal pictures to an artwork (Samuel, 2019); and
- Artificial morality (e.g., Misselhorn, 2018; Giubilini and Savulescu, 2018).

Moreover, Guo and Zhang (2020) utilized machine learning to analyze 48,043 articles published in The *Economist.* The articles compared the magazine's sentiment orientations towards Canada, France, Germany, Italy, Japan, the United Kingdom, the United States, and China. Finally, RT.com (2019) reported that a group of academics filed two patents on behalf of an artificial intelligence system. The system, known as the device for autonomous unified sentience (DABUS), is capable of 'inventive acts'. DABUS invented new products, such as special types of containers as well as a unique emergency warning light. This non-human inventor is not programmed to solve specific problems but to create its solutions. It is worthwhile to observe that the expanding landscape of AI and its scope in the United States is rooted in many sources especially (1) Human ingenuity, (2) Entrepreneurial spirit, (3) Organizations' drive for growth and willingness for risk-taking, (4) The intensity of domestic and global competition for technological leadership, (4) Life necessity, (5) Government support particularly via research grants, and (6) Society resource scarcity.

AI progress is also parallel to developments in such fields as analytics, algorithms, computer chips, neurosciences, epidemiology, and other scientific areas. The evolution of AI is likely to accelerate as (i) AI-oriented multinational companies (e.g., IBM, Alphabet) vie for market share and (ii) nations seeking technological superiority as well as global economic dominance. Bates (2015), for instance, remarked that the new global battlefield for technological supremacy is AI. Vincent (2019), on the other hand, reported in *The Verge* that Microsoft is investing $1 billion in Open AI projects. Several scholars (e.g., Webb, 2019, p. 98) believe that the acceleration of AI research, projects, and products/services are largely driven to satisfy consumer demand attributed to such factors as convenience, quality, and accessibility.

AI CHALLENGE

The view that AI is a threat to employment and, implicitly, economic prosperity is widespread and dominant. According to this view, long-term progress in AI in the form of inventions, innovations, and applications could lead to massive job destruction in the United States - and many other countries. Wilson and Daugherty (2018), for instance, mentioned that there is the fear that AI would ultimately replace the labor force as it rapidly encroaching on many human tasks. Wood and Evan (2018) reported that Stephen Hawking, Elon Musk, and Bill Gates have sounded the alarm about AI existential threat to human beings. The authors added that AI is expected to reduce the number of lawyers and doctors needed in the future.

More to the point, Marr (2018) said some indications show a future where machines not only will do the physical work ordinary performed by humans but also will do the thinking aspects of work such as planning, decision-making, and strategizing. Shelton (2019) adopted the position that predictions show that libraries would become obsolete in the future because of AI and robotics utilization. Kelly (2019) stated that the future job market will be determined by major forces including AI, technology, robotics, the aging population, globalization, politics, and the environment. The author added that AI technology and robotics will displace millions in the labor force and that doctors with shaky hands will be replaced by robots.

In the same vein, Lee (2018) asserted that (i) AI will displace a large number of jobs, (ii) that there is a need to find jobs that AI cannot do, (iii) that training for new jobs is a necessity, and (iv) that the education system ought to be reinvented. Dobrescu and Dobrescu (2018) reported that the United Nations warned that robotics could destabilize the world from the risk of mass unemployment. Moreover, the UN News reported that in November 2018 the UN Secretary-General Antonio Guterres said that "technology should empower not overpower us". Makridakis (2017), in elaborating on the impact of AI on employment and wealth distribution, wondered whether the AI revolution creates a utopian or dystopian future. On the other hand, AI is also perceived as a technology that brings great benefits and joy to humanity. For instance, Maney (2018) asserted that AI is creating new jobs in such areas as radiology and the fast-food industry.

