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THE IMPACT OF ARTIFICIAL INTELLIGENCE ON EMPLOYMENT: A PANEL DATA ANALYSIS FOR SELECTED COUNTRIES[*]

Yapay Zekânın İstihdam Üzerindeki Etkisi: Seçilmiş Ülkelere Yönelik Panel Veri Analizi

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Keywords: Artificial Intelligence, Technological Change, Employment, Productivity, Panel Data

JEL Codes: C33, J23, J24, O33

Abstract

Various artificial intelligence technologies such as robotics, machine learning, natural language processing, deep learning, and automation have developed rapidly in recent years and their use has become increasingly widespread in all areas that can affect the economy. These technologies have the capacity to optimize production processes, enhance efficiency levels, and play a decisive role in shaping trade and economic growth. Furthermore, they possess significant potential to exert notable impacts on employment and income inequality. The rise of artificial intelligence has sparked widespread debate, particularly regarding its potential impact on employment dynamics. The study analyzes the effect of artificial intelligence on employment in 29 countries from 2017 to 2021 using the System-GMM estimator. The results showed a statistically significant positive effect of artificial intelligence on employment. The analysis also considers the potential impact of labor productivity on employment in relation to artificial intelligence technologies by including an interaction term in the same model. The estimation results show that while the impact of artificial intelligence and labor productivity on employment is positive when considered individually, the interaction term diminishes this positive effect.

Anahtar Kelimeler: Yapay Zekâ, Teknolojik Değişim, İstihdam, Verimlilik, Panel Veri.

JEL Kodları: C33, J23, J24, O33

Öz

Robotik, makine öğrenimi, doğal dil işleme, derin öğrenme ve otomasyon gibi çeşitli yapay zekâ teknolojileri son yıllarda hızla gelişmiş ve ekonomiyi etkileyebilecek tüm alanlarda kullanımları giderek yaygınlaşmıştır. Bu teknolojiler, üretim süreçlerini optimize etme, verimlilik düzeylerini yükseltme ve ticaret ile ekonomik büyüme üzerinde belirleyici bir rol oynama kapasitesine sahiptir. Bunun yanı sıra, istihdam ve gelir eşitsizliği üzerinde de kayda değer etkiler yaratabilme potansiyeli bulunmaktadır. Yapay zekânın yükselişi, özellikle istihdam dinamikleri üzerindeki potansiyel etkisi konusunda yaygın tartışmalara yol açmıştır. Çalışma, yapay zekânın 2017-2021 yılları arasında 29 ülkede istihdam üzerindeki etkisini Sistem-GMM tahmincisini kullanarak analiz etmektedir. Sonuçlar, yapay zekânın istihdam üzerinde istatistiksel olarak anlamlı pozitif bir etkisi olduğunu göstermiştir. Analiz, aynı modele bir etkileşim terimi dahil ederek yapay zekâ teknolojileriyle ilişkili olarak işgücü verimliliğinin istihdam üzerindeki potansiyel etkisini de dikkate almaktadır. Tahmin sonuçları, yapay zekâ ve işgücü verimliliğinin ayrı ayrı ele alındığında istihdam üzerindeki etkisinin pozitif olduğunu, etkileşim teriminin ise bu pozitif etkiyi azalttığını göstermektedir.

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1. Introduction

The remarkable advancement of artificial intelligence (AI) technologies, such as machine learning (ML), deep learning (DL), machine vision, natural language processing (NLP), and robotics has given rise to intense discussions concerning their potential influence on labor. The debates have led to a divergence of opinion in the literature regarding the impacts of AI on employment. This paper aims to examine the multifaceted potential effects of AI on employment and, in this context, contribute to a better understanding of the complex relationship between AI and employment. The study makes this contribution not only through a theoretical framework that encompasses all the potential impacts of developments in AI technologies on labor and labor market dynamics but also through an empirical analysis that provides robust insights into these dynamics based on real-world data.

AI is a technology that has become widespread in modern society. It is the driving force behind the fourth and fifth industrial revolutions, and its evolution since the 1950s has led to a penetration rate that will affect nearly every aspect of the economy. Based on Andrew NG's (2018) definition of AI as the "new electricity," it is not difficult to estimate the potential benefits that AI can provide. However, it is also crucial to debate the potential harms that may occur alongside these benefits. Because it is crucial to consider both the potential benefits and the possible harms of AI, Ernst and Mishra (2021) portray AI in two distinct contexts: utopia or dystopia. To this end, Ernst and Mishra depict AI in two contexts: utopia or dystopia.

