The Scientific Journal of Business and Finance

https://caf.journals.ekb.eg

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Published online: September 2024.

To cite this article: Alenezi, Abdullah Feraih. **Exploring the Role of Artificial Intelligence on Unemployment Rates in Kuwait** The Scientific Journal of Business and Finance,

44, (3),114-134.

DOI: 10.21608/caf.2024.377981

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Article History
Received 28 July 2024, Accepted 20 August 2024, Available online September 2024.

Abstract

This study aims to examine the role of artificial intelligence (AI) on the level of unemployment in the context of Kuwait. This study collected secondary data based on the available data from Kuwait authorities. The inclusion criteria covered all the relevant studies that aimed to assess the effects of introducing AI through an economic model. This study highlights the effect that AI could have on the economic growth of any given country (i.e., Kuwait); it relies on Cobb-Douglas technology, Baumol's cost disease, and the Galor-Zeira models to predict the kind of reaction and results that Kuwait should expect to experience assuming their current trajectory is not reviewed. The findings of this study helped develop a conclusion regarding the effects that AI will have on the Kuwait. As such, it indicates that the number of tasks automated over time will be greater than the number of labor-intensive tasks created.

Keywords: Artificial intelligence, Cobb-Douglas technology, Baumol's cost disease, Galor-Zeira models, Unemployment rate, Kuwait

1. Introduction and motivation

Artificial intelligence (AI) refers to all instantiations that aim to simulate human intelligence in machines (Capatina et al., 2020; Huynh et al., 2020; Sohrabpour et al., 2021). Natural intelligence portrayed by humans and animals is characterized by self-learning, problem solving, consciousness and emotionality (Finlay & Dix, 2020; Goralski & Tan, 2020; Russell & Norvig, 2002). AI aims to imitate these aspects of human awareness by creating systems that replicate these attributes in different spheres of people's lives (Briganti & Le Moine, 2020; Nilsson, 2014).

The primary intention of an AI system is to make those rationalizations and decisions that have the greatest chance of success when inserted into human or organizational subsystems; the system acts as the underlying framework providing the logic that connects all such decisions to create a seamless network (McCarthy, 2007; Mitchell et al., 2013). To achieve this in its execution, a system will mimic human intelligence by describing human cognition in binary notation with the goal of making rapid and informed decisions for a range of tasks from simple or to complex (Aristodemou & Tietze, 2018; Korinek & Stiglitz, 2019; Siau & Wang, 2018).

The foundation of AI as an academic principle can be traced back to 1955, and there have been multiple surges in interest since then in its evolution (Millauer & Vellekoop, 2019; Vochozka et al., 2018). Substantial attention was invested in this effort when AlphaGo, an artificial intelligence system dedicated to playing Go, defeated a professional player in 2015 (Wang et al., 2016). Prior to this even, the discipline had experienced a widespread lack of funding (the AI winter) for several decades because of the fear attached to the AI concept (Al-Qudsi et al., 2021; Betz et al., 2019; Penmetsa et al., 2019). The Turing test, a test that aimed to assess the level of intelligent human behavior a computer could emulate, was developed immediately around the beginning of the AI winter (Oppy & Dowe, 2003; Powell, 2019; Reinbold, 2020). The Turing test specifically aimed to test whether a computer could be indistinguishable from a human being (Jaiswal et al., 2021; Levesque, 2017), and it garnered immense attention that led to subsequent controversy because of the fear that these machines might replace human beings as soon as they could imitate them (Ford, 2013; Natale, 2021). This resulted in a massive decrease in funding for the discipline until recently (Mutascu, 2021). Most of the research concerned with AI has been divided into subdisciplines, and these disciplines often fail to communicate with one another (Abdeldayem & Aldulaimi, 2020; Jia et al., 2018; Maduravoyal, 2018; Tambe et al., 2019). Rather than adopting a generally mindful approach to cognition as a person's brain would, these research implementations usually focus on specific subjects that they attempt to solve (Peters, 2019). The research tends to be contextualized along the lines of the problem it intends to solve by using specific and particular tools (Marchant et al., 2014). For example, fields such as robotics and machine learning employ AI by using artificial neural networks to create systems in vehicles and aircraft that are autonomous and capable of self-navigation (Facchinetti & Hügli, 1994). Innovation indicates that systems may soon exceed the capacity of humans to learn and make rationalizations (Su, 2018).