In July 2019, the government of New York state passed a law for examining the opportunities and risks posed by AI. A 13-member committee was formed to review the emerging technology and its implications for the State's residents. Finally, a recent article in the *Foundation for Economic Education* (Vilbert 2019) declared that the news headlines say that machines will replace humans. Artificial intelligence will outpace people. There will be no jobs for the poor. Chaos! Famine! Technology is casting a shadow over the future. This is the current mainstream outcry—or could we say paranoia?

TECHNOLOGY AND JOB CREATION

Technology is the livelihood of the U.S. economy. It is found in agriculture, services, transportation, industry, education, and a host of other sectors and subsectors. Technology is nurtured with innovation, risk-taking, and funding. In a book entitled *What Technology Wants*, Kelly (2010, p. 269) replies "When a technology has found its ideal role in the world, it becomes an active agent in increasing the options, choices, and possibilities of others". The author added that "Our task is to encourage the development of each new invention toward this inherent goal".

Lee (2018) classifies AI job replacement risks into two major categories: (1) social and (2) asocial outcomes and that each of which is clustered into four zones: (A) human veneer zone that includes teachers, general practitioners doctors, wedding planners, tour guides, financial planners, café waiters, bartenders, (B) safe zone that includes criminal defense lawyers, chief executive officers, social workers, psychiatrists, physical therapists, and dog trainers, (C) slow creep zone that includes graphic designers, artists, scientists, legal analysts, media researchers, financial analysts, taxi drivers, house cleaners, night watch security, aerospace mechanics, and (D) danger zone that include general factory workers, cashiers/tellers, fast food preparers, restaurant cooks, dishwashers, fruit harvesters, assembly line inspectors, and track drivers.
In short, the author believes that routine jobs that required minimum thinking skills are in danger of replacement by AI technology in the foreseeable future, while jobs that demand high-level skills or strategic thinking will be difficult to be replaced in the intermediate or even in the long-term.

EXAGGERATED FEAR

Aoun (2017, p. xiii), in referring to AI revolution, argued that "This is not the first time we have faced a scenario like this. In past industrial revolutions, the ploughmen and weavers who fell prey to tractors and spinning jennies had to withstand a difficult economic and professional transitions". Vilbert (2019) pointed out that "the headlines are disturbing that 2019 has been the year to terrify people about technological development. But is there any validity to it? What does the future hold for us? Will there be mass unemployment? Not really". Vilbert added that "We will be just fine. Both history and available data show that far from making working humans obsolete, technology has long been a "great job-creating machine." The fear that progress in, and adoption of, AI technology could cause widespread unemployment in the country appears to be unrealistic for several reasons.

First, the U.S. economy is resilient, diverse, and growing. With a gross domestic product (GDP) of $21.44 trillion in 2019 - according to the U.S. Bureau of Economic Analysis - the county's economy is the world's largest. It is relatively insulated from major global economic shocks. Moreover, in 2019, for instance, the country's total imports (on a census basis) amounted to 14.5 percent of GDP, while total exports (on a census basis) amounted to 12.1 percent of GDP. The data imply that the country, unlike many other developed nations such as Japan and Germany, is less dependent on international trade. Besides, the U.S. administration has in recent years been encouraging domestic production by increasing tariffs imposed on imports.

Second, as a result of a vibrant economy and political stability, employment opportunities have been plentiful and expanding. For example, according to the U. S. Bureau of Labor Statistics, civilian employment of 16 years old and over increased from 139.5 million in 1999 to 163.5 million in 2019, a jump of 17.3 percent. The jump in employment took place despite technological progress and the adoption of many AI-enabled applications by U.S. industries, consumers, and government agencies. As the economy grows, so will the demand for labor force employment. A growing economy implies the demand for goods and services is flourishing along with investment, output, and consumption.

Third, as evidenced by Microsoft, Apple, Amazon.com, Tesla, Twitter, DocuSign, Disney, Airbnb, and numerous other companies, the United States is a land of entrepreneurship, innovation, and resources. Entrepreneurs have built the country, that the entrepreneurial spirit is thriving, and that entrepreneurs and entrepreneurial companies are likely to continue expanding the country's employment at a higher rate than AI-induced job destruction.