The potential benefits that AI has brought and is expected to bring since its inception have encouraged companies, research institutions such as universities, and governments to increase their investments in AI. In recent years, there has been a notable increase in investment in AI technologies, particularly by firms. The growing investments in AI technologies by firms are driven by a desire to expand production, reduce costs, and maximize profits. As illustrated in Figure 1, the total amount of global private investments in AI increased from 5.1 billion dollars in 2013 to 132.3 billion dollars by 2021. The most striking increase in Figure 1 is the doubling of the investment amount in a single year, from 2020 to 2021. In the present era, the level of investment has diminished, yet it remains considerable, amounting to $95.99 billion. Despite recent small declines, private AI investment has grown significantly globally over the last decade.

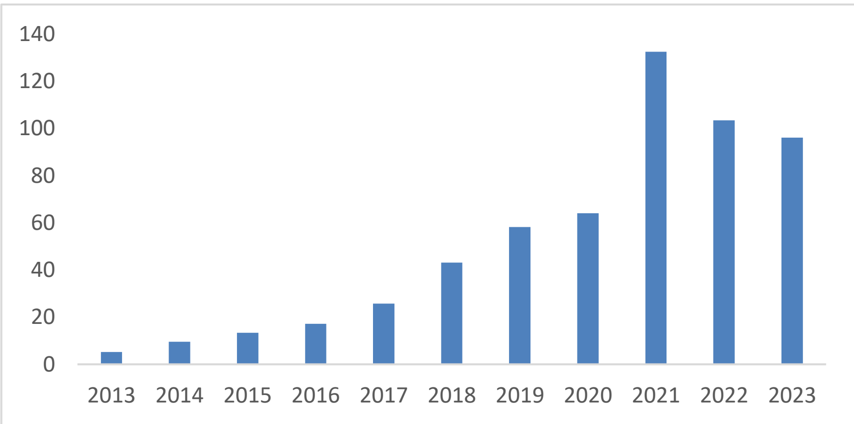

Figure 1. Private Investment in AI (billions in U.S. dollars)
Source: Maslej et al. (2024).

Figure 2 illustrates the disaggregated investment data presented in Figure 1, organized by country. Between 2013 and 2023, the country that invested the most in AI was the United States, with a total investment of $335 billion. China followed with an investment of $103 billion, while the United Kingdom invested $22 billion. AI can contribute to enhanced economic activity on a global scale. As AI technologies evolve, this potential will be gradually accelerated (Aarvik, 2019). These potential impacts will vary according to each country's economy. These differences will be reflected in countries' economic activity and the capacity of countries to adopt the technology (Nguyen and Vo, 2022). A country's access to AI technologies provides a competitive edge that can reshape global supply chains and trade patterns. This, in turn, can facilitate the growth of both the national and global economies. Consequently, the economies of countries that own and adopt AI technologies will be at an advantage in creating and attracting talent to utilize these technologies relative to other relatively weak economies in ownership and adoption.