As AI has advanced, the benchmark for the definition of AI has been constantly pushed higher because it has been outdated by human perception (Lengnick-Hall et al., 2018; Paschen et al., 2020). Machines that can perform basic arithmetic or utilize optical character recognition to distinguish texts and images are no longer considered to set the bar for AI because humans now perceive these functions and abilities as essential to computers. Each AI system must possess the capacity to weigh the consequences of each action it takes, as each will directly affect the final outcome of that situation. A self-navigating vehicle in this instance would need to account for all the data that a typical driving experience includes and process it in a way that would prevent the occurrence of a collision.

Artificial intelligence is primarily described as comprising two categories: weak and strong AI. Weak AI refers to a system that is designed to execute one specific task (Ford, 2013), for example, systems representing game opponents such as in chess or personalized smartphone assistants such as Siri or Alexa that are designed to respond to queries from phone users.

Strong AI systems, however, are systems that aim to take on more human-like tasks (Flowers, 2019). They are usually designed to function and solve problems in situations where human reaction is sluggish or lacking altogether. They are inherently more complicated and can include self-navigating systems for vehicles.

These advancements in the industry have pushed back the advent of another AI winter because AI has become commercially viable. An AI system with the capability to teach itself, get better at doing things, and become more diverse in what it can do is worth the costs incurred in generating it. The need for human involvement in many situations has been reduced, resulting in increased investments in the sector from companies and governments.

A major concern that is raised by the advancement of this discipline is the effect it will have on human employment (Horwitz, 2013). Many industries are looking to AI for the automation of various roles and jobs, resulting the implementation of AI in many systems and machines that are necessary for organizational processes (Asem, 2020). There are many benefits associated with this automation for organizations, as they can reduce the various costs and safety risks associated with using human employees (Ali et al., 2020). While the company will gain much value from making these concessions, the introduction of an AI-powered system or machine to the workplace to support or replace the current employees of that division will result in the subsequent loss of multiple jobs to create room for it (Al-Qudsi et al., 2021). A company is likely feel the need to create organizational leanness after the addition of an AI system to its structure by reducing the number of human employees under it. This raises widespread concern over how far AI should be allowed to affect human employment (Jr et al., 2020).

Kuwait has also not been left behind in these advances. It has clearly shown it is interested in the importance of AI conveys by making it one of the tenets of their Vision 2035, a framework that represents Kuwait's solution to achieve independence from oil exports and that consists of various economic and social policies that will reinvent this country as a global pioneer in various technologies and fields (Alkhaldi & Altaei, 2021; Khan et al., 2021; Razzaque et al., 2021). One of its aims is to leverage AI for a sustainable and well-developed future. It aims to rank among the top 15 countries in the field by 2035 and to be a global leader in AI strategy and policy development.

To this end, Kuwait has developed a government agency called the Kuwaiti Data and Artificial Intelligence Authority with three key responsibilities (Razzaque et al., 2021). The organization is meant to develop and oversee the execution of national data and AI strategies and to raise awareness on the same while communicating these achievements locally and globally. Its operations are linked to three other governmental bodies, as follows:

- The National Data Management Office is the main data and AI regulatory authority, focusing on data and AI regulations, compliance and standards.
- The National Information Center is the primary authority concerned with operating the national data infrastructure and providing the government with key AI, powered insights and analytics.
- The National Centre for Artificial Intelligence (NCAI) is the primary authority championing advancements in AI innovation and providing strategic advice on the subject matter to the government. It also promotes AI education and awareness.

The country has also taken other steps to demonstrate its seriousness in wanting to become a global pioneer and springboard for international collaboration on AI by launching the Global AI Summit, which has provided a platform for useful discussions on the issues that AI intends to solve (Butler, 2017). These discussions aim to bring experts, researchers, decision makers and professionals from the private and public sectors together to generate real value (Yafooz et al., 2021).