Lastly, it is expected that AI revolution will cause a shift in the structure and composition of the labor force as was the case with the industrial revolution. For example, employment of college graduates (25 years old and over) increased in the civilian labor force by 64.6 percent from 1999 to 2020 according to the U.S. Bureau of Labor Statistics, this trend of increasing demand for college graduates will continue to be propelled mainly by business firms' adoption of AI-enabled applications. On the other hand, the employment demand for individuals with low skills (i.e., only high school diploma) declined by 16.5 percent during the same period under discussion. Undoubtedly, the employment needs for low skills individuals will continue to decline in the future along with the country's technological advancement.

DATA ANALYSIS

It is postulated in this paper that the advancement in artificial intelligence is the manifestation of inventions innovations in the form of patents granted (utility patents, design patents, and plant patents). It is further suggested the existence of a long-term relationship between U.S. patents and the country's employment: the higher the rate of patents granted, the greater the level of employment. On the other hand, it is hypothesized the existence of a correlation between U.S. gross domestic investment and the nation's employment: the higher the rate of investment, the higher the level of employment. This study uses time-series data for the United States from 1970 to 2019 to assess the impact of patents and gross domestic private investments on employment. The employment data were obtained from the Economic Research Division, Federal Reserve Bank of St Louis, while patents data were obtained from the United States Patent and Trademark Office (USPTO). The relationships among the variables indicated above were subjected to regression analysis as discussed in the following section. Table 1 (Appendix) presents the data on the number of patents granted by the USPTO from 1970 to 2019, for selective years. The data below presents all the three types of patents, i.e. Utility, Design, and Plant. For this study, we rely on the number of patents granted by USPTO in the Utilities and design categories. Utilities patent relate to 'processes, compositions of matter, machines, and manufactures that are new and useful', while design patent is issued for 'a new, original, and ornamental design embodied in or applied to an article of manufacture'.

Research indicates that Patents are taken as a proxy for AI and technological development and innovation (Burhan, Singh & Jain, 2017)[1]. The US Patents and Trademark Office (USPTO) and World Intellectual Property Organization (WIPO), publications show that patent data is the base for research on the growth of Artificial intelligence. Therefore, we postulate that the advancement in artificial intelligence may be taken as a manifestation of inventions and innovations, that are granted in the form of utility patents, design patents, and plant patents.

For our preliminary analysis of the impact of artificial intelligence on employment, we looked at the data of "Total patents granted (Plant, design, and Utility) granted the past 50 years and employment in the USA. The graph above shows the number of Patents filed and employment from 1960 to 2020 (50 years). As shown in Figure 1(Appendix), the line graph indicates that both thappendixe graphs are positive and there appears to be there is no negative relationship between employment and patents. While the number of patents filed in a year seems to be growing steadily, indicating innovation and technological advancement trends like artificial intelligence. The only period of negative growth in patents in 2000-2005 seems to correlate with a stagnating and negative trend in employment.

Model Specification

This analysis utilizes the Autoregressive Distributive Lag (ARDL) methodology proposed by Pesaran and Shin (1999) to investigates the relationship between employment (EMP), utility patents (UT), design patents (DE), plant patents (PL), and gross domestic private investment (GDPI). The inclusion of gross domestic investments in the regression highlights the contribution of the latter to technological change and innovations. This analytical approach is desirable since estimation using ordinary least squares for nonstationary time series produces spurious or misleading results about the relationship between EMP and the variables that affect the latter. To specify the relation, we identified the following log-log function that expresses the relationship between the dependent variable and independent variables:

$$lnEMP = \beta_0 + \beta_1 lnUT_t + \beta_2 lnDE_t + \beta_3 lnPL_t + \beta_4 lnGDPI_t + \varepsilon_t \quad (1)$$