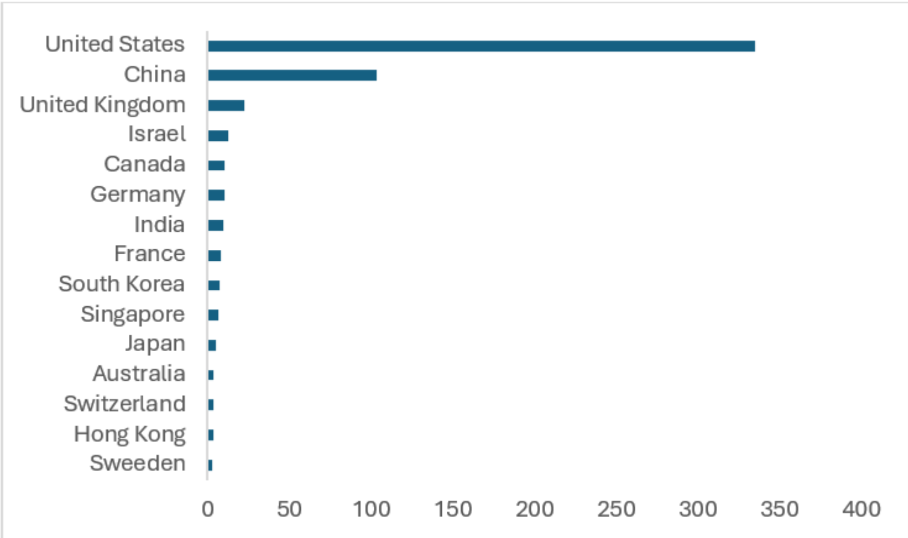

Figure 2. Regional Allocation of Private AI Investment, 2013-2023 (sum) (billions in U.S. dollars)
Source: Maslej et al. (2024).

The super growth in computing power and the interconnectivity of systems and devices have made it possible to collect and share vast quantities of data, which is now more accessible than ever before. This has created a significant momentum for AI technologies. One of the most important indicators of this is the worldwide increase in patents in the field. Firms, governments, and research organizations that invest in AI will gain a competitive advantage by becoming more innovative, as they will be able to utilize outputs such as patents that result from a range of research and development (R&D) activities. Figure 3 presents an analysis of the global increment in AI patent grants between 2010 and 2022. As illustrated in Figure 3, there has been a notable increase in the number of AI patents granted globally from 2010 to 2022. During the past decade, a notable increase has been observed in the number of patents related to AI, with a particularly sharp increase observed in the last few years. Patents represent the possession of monopoly rents derived from the invention of new technology in a Schumpeterian frame. As new technologies that enhance productivity are invented, old technologies are eliminated in a process of creative destruction. As new technologies emerge, firms tend to become more productive, which may result in an environment of increasing returns to scale. Consequently, countries with higher patent intensity may indicate higher levels of productivity, output, and economic growth (Gonzales, 2023). The implementation of AI technologies, developed through the utilization of obtained patents, is predicted to save costs and time, consequently enhancing productivity in production and stimulating economic growth. It is therefore of great interest to examine how these effects will be reflected in the labor market.

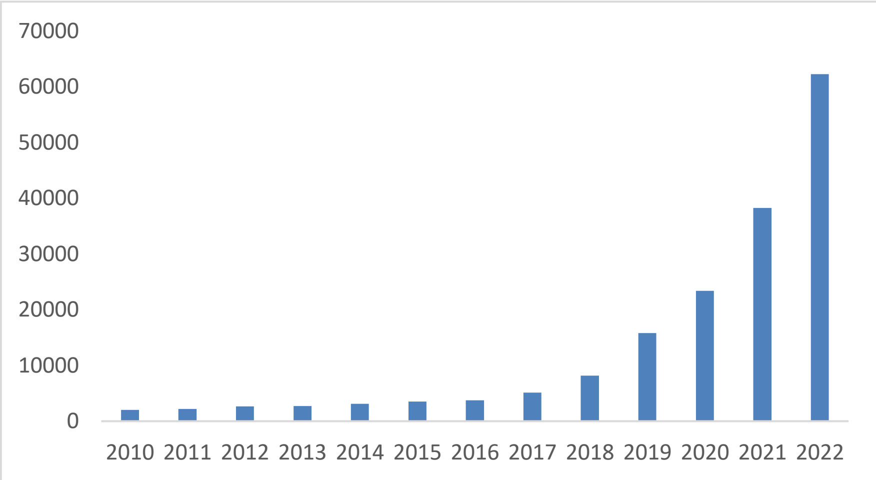

Fig. 3. Number of AI Patents Granted (in thousands)
Source: Maslej et al. (2024).