However, there is a cost to saving humans from the chore of repetitively perform tedious tasks by automating them, which is that a number of those jobs will fully disappear, leaving a considerable portion of the skilled workforce unemployable (Alwakid et al., 2017). Widespread disruptions in various fields are expected due to these considerations.

The Future of Jobs Report of 2020 by the Economic World Forum posited that approximately 85 million jobs would be eliminated globally by 2025, while 97 million new jobs would be created, and they attributed this shift to AI-powered systems in the division of labor (World Economic Forum, 2020). AI technology is expected to have immense effects on the nature of the work that humans perform. Ultimately, people will be required to undergo reskilling to be competent for newer, more complicated jobs.

Proponents of the discipline would argue that there are various benefits associated with implementing AI on a national level (Ionescu, 2019). These automated systems, such as robots that are expected to replace most low- and middle-level skilled jobs across a multitude of industries, will create opportunities for higher value employment as long as people invest in reskilling opportunities (Sorells, 2018). The new jobs created by massively introducing automated systems into the workplace are expected to pay better and generally reduce the pricing of the services and products they deliver (Nica, 2018). It is also expected that there will offer a greater variety of products and services because AI offers flexibility in innovation (McClure, 2018). There will also be an increase in the quality of labor and total factor productivity that will result in higher living standards for the general population through labor productivity growth, measured as output per hour, which will increase exponentially (Ristiandy, 2020).

It is expected that this increased productivity will be accompanied by an exponential increase in the gross domestic product (GDP) of nations that embrace these technologies. Various papers (Chiacchio, Petropoulos and Pichler, 2018; Jung and Lim, 2020; Karabegović 2016) on the positive effects of using robots in the economy purported the same as found that increasing the use of industrial robots over that time period resulted in an annual growth of the economy.

While many conversations on the subject have been based on the value that AI is expected to generate, there is much more conversation needed on the value to be lost. This paper aims to examine in further detail the impact that AI has had or will have on unemployment rates within Kuwait.

2. Literature review

The following discussion of the literature aims to define the relevant theories and studies that have informed the industry of technological revolutions and AI.

2.1. Instances of technological revolutions

A study on the history of human evolution chronicled that there have been three major industrial revolutions responsible for the immense changes experienced by human society (Pozdnyakova et al., 2019). For the first two changes, humans lived through the introduction of steam engines in the nineteenth century and of electrification and mechanization in the twentieth century; both had jarring effects on the economic and social development of each of these periods (Corrado & Hulten, 2010; King & Nesbitt, 2020; Lucas, 2002). Each of these revolutions was characterized by breakthroughs that generated substantial stress and shock for their labor markets, with a considerable number of traditional jobs being replaced by new technology and equipment (Bonciu, 2017; Popkova, & Gulzat, 2019). The Luddites were textile workers during the second change who were fearful of the complications these advancements would present and even went as far as to protest and burn down these factories (Marengo, 2019), but this did not prevent the widespread mushrooming of mechanization and new fields that required new expertise. Most of the workers at that time were not capable of meeting the new requirements, indicating that reforming workers' competence is a fundamental input (Marengo, 2019).

Computers contributed massively to increased productivity and faster communication in the third revolution, which spanned a global audience when it was introduced. In their application and utilization, computers substantially reduced the need for paperwork, resulting in the subsequent redundancy of those job opportunities (Popkova et al., 2019; Walsh, 2017). This phase was also not without concerns that these technological innovations would holistically replace the need for employees in many job categories. AI, in this same fashion, has also brought about its own industrial revolution, which is exerting substantial stress on the traditional employment model in industries. It has greatly accelerated the transformation of various industries in the global economy, including Kuwait, by eliminating or aiming to make the various job opportunities they offered redundant (Alkhaldi & Altaei, 2021). The World Economic Forum posits that AI-enabled machines will perform more tasks than humans by 2025, shifting the 71% dichotomy that currently favors humans (World Economic Forum, 2018). The most glaring examples of the effect that AI has had on the workplace concerns replacing the most repetitive physical tasks, such as assembly line production, with robots (Yeh et al., 2021). These concerns are, however, tempered by the ability to automate those processes and a sector-level case-by-case need for product enhancement. The World Economic Forum study also, however, reveals that even with the substantial erasure of job opportunities, more opportunities were subsequently created (World Economic Forum, 2018). The rate at which this happens is, however, insufficient, as men can be expected to gain one job for every three that are lost, while women will gain one job for every five that are eradicated (World Economic Forum, 2018).