where ε is a random error term. The ARDL, although is a relatively recent approach, cointegration techniques offer useful insights into this relationship. The ARDL became recently important through the works of Pesaran and Shin (1999) and Pesaran et al. (2001). The dependent variable and the independent variables are not only contemporaneously related they are related across their historical lagged values. The key advantage of the ARDL is that, unlike the Johansen and Juselius cointegration model, it performs well with small samples. Also, the ARDL does not restrict the variables in the regression to be integrated in the same order and can be applied when the variables are a mixture of integrated order of zero I (0) and one I (1) (Pesaran et al. 2001). Drawing from Pesaran and Shin (1999) and Pesaran et al. (2001), the ARDL can be written as follows:

$$\Delta logEMP_t = \alpha_0 + \sum_{i=1}^{n} \alpha_{1t}\, \Delta lnUT_{t-1} + \sum_{i=0}^{n} \alpha_{2i}\, \Delta lnDE_{t-1} + \sum_{i=0}^{n} \alpha_{3i}\, \Delta lnPL_{t-1} + \sum_{i=0}^{n} \alpha_{4i}\, \Delta lnGDPI_{t-1} + \delta_1 lnEMP_{t-1} + \delta_2 lnUT_{t-1} + \delta_3 lnDE_{t-1} + \delta_4 lnPL_{t-1} + \delta_5 lnGDPI_{t-1} + \varepsilon_{1t} \quad (2)$$

where, the parameter δ_j represents long-run multiplier, and αs are short-run dynamic coeffcients of the ARDL model. The Granger causality test is used to determine the short-run and the long-run relationship among the variables of the model. We use the following equation to conduct the test:

$$\Delta lnEMP_t = \alpha_0 + \sum_{i=1}^{n} \alpha_{1i}\, \Delta lnEMP_{t-1} + \sum_{i=0}^{n} \alpha_{2i}\, \Delta lnUT_{t-1} + \sum_{i=0}^{n} \alpha_{3i}\, \Delta lnDE_{t-1} + \sum_{i=0}^{n} \alpha_{4i}\, \Delta lnPL_{t-1} + \sum_{i=0}^{n} \alpha_{5i}\, \Delta lnGDPI_{t-1} + \lambda ECT_{t-1} \quad (3)$$

where, λ measures the speed of adjustment and the ECT is the residuals from the estimation of equation (3). The error correction term can lead to a better understanding of the nature of non-stationarity among the series and can also improve long-term forecasting.

Regression Results

We tested for the stability of the data to determine whether the data is stationary or not and to confirm the adequacy of the selected model in estimating the time series. The null hypothesis is that the variables under investigation have unit roots and are not stationary against the alternative that the variables are stationary. Engle and Granger (1987) found that running ordinary least squares estimates on non-stationary time series data will lead to spurious or nonsense regression results. The Augmented Dickey-Fuller (1981) reported in Table 2 (Appendix), suggests that the null hypothesis of unit roots after the first difference is rejected for all the series.

The number of lags is in brackets and was determined using the Schwarz Information Criterion with a maximum lag of 10. Critical values for intercepts at 1% and 5% are -3.62 and -2.94 and for intercept and trend were -4.23 and -3.54 respectively. * and ** indicate significance at 1% and 5%.

Table 3 (Appendix) below shows the estimates of the long-run coefficients calculated by normalizing employment (EMP). The dependent variable is the logarithm of employment (EMP) while the regressors are utility patents (UT), design patents (DE), plant patents (PL), and gross domestic private investment (GDPI). The results reveal that utility patents have a negative and significant long-run effect on employment. Design patents were found to have a positive and significant effect on employment. Likewise, gross domestic investment was found to have a strong and significant effect on employment. The results, however, show little evidence of a long-run significant effect of plant patents on employment; the effect is positive and significant at 10 percent.