It is difficult to predict the potential social and economic implications of AI and the kind of world it might create. This study explores the question of whether current AI technologies and applications are designed to reinforce or disrupt the labor market. Considering this research question, the aim of this study is to address the existing gap in the literature by investigating the impact of AI on employment in 29 countries from 2017 to 2021 using the System Generalized Method of Moments (System-GMM) estimator. The analysis employs advanced econometric techniques to investigate the dynamic interplay between AI technologies and outcomes in the labor market. This contribution is significant in two respects. Firstly, it addresses a critical gap in the literature by focusing on the employment implications of AI on a macroeconomic scale. Secondly, it offers valuable policy recommendations for navigating the challenges and opportunities posed by technological advancements in AI. This study also makes a unique contribution to the existing literature in several key aspects. Firstly, this study employs a variable that serves as a comprehensive representation of AI. This approach differentiates the study from the existing empirical literature, which frequently relies on proxies such as R&D expenditures, high-technology exports, ICT exports, patents, or robot counts. Secondly, it focuses on the most recent period during which AI has gained significant prominence. Lastly, the study corroborates the optimistic scenario envisaged by theories, demonstrating a net positive effect of AI on employment through econometric analysis. This effect is characterized by the displacement of workers by AI being counterbalanced by new labor demand in emerging jobs and tasks. Furthermore, the analysis of the interaction between AI and labor productivity offers a refinement to the theory: it quantifies the condition that sufficient productivity gains are crucial for AI’s positive employment effect to materialize. This nuance contributes to the literature by highlighting that the balance between displacement and new job creation can tilt depending on productivity dynamics. In sum, the study not only provides a contemporary dataset comprising a more comprehensive measure for AI but also strengthens the theoretical understanding of AI's labor market impact by providing real-world evidence that supports and adds nuance to, the substitution–creation–compensation mechanism framework. Based on this curiosity and purpose, the study provides a brief introduction to the subject. The second section presents a review of the existing literature on the subject, discussing the potential effects of AI on employment, and the mechanisms through which these effects may occur. The third section presents the econometric analysis of the impact of AI on employment. While the fourth section presents the findings of this econometric analysis, the fifth section discusses the conclusions derived from that analysis, along with policy recommendations aimed at addressing the implications of AI on employment and labor market dynamics. Finally, the study presents limitations and future directions of the research.

2. Theoretical Background and Literature Review

Considering the advanced technological capabilities of countries, it is an intriguing issue to consider how AI will affect a variable such as employment in economies. The potential effects of AI technologies on labor and the labor market are complex. Therefore, the literature on the effects of AI on employment exists with differing opinions. This study aims to examine the multifaceted potential effects of AI on employment and, in this context, to present a more nuanced understanding of the complex relationship between AI and employment. It does so by relying on a theoretical framework that encompasses all the potential impacts of developments in AI technologies on labor and labor market dynamics.

It is essential to first define the theoretical framework that informs this investigation before embarking on a review of relevant literature. The impact of AI on labor is contingent upon the specific types and levels of skills possessed by workers in a given sector, as well as the pace of adoption of new technologies in a particular country. The internal dynamics of each sector and the level of technological advancement in each country may influence the way AI affects labor. So, AI can affect labor in two distinct ways: the displacement effect, whereby AI technologies replace labor and directly remove labor from the workplace, and the productivity effect, which increases the demand for labor as AI technologies boost labor productivity.

The displacement effect is the dystopian scenario of those who argue that AI will negatively impact employment. In contrast, the productivity effect is the utopian scenario of those who argue that AI's effects on employment will be positive. Considering these two scenarios, the mechanisms of AI's impact on employment appear as a substitution effect, a job creation effect, and a compensation mechanism.

2.1. Substitution Effect

The apprehension that novel technologies will displace workers is not a phenomenon exclusive to the contemporary labor force. Its historical roots can be traced back to the First

Industrial Revolution. Because over the past centuries, technological developments have precipitated the loss of employment for a considerable number of workers, giving rise to social unrest. The most illustrative example of this phenomenon is the group of textile workers in 19th-century England who self-identified as Luddites, due to the significant job losses resulting from the Industrial Revolution (Van den Berg, 2001). The Luddites are remembered today as a technophobic group, but they are living examples of the fear created by the threat of structural unemployment. The exponential pace of technological advancement indicates that society must urgently address the impending unemployment problem that AI will undoubtedly present. Because AI has the potential to displace numerous workers, resulting in significant economic and social challenges. This is achieved by substituting for the work that labor is already doing.

The substitution effect causes the elimination of jobs through the substitution of technologies for the work previously done by labor. If AI fails to enhance labor productivity, but rather replaces human labor, it may result in a reduction of the labor share in value added. This could subsequently lead to a decline in labor demand. In the absence of productivity gains that contribute to labor demand, workers will be displaced by new technologies (Acemoglu and Restrepo, 2019).