2.2. Evolution of artificial intelligence

Another paper described the evolution of AI as a predictable spectacle (Huang & Rust, 2018). It first emphasized that there were four types of intelligence required by a person for them to be eligible or competent for service tasks: mechanical, analytical, intuitive and empathetic. It also described a job as a series of tasks. The theory hence posited that the implementations of AI aimed to emulate these intelligences in this specific order, surmising that AI job replacement would overall occur on the task, not job, basis and that this replacement would give precedence to tasks that were easily emulated by AI. In this fashion, AI would first replace some of a service job's tasks and then slowly proceed in its advancements until it had achieved the ability to perform all of them, when it would replace human labor completely. This progression in the replacement of tasks by AI from lower to higher intelligences will result in predictable phases that are expected to take place as the technology at our disposal evolves. This raises the notion that AI will reduce the need for our analytical skills and, after ultimately emulating our empathetic intelligence in the workplace, subsequently proceed to become a fundamental threat to the need for human employment (Vrontis et al., 2021).

Instantiations of AI in Kuwait can be categorized into all four categories of intelligence. AI has demonstrated mechanical intelligence in the application of robots in the workplace and factories, which in turn could increase size of Kuwaiti economy by 2035 (Rababaah & Rabaa'i, 2020). Analytical and intuitive intelligences are prescribed in the design of systems that aim to process financial or operational information and make informed decisions with the ability to report back to human processors if such a need is determined. Such applications can be seen in credit card fraud and supply chain management systems. Empathetic intelligence that aims to reflect human consideration in its interactions is evident in the application of chatbot technologies and the adoption and evolution of systems such as the humanoid robot Sophia.

One theoretical study argued that the effects of AI and automation on employment were mostly reliant on the institutions and underlying policies that were used to implement them (Aghion et al., 2019a, 20190b). It provided a twofold argument that, in its first section, posited that AI is capable of spurring growth by replacing labor with capital in the production of goods and services and in the production of ideas. The paper, however, subsequently made the counterargument that AI is also capable of inhibiting growth when combined with inappropriate policies for competition. This second main argument was based on an empirical discussion of the robotization of employment in France over the period stemming from 1994 to 2014. The discussion showed that robotization primarily reduced net employment on an aggregate basis and that non-educated workers were more negatively impacted than educated workers. The study summed these arguments with the notion that inappropriate labor policies holistically reduced the positive impact of AI and automation on employment.

The Kuwaiti workforce is primarily categorized as reliant on expatriates, and its professionals are usually acquired from international sources; estimates are that the workforce consists of more than 60% expatriate workers (Rickli, 2018). Kuwait has one of the youngest populations, with 60% being below 30 years of age. However, 16% of Kuwait youth between 20 and 24 are classified as not engaged in education, employment or training. This raises serious concerns because it presents a notable gap between the skills that an AI-driven society will require and the skills that these youth possess (Alhammadi, 2022).

Another study posited that these skill-biased revolutions that primarily emphasize a deskilling of the current work force and the requirement that they learn new skills trigger reallocation of capital from slow to fast learning workers, hence reducing the relative and fixed wages that could be expected by an employee in the former context (Caselli, 1999). This study empirically determined that there had been widespread dispersion in the capital labor ratios of various industries since 1975 that could be related to the skill composition of that labor force. Taking this notion into consideration when assessing Kuwait would reveal that its economic disposition is at an even larger risk of failure because it is trying to emphasize the need to adopt AI without a workforce capable of taking on these job opportunities (Alhammadi, 2022).