The optimum number of lags in the ARDL model was selected using the Akaike Information. The selected lags were used in calculating the long-run coefficient estimates. The symbols *, ** indicate significance at 1% and 5% level, respectively.

Table 4 (Appendix) shows the critical values for the bound test generated by Narayan (2004). The two sets of critical values I(0) and I(1) represent lower critical values and upper critical values. The critical F-statistic (4.193) is greater than the upper and the lower bound critical values at 2.5% using restricted intercept and no trend. The results indicate that the null hypothesis is rejected in favor of the alternate hypothesis that there is a cointegrating relationship between employment, utility patents, design patents, plant patents, and gross domestic investment.

The estimates shown in Table 5 (Appendix) indicate a negative and significant error correction term, implying the existence of a short-run relationship between the variables of the model. The speed of adjustment to the equilibrium state per period is 22.8 percent, suggesting that the 22.8 percent of the variables' deviations from their long-run equilibrium will be corrected within a year. The estimates also show that previous employment significantly affects current employment. Utility patents have a negative short-run effect on employment, but it significantly affects employment in the long-term. For instance, with a p-value of 0.0109, a 1 percent increase in design patents will increase employment by 1.09 percent. Gross domestic private investment has a robust and positive effect on employment.

Table 6 (Appendix) shows the outcomes of residual diagnostic tests. The results of the normality test based on Jacque-Bera indicate that the errors are normally distributed. The estimates also show that the errors are not serially correlated and the model thus will produce efficient estimates. The errors were found to be constant and there is no evidence of heteroskedasticity. The stability of the estimated model was tested by applying the cumulative sum (CUSUM) and the cumulative sum of squares (CUSUMQ) to recursive residuals estimated from the ARDL model as shown in Figure 2 (Appendix).

The plots of CUSUM and CUSUMQ are within 5 percent critical boundaries that indicate the long-run coefficients of the model are stable. The ARDL model exhibits an autoregressive structure and is dynamically stable.

In summary, the analysis in this paper deployed Autoregressive and Distributed Lag bound testing procedure for the period 1970 through 2019 to investigate the relationship between employment, in the United States on the one hand, and grants (as a proxy for artificial intelligence) and gross domestic investment, on the other hand. The ARDL approach is plausible in small samples and also in situations where certain variables in the series are integrated of different orders. The results from the ARDL bound testing cointegration estimates suggest that employment, utility patents, design patents, plant patents, and gross domestic private investment have a significant long-run relationship. The number of lags for the unit root tests was determined using Schwarz Information Criterion with a maximum lag of 10. The speed of adjustment to the long-run equilibrium is -0.228 percent implying that 22.8 percent of the deviations from the long-term equilibrium are corrected each year.

Moreover, the analysis reveals that, in the long-run, utility patents have a negative and significant effect on employment while design patents were found to have a positive and significant effect on employment. Gross domestic private investment and plants patent were found to have a significant and positive impact on employment. The estimates also show that previous employment significantly affects current employment. Utility patents have a positive short-run effect on employment, but a long-term negative influence. The diagnostic tests are consistent and the ARDL model structure is dynamically stable as revealed by the CUSUM and the CUSUMQ tests. The overall results suggest that U.S. patents as embodied in artificial intelligence contribute to greater employment in the United States.

RECOMMENDATIONS

The rapid growth of AI technology (especially progress in such fields as data analytics, algorithms, and supercomputers) is likely to change the future work structure in the United States. New and improved skills for the majority of the labor force will be needed and the demand for traditional, repetitive, and routine skills will gradually be diminished. Organizations (e.g., governmental agencies, educational institutions, business firms) need to develop long-range strategic initiatives that enable them to prepare for the changing environment and the challenges ahead. The following are recommendations that could help the country prepare itself for AI demands:

- Understanding the opportunities, challenges, and risks that AI brings to society at large.
- Mid-sized and large firms as well as other organizations should develop training programs for their employees to acquire/ hone anticipated AI skills need.
- Educational institutions especially business schools need to offer AI degrees and incorporate AI in entrepreneurship programs.
- Governmental agencies (e.g., Small Business Administrations, states economic development departments) might offer free (or low fee) workshops or other training venues in AI-enabled applications for the would-be entrepreneur and support entrepreneurial attempts to create AI-oriented business ventures.
- Venture capitalists, angel investors, and financial institutions should prioritize their lending operations and expertise to AI-promising entrepreneurial ventures.
- Government encouragement - via grants and tuition reimbursement - of women and minorities to enroll in AI courses/programs.
- Individuals' initiatives to learn about the nature, benefits, and applications of AI.
- Mid-sized and large firms could expand their internship programs for high school and college students for training in some AI-enabled applications.
- The establishment of a national committee/agency to promote AI research and education.

CONCLUSION

The flow of disruptive technology stemming from AI-enabled applications is causing anxiety in many U.S. circles because of the perception that advanced technology could eventually lead to great job destruction and the possibility of a widespread unemployment crisis. Large-scale unemployment for an extended period could cause pervasive discontent and suffering. On the other hand, the opposite view holds that progress in AI will pave the way for new avenues of increasing national employment opportunities.

Disruptive technology is not a new phenomenon in the U.S. for it has been the major vehicle for the country's economic progress and global technological leadership. The rise of the so-called "technological unemployment or labor-saving machines" that Maynard Keynes observed in the early 1930s (Dormehl, 2017, p.129) appears to miss the mark as far as the notion that AI tends to cause extensive unemployment in the United States. Technology has always created new jobs, business opportunities, and economic development. The massive job destruction view of AI lacks supportive evidence and appears to be highly exaggerated. It is worthwhile to note that, there are many predictions of AI but perhaps none is as extreme as the following: Vega of the New York Post reported what Elon Musk said recently "AI will soon make us look like monkeys", and that "it's like a smart human, but it's going to be much more than that". No doubt that AI will have a significant impact on work life and well being, through its impact on economic performance, productivity and growth. However, the structure of employment will continue to change to meet this challenge, and the right people with the desired skills will be required to meet up with the new dynamics (see for example, Dahlin, 2019).

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APPENDIX

Table 1
USA: Distribution of Patents by Type and Employment for Selected Years

Year	Utility	Design	Plant	Total Patents	Employment
1970	47,072	3,214	52	50,338	71,007
1975	46,715	4,282	150	51,147	77,071
1980	37,355	3,949	117	41,421	90,532
1985	39,555	5,066	242	44,863	97,529
1990	47,391	8,024	318	55,733	109,530
1995	55,739	11,712	387	67,838	117,410
2000	85,068	17,413	548	103,029	132,018
2005	74,637	12,951	716	88,304	134,022
2010	107,791	22,799	981	131,571	130,337
2015	140,969	25,986	1,074	168,029	141,804
2019	167,115	34,794	1,275	203,184	150,935

Source: U.S. Patent and Trademark Office and US Department of Labor

Table 2
USA: unit root tests for stationarity,1970-2019

Variable	Level		First difference	
	Intercept	Intercept and trend	Intercept	Intercept and trend
EMP	-1.907	-1429	-5.043*	-5.361*
UT	0.311	-2.088	-8.653*	-9.284*
DE	-0.391	-3.187	-7.408*	-7.328*
PL	-1.026	-5.038*	-5.946*	-5.901*
GDPI	-2.637	-2.380	-5.721*	-6.030*

Table 3
Estimated Long-run Coefficients results using ARDL (3,4,2,0,4)

Variable	Coefficient	t-Statistics	Prob
UT	-0.1230	-3.6475	0.0011
DE	0.1268	3.7116	0.0009
PL	0.0360	1.9841	0.0571
GDPI	0.1903	8.9680	0.0000
C	4.4376	59.5072	0.0000

Table 4
Bound test for a cointegrating relationship, null hypothesis: No levels relationship

Test statistics	Value	Significance level	I(0)	I(1)
F-statistics	4.193	10%	2.2	3.09
K	4	5%	2.56	3.49
		2.5%	2.88	3.87
		1%	3.29	4.37

Table 5
Estimated Short-run ARDL cointegrating error correction model, 1970-2019 ECM-ARDL (3,4,2,0,4).