AI has the potential to displace a significant amount of both physical and mental labor. This is a distinctive feature of AI technologies that differentiates them from previous technological revolutions, which have not reached this level of sophistication. For example, in their study of occupations in the United States (US) economy, Frey and Osborne (2013) concluded that approximately 47% of total employment is categorized as elevated risk. The study predicts that these jobs are in the transportation and logistics, office and administrative support, and manufacturing sectors and finds that jobs in the service sector are highly susceptible to computerization. The authors believe that these high-risk occupations may be automated within the next decade or two, with AI substituting human labor. Unlike past technologies that mostly automated routine tasks, today's AI can handle non-routine cognitive tasks (e.g. image recognition, language translation, coding), which expands the range of occupations vulnerable to automation.

The explosive rise in the quantity of data and the rapid advances in ML and DL algorithms have significantly expanded the range of occupations that can be automated and substituted for labor. AI is enabling machines to perform an increasing range of non-routine cognitive tasks, including face and voice recognition, NLP, and computer program generation. Similarly, the advancement of skilled robotics has reached a point where machines can be equipped with the necessary technology to perform non-routine manual tasks (Fossen and Sorgner, 2022). The study conducted by Wang et al. (2023), on China's workforce finds that the majority of workers in production and transportation equipment operations, as well as the majority of service personnel, are highly sensitive to substitution. Furthermore, the findings suggest that medium-risk jobs in management and research will be subject to substitution over time. The last low-risk occupations to be substituted are those that require intuitive, professional technology and social interactions, such as managerial roles. Such positions are particularly challenging to automate, as they necessitate a high degree of social intelligence. Furthermore, certain highly professional technical occupations, such as those of lawyers and doctors, are also low-risk jobs that require creativity and social intelligence. In contrast, occupations that entail manual labor are classified as low-skilled and are particularly vulnerable to AI-driven substitution, posing a significant risk to their continued existence. As AI develops, industrial robots with enhanced senses and dexterity may enter more industries to perform a wider range of non-routine manual tasks, thereby threatening more low-skilled labor (Wang et al., 2023). While some studies have reached the conclusion that AI technologies are responsible for the displacement of jobs, there is currently no conclusive evidence that the overall impact on employment is significant for all countries. Because the impact of AI-driven substitution varies markedly between high-income and low-income economies. Advanced economies, with their higher adoption of AI and larger shares of white-collar jobs, face greater exposure to automation. IMF estimates suggest about 60% of jobs in advanced economies are exposed to AI, compared to only 26% in low-income countries. Many jobs in rich countries - including professional and managerial roles- involve cognitive tasks that current AI can potentially learn, raising the risk of displacement even for some high-skill occupations (Georgieva, 2024). By contrast, workers in developing countries are concentrated in occupations that are less immediately susceptible to AI automation (often due to lower technology adoption and more informality), so only around 0.4% of total employment in low-income countries is at risk of automation by generative AI, versus 5.5% in high-income countries (Gmyrek et al., 2023). Paradoxically, this means poorer countries might face fewer immediate job losses from AI. However, they could suffer in the long run if they cannot adopt AI to boost productivity, as the technology diffuses globally.

Overall, the substitution effect of AI is real and significant, especially in the early phase of AI adoption, but its magnitude varies by country context and is moderated by the pace of adoption. National economies do not operate in isolation. Instead, they are integrated into a complex global system, interacting with other economies in a manner that is both reciprocal and interdependent. In light of the difficulty in determining the general and clear impact of AI on employment, it is important to consider that unemployment, which is a significant potential consequence of AI, should not be ignored, particularly in the long term.

2.2. Job Creation Effect

Despite years of recurring concerns that new technologies will result in job losses, there have been significant positive developments in society. The economy has continued to grow, technology has advanced, and workers have retained their employment. It is evident that the automation and technological advancement that have occurred over the past two centuries have not resulted in the obsolescence of human labor.

An examination of contemporary technological advancements presents that AI has the potential to significantly impact the employment landscape, as machines begin to replicate the complex cognitive processes of the human brain, thereby displacing human workers in several roles. This could not only enhance productivity but also generate a multitude of knowledge-intensive roles, thereby influencing the structure of the labor market (Acemoglu and Restrepo, 2019). The initial effect of a new technology like AI is, without a doubt, the displacement of human labor. However, over time, as productivity and capital deepening increase, the growing economy will create new demands for labor. Adjustments to the labor market, though slow, will create new roles in which labor exhibits a comparative advantage over machines (Crafts, 2022).