This issue was underscored by a study that highlighted the notion that Kuwait was registering newer numbers of graduates (Shayah & Sun, 2019). However, its lackluster education system meant that the graduates, who were also this nation's largest demographic group, had not received the necessary skills and attitudes or a productive work ethic (Shayah & Sun, 2019; Essoussi, 2019). This problem was further exacerbated by the fact that the government was intending to shift the underlying framework of association and implementation for a variety of roles in the nation to an AI-based one (Abdullah & Fakieh, 2020). The government's solution, Kuwaitization, which has consisted of repatriating the white-collar job expatriates to create room for local employees, does not begin to address the massive deficit created by removing the expatriates in the public and private sector and trying to fill these roles with Kuwaiti graduates entering the job market (Abdulla et al., 2020). There is also widespread fear that the Kuwaiti government may not be able to sustain itself, attributed to the fact that its wage bill surpasses more than 50% of its total expenditure and is 16% above gross domestic product (Abdulla et al., 2020).

This challenge is further enhanced by the fact that employees entertain paradoxical attitudes toward interacting with AI (Lichtenthaler, 2019). It has been posited that many corporations will experience multiple obstacles to their implementations of AI because their employees will have negative attitudes and associations. One proposed concept is that of attitudes toward a lack of human interaction that emphasize the preference among employees to work with fellow humans rather than having to deal with virtual colleagues. Such employees would, however, exhibit positive attitudes if and when they perceived a benefit from voluntarily associating with this AI, creating a positive intelligent automation attitude. These two were considered two halves of one whole that paradoxically described the attitude a person would have toward working with AI depending on how that situation unfolded.

The result is that Kuwait will contextually push for the adoption of AI in a majority of its nation's systems and subsystems, but a large degree of its workforce and a relevant portion of this generation will be unable to take advantage of these developments because they will be deskilled.

3. Methodology

This section aims to review the empirical and relevant literature that describes the effect AI has had on unemployment in Kuwait.

3.1. Data collection

For data collection, the paper will review empirical research studies on the focal subject to inform its assessment. The inclusion criteria will span all the relevant studies that have aimed to assess the effects of introducing AI into an economic model. It will review studies that aim to empirically compute the effect that AI could have on the economic growth of any given country. It will hence use this model to predict the kind of reaction and results that Kuwait should expect to experience assuming its current trajectory does not shift. This paper will hence help to provide a conclusion on the effects that AI will have on Kuwait.

3.2. Formulae

The empirical study of Aghion posited the simplest model that could be utilized to illustrate how AI can boost economic growth for any given country. It used a version of the Zeira model that assumed that the final output is produced according to Cobb-Douglas technology (Aghion, 2017):

$$\boldsymbol{Y = AX_1^{\alpha 1}.X_2^{\alpha 2}\dots X_n^{\alpha n}}$$

where Σαi=1, and intermediate inputs Xi are produced according to:

$$X_i = \begin{cases} L_i \text{ } if \text{ } not \text{ } automated \\ K_i \text{ } if \text{ } automated \end{cases}$$

Zeira likened Xi to intermediate goods, but this study decided to modify this approach and view them as tasks (Acemoglu & Autor, 2011). In this approach, unautomated tasks are carried out in a one-to-one ratio by the associated labor. However, when a task is automated, a unit of capital is used instead of labor (Aghion, 2017). This is because automation would spur economic growth by replacing labor, which theoretically has a finite supply, with capital, which has an unbounded supply, as the basic input of production.

Letting K and L denote the aggregate capital stock and labor supply, respectively, it is possible to express the above equation for final good production as:

$$Y = AK^{\alpha}L^{1-\alpha}$$

where α will reflect the overall share of tasks that have been automated.

The rate of growth in per capita GDP (i.e., of y=Y/L) is equal to:

$$g_y = \frac{g_A}{1-\alpha}$$

Automation will increase α, which will subsequently result in the acceleration of growth, which is denoted by an increase in gy.

3.3. AI and Baumol's cost disease

Another expansion to theory emphasized that the complementarity between existing tasks that are automated and those that are labor-intensive, coupled with the notion that labor increasingly becomes scarcer than capital over a given period of time, will allow for the possibility that the capital share and the growth rate will both remain constant over time (Aghion, 2017).