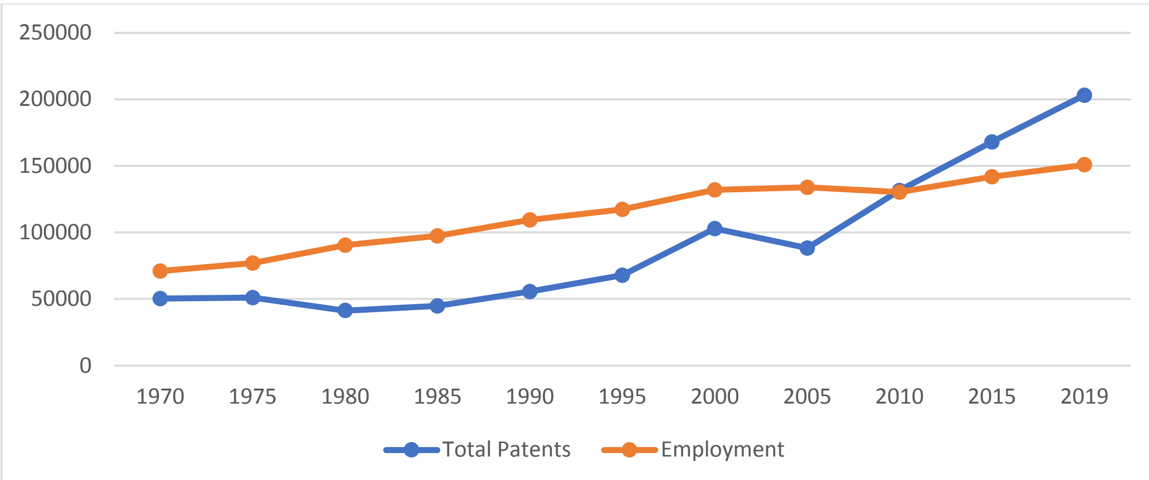
Dependent Variable: ΔlnEMP

Variable	Coefficient	t-Statistic	Prob.
Δ(EMP(-1))	0.503	3.890	0.0006*
Δ(EMP(-2))	0.428	2.674	0.0124**
Δ(UT)	-0.025	-2.735	0.0107**
Δ(UT(-1))	0.006	0.726	0.4740
Δ(UT(-2))	0.014	1.993	0.0561
Δ(UT(-3))	0.025	3.528	0.0015*
Δ(DE)	0.019	2.726	0.0109**
Δ(DE(-1))	-0.013	-1.935	0.0632
Δ(GDPI)	0.182	18.556	0.0000*
Δ(GDPI(-1))	0.018	0.780	0.4419
Δ(GDPI(-2))	-0.066	-3.445	0.0018**
Δ(GDPI(-3))	-0.024	-1.814	0.0803
CointEq(-1)*	-0.228	-5.445	0.0000**
R-squared	0.947		
Adjusted R-squared	0.928		
Durbin-Watson stat	2.229		

Table 6
Diagnostic Tests

Diagnostic Test	LM Version	F Version
Jacque-Bera normality test	2.461 [0.292]	
Breusch-Godfrey serial correlation	3.932 [0.140]	1.215 [0.313]
Heteroskedasticity test	16.880 [0.463]	0.955 [0.528]

Figure 1
United States: Evolution of Patents and Employment
1970-2020



Source: Authors' calculations based on data from U.S. Patent and Trademark Office

Figure 2
Plots of Cursive test of recursive residuals