The job creation effect leads to the creation of new types of jobs in which labor has a comparative advantage. History reveals that technological advancements have consistently led to the emergence of new business opportunities, often creating roles that did not previously exist. The advent of AI has given rise to a multitude of novel job opportunities, including those in the fields of data analysis, engineering, data labeling, and data protection. The recurrence of historical patterns suggests that concerns about AI technologies may be unwarranted.

The advent of AI-derived automation technologies coincided with the emergence of new tasks in which labor retained a competitive advantage due to the simultaneous development of other technological innovations. For example, the advent of agricultural mechanization in the latter half of the nineteenth century initially resulted in a decline in employment opportunities within the agricultural sector. However, this shift led to the emergence of new job roles in manufacturing and services, thereby increasing the demand for labor. In general, new technologies have displaced labor from specialized work. However, at the macroeconomic level, labor has benefited from technological advances through the creation of new jobs. At this pivotal moment, without sufficient consideration of the invention and creation of demand in lieu of the displacement of labor, this will be an inadequate form of AI from a social and economic perspective. In contrast to the objective of promoting productivity growth, employment, and shared prosperity, the widespread implementation of automation is likely to result in suboptimal economic growth and increased inequality (Acemoglu and Restrepo, 2019). It is also important that the new positions and responsibilities established are highly productive with respect to human labor. The potential for AI to create labor-intensive tasks that can only be performed by humans represents a crucial mechanism for counteracting the displacement effect of AI and ensuring that the productivity benefits of AI are equitably distributed among workers (Lane and Saint-Martin, 2021). While AI is responsible for the creation of new jobs and tasks, it is important to consider the potential mismatch between the requirements of these new roles and the skills of the workforce. The new qualifications or skills required for new jobs and tasks may prove to be slow to align with the existing labor force. In order to achieve balanced growth, it is essential that both the new technologies, the new jobs and tasks they create, and the labor supply move in tandem with these trends (Acemoglu and Restrepo, 2018b).

It is also important to note that the job-creation capacity of AI is not uniform worldwide. This capacity depends on a country's economic structure, skill base, and innovation ecosystem. High-income countries are generally better positioned to generate new AI-related industries and roles. They have the education systems to produce AI researchers and skilled workers, the financial markets to fund AI startups, and consumers with the purchasing power to demand AI-enabled products and services. Thus, robust job growth is observed in fields such as software development, AI research, digital marketing, and fintech in many advanced economies – areas that were scarcely present decades ago. Moreover, AI’s productivity boost in traditional industries (like manufacturing or healthcare) can lead to expansion and hiring in those sectors in advanced economies, as firms can scale up output. In contrast, lower-income countries often face greater challenges in realizing AI-driven job creation. Their workforce may not have as many advanced STEM skills, limiting local development of AI innovations. They may also lack the infrastructure (e.g. reliable internet, electricity) needed to implement AI at scale, as well as financing for entrepreneurial ventures. The uneven ability to capitalize on the job creation effect of AI is one reason experts caution that AI could widen global inequality – advanced economies reap most of the new jobs and growth, while poorer ones lag behind. This makes capacity-building (education, digital infrastructure, innovation support) crucial for low-income countries to fully participate in AI-driven job creation (Georgieva, 2024).

2.3. Compensation Mechanism

It is anticipated that the widespread use of AI and the subsequent increase in the use of related technologies may result in potential job losses in the short term. However, it is believed that these losses will be compensated for by offsetting mechanisms that will increase the demand for labor in the long term, due to the higher productivity that can be achieved using these technologies.

The compensation mechanism occurs in the form of an increase in productivity brought about by AI technologies, which saves labor, expands the scale of the relevant industry, and compensates for the decrease in the number of jobs per output through the expansion of scale. The application of AI technologies enables firms to expand their production capabilities, saving the time and cost associated with production processes. Consequently, the necessary conditions for the increase in the number of production lines and jobs will be provided, thereby increasing consumer demand by selling products produced at lower prices with the expansion in productivity. Therefore, the compensation mechanism will function effectively in firms with an increased production scale (Sarker, 2022).