Final output will hence be produced according to:

$$Y_t = A_t(\int_0^1 X_{it}^{\rho} di)^{1/\rho}$$

where tasks are complementary, which is notated as ρ<0, A represents knowledge, which grows at constant rate g, and, as was previously described in the model by Zeira (1998):

$$X_u = \begin{cases} L_u \text{ if not automated} \\ K_u \text{ if automated} \end{cases}$$

By allowing βt to denote the fraction of tasks that have been automated by date t, the above aggregate function can be rewritten as:

$$Y_t = A_t(\beta_t^{1-\rho} K_t^{\rho} + (1-\beta_t)^{1-\rho} L^{\rho})^{1/\rho}$$

where Kt denotes the aggregate capital stock, and Lt ≡ L denotes the aggregate labor supply. The ratio of the capital share to the labor share at equilibrium can be represented as equal to:

$$\frac{\alpha_{Kt}}{\alpha_L} = (\frac{\beta_t}{1-\beta_t})^{1-\rho}(\frac{K_t}{L_t})^{\rho}$$

To this end, an increase in the fraction of automated goods BT would possess two offsetting effects on αKt/αL. It would have a direct positive effect that is expressed by (βt/1–βt)1—ρ, and it would also have a negative indirect effect that would be expressed by the term (Kt/Lt) ρ because p<0. This second effect is easily related to Baumol's cost disease, as Kt/Lt would increase because automation and labor would become scarcer than capital, and together with the notion that labor-intensive tasks are complementary to automated tasks, this would imply that labor is commanding a sustained share of total income.

To include long-run growth in the model, it is necessary to first consider an instance where a constant fraction of unautomated tasks become automated in each period; this would be notated as:

$$\beta = \theta(1 - \beta_t)$$

This enables one to postulate that the growth rate converges to a constant in the long run.

A case where all tasks become automated in a finite time period would be represented as βt≡ 1 for t>T. For t> T, the aggregate final good production would become:

$$Y_t = A_t K_t$$

such that when capital accumulates over time according to

$$K = sY - \delta K$$

one would arrive at a long-run growth rate that is equal to:

$$g_y = g_A + sA - \delta$$

This would increase unboundedly over time as A grows at an exponential rate gA

This would mean that even with the unemployment attached to AI, it is possible to expect a surge in growth. While this is a theoretical model, it can be used to make inferences. This model was coupled with an adapted economic growth model posited by Accenture that included AI as a discrete factor. The combined model estimated that the economic growth rate would increase 1.1%, with a gross value-added approximated at USD 215 billion (Al-Qudsi et al., 2021).

To provide a basis of reference, papers that aimed to compute the effects of automation were considered. While many papers aimed to posit how automation affects routine jobs, very few papers computed this actual automation. Some computed measures for computers (Krueger, 1993), while others computed automation-related patents (Mann, 2018). Some recent papers calculated impact based on the number of robots, which is used to represent automation and AI. These papers will provide the basis of discussion and serve as a reference for the inferences made (Acemoglu & Restrepo, 2017).

The relevant literature addressing the impact of robots on net employment provides mixed evidence. Chiacchio et al (2018) reported negative effects, more specifically positing that one robot per thousand workers reduced the employment rate in six EU countries by 0.16 to 0.20 percentage points. Autor et al (2015) and Graetz and Michaels (2018), however, found no effect of automation on aggregate employment. Dauth et al (2017), using German data, found no evidence that robots cause total job losses, but a negative effect on employment in the manufacturing industry was realized. Specifically, each additional robot per thousand workers reduced the aggregate manufacturing employment-to-population ratio by 0.0595 percentage points.

Acemoglu and Restrepo (2017) analyzed the effect of the increase in industrial robot usage between 1997 and 2007 on US labor markets by using in-country variation in robot adoption. Utilizing a theoretical model that posited humans and robots as substitutes, they derived equations and calculated the aggregate impact of robots on employment and wages. They proved that for each respective labor market, it was possible to estimate the effect of robots on jobs by regressing the change in employment and wages on the exposure to robots; they find that one additional robot per thousand workers would reduce the employment-to-population ratio by 0.37 percentage points and wage growth by 0.73%.