The compensation mechanism, which also functions in the form of the creation of new tasks requiring significant labor through the re-engagement of labor in new activities or lines of business, has also been defended by Acemoglu and Restrepo (2018b, 2019) on the grounds that the effects of productivity, capital accumulation, and the spread of automation can eventually compensate for any reduction in labor demand.

The advent of AI technologies has the potential to change the relationship between capital and labor. By reducing costs in production and increasing the demand for labor in non-automated jobs, AI technologies may lead to substituting capital for labor, particularly if they make certain tasks cheaper than labor. This results in a reduction in the price of goods and services whose production process is automated, while simultaneously increasing the demand for those goods and services (Autor, 2015). The reduction in prices for goods and services in sectors where the production process is automated has the effect of increasing the wealth of households, which in turn leads to an increase in the overall demand for goods and services. This increase in the overall demand for goods and services consequently gives rise to an increase in the demand for labor (Wolla et al., 2019). The resulting demand for labor in other sectors can serve to offset the negative displacement effect of automation. One historical case study exemplifying this phenomenon is the adaptation of the US and many European economies to mechanization in agriculture. As a consequence of the reduction in food prices resulting from the advent of mechanization, consumers were able to demand a greater quantity and variety of non-agricultural products (Herrendorf et al., 2014), while simultaneously creating employment opportunities for a significant proportion of the workers who had been initially displaced by the mechanization process. However, since this compensatory effect works by increasing the demand for goods and services, it tends to increase inequality. If the increase in real incomes generated by AI falls into the hands of those with a low marginal propensity to consume, these stabilizing compensatory forces will be weakened and operate much more slowly. Consequently, there is a possibility that this imbalance in the distribution of AI-generated earnings may impede the creation of new employment opportunities (Acemoglu and Restrepo, 2018b).

Another compensation mechanism depends on firms' decision to support new investments. A delay in the reflection of the reduction in the costs brought about by AI technologies on the decline in prices may result in excess profits for innovative entrepreneurial firms. Conversely, the transformation of these profits into investments is delayed in the context of new production and job opportunities. If these investments are only capital-intensive, the offsetting effect will be partial at best. An even more problematic scenario is that profits may not consistently inform new investment decisions. The actions of firms that act in accordance with Keynes' "animal spirits," leading to a pessimistic outlook, have the potential to create significant structural technological unemployment by interfering with the functioning of the compensation mechanism (Piva and Vivarelli, 2017).

It is evident that there is no assurance that compensation mechanisms will function with absolute reliability. It is possible that critical issues may result in a reduction in the effectiveness of these mechanisms. In oligopolistic or less competitive market structures, the translation of low costs into low prices is not always guaranteed, which may reduce the effectiveness of the compensation mechanism. Secondly, the initial impact of labor-saving technology is a decline in overall demand from those who have been laid off. It is therefore evident that the compensation mechanism must be capable of doing more than merely offsetting the initial decline in aggregate purchasing power. The postponement of this compensation mechanism is important; however, it can also result in the emergence of structural unemployment, which persists over an extended period (Piva and Vivarelli, 2018).

Recent decades have seen productivity growth alongside a falling labor share of income, meaning workers have not captured the gains proportionately. This suggests that while output has grown, wages and employment haven't grown as fast. Nonetheless, the fundamental logic of the compensation effect remains a cornerstone for optimistic projections: AI-driven productivity growth can lead to larger economic output that ultimately requires more workers in the aggregate, even if specific jobs are lost (Autor, 2015; Piva and Vivarelli, 2017; Acemoglu and Restrepo, 2018a). The strength of this mechanism may vary by country's income level. In high-income countries, consumers are wealthier and more likely to increase spending when prices drop, fueling demand for new goods and services. These economies also tend to have diverse industries, so workers displaced in one sector (e.g. manufacturing) can often find work in expanding sectors (e.g. healthcare, tech services) if retrained. In lower-income countries, a smaller middle class and limited consumer spending power mean the demand stimulus from cheaper goods might be weaker. Additionally, if much of the AI-driven productivity gain in a developing country's export sector results in cheaper export prices, the benefit (higher real income) accrues to consumers abroad rather than locally. This could dampen the local compensation effect. On the other hand, developing economies stand to gain from technology-driven lower prices for capital goods and software, which could make it easier to start new enterprises and industries, potentially creating jobs if other conditions (like skills and infrastructure) are in place (Bonsay et al., 2021). Overall, the compensation mechanism highlights that the net employment impact of AI is not just a function of substitution and new job creation, but also of macroeconomic feedback loops.