4. Discussion

To recapitulate, AI as a subject and the effect it has had on employment has not received sufficient attention; hence, empirical estimates that compute such effects are not in circulation. There have, however, been various related studies that compute the effect of automation on employment. Empirical studies have employed a broad approach to automation to gauge its effects. The underlying assumption that they utilized asserted that "traditional" automation will replace routine jobs, creating a higher demand for nonroutine jobs that require skills that machines cannot perform. This assumption was empirically evaluated in a study highlighting that automation necessitated the creation of more high- and low-skilled jobs while crowding out medium-skilled jobs. Other studies brought to light how manufacturing and routine jobs were gradually being replaced, signaling the structural changes brought by automation to the labor market.

The methodology section of this paper aimed to provide an empirical theoretical relationship between the introduction of AI to an economy and the effects it would have on the growth and employment of the given nation. The Douglas model posited above computed total production, Y, as the product of A, L, K and α, which respectively represent total factor productivity, labor input, capital input and the overall share of tasks that have been automated. This model can subsequently compute the rate of growth per capita, y, as the ratio between total production, Y, and labor input, L. The Zeira model previously posited that an unautomated task is carried out in a one-to-one ratio by the associated labor unit and that when it became automated, a unit of capital replaced the unit of labor.

An expansion of the Zeira model relied on Baumol's cost disease. It computed total production as a differential function of knowledge, A, that grows at a constant rate, g, and tasks, X, that are complementary. This expanded model posited that the number of tasks being automated over time is greater than the number of labor-intensive tasks being created that would compensate for this automation. As a result, the second negative indirect effect associated with this function established that labor will become scarcer than capital.

Since there were no relevant papers that actually computed the effect of AI on the unemployment levels of Kuwait, or any developed nation for that matter, papers that substituted AI with automation, more specifically robotization, were considered. There was a general lack of consensus about what to expect when robots were introduced into the work environment in these discussions; however, this study settled on the review by Acemoglu and Restrepo as the basis of its explanation. These authors provided a theoretical model for US labor markets that substituted humans with robots and found that there was a negative effect on the employment-to-population ratio of 0.37 percentage points.

Drawing from all these examples, it is possible to infer that the introduction of AI into Kuwait will have negative results on unemployment rates for the nation. These negative effects are further enhanced by the fact that the recent COVID-19 epidemic resulted in the foreclosure and realignment of various business efforts that were needed to enable firms to stay afloat (Al-Qudsi et al., 2021). Businesses were forced to change their workforce policies to ensure that they were able to keep up, and they accelerated the adoption of AI into various roles and levels of their work processes. This was all with the aim of reducing the dependency and need for actual human employees, as there were strong restrictions on movement and interaction. The pandemic resulted in a record high for unemployment in Kuwait that was enhanced by the protracted rate of prevalence of the epidemic (Abdulla et al., 2020).

As a result of this unplanned implementation of AI that could be expected from introducing AI into the workplace were subsequently eroded because of the low rate of high value employment creation subsequent to task automation. This proves that the introduction of AI into an economic system can and will have negative effects on employment rates if it is coupled with undesirable policies, implementation methods, and interfaces.

The above findings provide useful information on the unemployment levels of Kuwait. The current skill level of the youth of Kuwait suggests that unemployment levels will not decrease for a considerable amount of time. The country subsequently will experience a skill shortage that will reward those who are quick to take up these new skills, but considering the reluctance of its people to engage in most private sector jobs, there will be considerable unemployment after the public sector jobs are filled again.

To address this effect, the country is and will continue investing in measures and policies that expose its citizens to AI in their schools and workplace environments to mitigate the expected issues. The new jobs that will be created are expected to derive more value for the country and are also expected to pay better. This will hence free much of the populace from having to engage in repetitive menial tasks and limit them to high skill and return-based job opportunities. This will have considerable positive effects on the economy of Kuwait, as only highly skilled opportunities that are rewarding will be available.

5. Conclusion and recommendations

While it was expected that a surge in growth would be observed following AI implementation, practical observations have actually shown the opposite. This, coupled with recent propagation of the coronavirus pandemic, which greatly hampered economic operations and resulted in widespread job retrenchments due to a lack of demand, resulted in the need for an equally extensive adoption of AI to meet employment opportunities at a lower cost than conventional employment in Kuwait and other countries. This outcome demonstrates that given the right economic situations, AI was and will continue to play a role in all-encompassing unemployment situations.

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