The efficacy of compensation mechanisms remains uncertain, contingent upon a multitude of variables, including the degree of competition, the elasticity of demand, and the shaping of business expectations (Piva and Vivarelli, 2017). Considering the aforementioned considerations, an emphasis on empirical analysis is therefore recommended.

2.4. Literature Review

The influence of AI on economic processes is pervasive, encompassing a multitude of domains, including employment, inequality, productivity, and economic growth. While the general outlook and potential economic implications of AI are predominantly conceptualized in academic literature, empirical studies remain scarce, representing a significant gap in research that necessitates further investigation.

Acemoglu and Restrepo (2018a) examine the effects of automation, AI, and robotics technologies on employment by transforming the static model, which posits a fixed capital accumulation and exogenous technology, into a dynamic model by endogenizing capital accumulation. By setting the model in a framework that allows for the automation of jobs and tasks performed by labor and novel versions of existing jobs and tasks where labor possesses a comparative advantage, the authors observed that in the static model, automation reduces employment, labor share and wages. Conversely, when new roles and tasks are created or novel versions of existing roles and tasks where labor possesses a comparative advantage, the opposite effects are present (Acemoglu and Restrepo, 2018a). In their study on the effects of automation and AI on labor demand, wages, and employment, Acemoglu and Restrepo (2018b) conclude that automation and AI, as machines, replace labor through the displacement effect, which tends to reduce labor demand and wages. They argue that although increased production from additional capital accumulation leads to higher wages per worker, the share of labor in national income declines—an outcome that is eventually offset by a productivity effect resulting from cost savings and increased demand for non-automatable jobs. A hypothesis suggesting that a negative impact on employment is expected in settings where AI primarily replaces human labor is based on these views. This displacement effect is likely to be more pronounced in high-income countries with advanced technological infrastructures, where the automation potential is higher.

Gries and Naudé (2018) examined the potential impact of AI as a technology service that can substitute or complement labor in an economic growth model with constraints on aggregate demand. Their findings suggest that strong substitution elasticities may result in a reduction in employment, wages, and the labor share of income, which will lead to inequality. Furthermore, the authors conclude that in the absence of benefits to labor income from the economic gains generated by AI progress, consumption may stagnate, which may act as a constraint on growth. Nevertheless, the authors also observe that due to the gradual diffusion of AI, there will be no spike in unemployment. Additionally, wages may decline to sustain employment levels in conjunction with sluggish GDP and productivity growth, as economies fail to capitalize on the potential for expansion in the supply of these technologies (Gries and Naudé, 2018). Building on this, a hypothesis posits that the positive effects of AI on employment -through enhanced productivity and job creation- will dominate when AI is used to complement human labor. However, these positive effects may be moderated by the substitution effect in sectors where routine tasks are automated. This duality helps explain the mixed empirical evidence in the literature, where some studies report net job losses while others observe job creation, depending on the economic context and stage of AI adoption.

Webb (2020) used the similarities between job descriptions and patent definitions of occupations in his methodology to estimate the effects of different digital technologies on occupations. By employing AI, software, and industrial robotics as exposure measures, Webb presents empirical evidence on the relationship between AI technologies and employment and wage dynamics at the occupational and industry levels in the US for the period between 1980 and 2010. The results show that the labor market effects of software and robots are quite unlike those of AI, as AI-related occupational exposure differs among various socioeconomic groups. In consequence, low-skilled and low-wage male workers are more exposed to robots, while those in middle-skilled jobs are more vulnerable to software, and those in high-skilled jobs are more vulnerable to AI. Furthermore, it was determined that AI was more likely to affect workers with higher education levels and older ages than previous technological impacts. This was observed to result in a negative impact on the wages and employment of occupations that were exposed to the technologies under study. The main contribution of Webb's study is that AI is qualitatively unlike software and robots and, as a result, is likely to affect different types of jobs and people. Building on the work of Webb (2020), Fossen et al. (2022) examined the individual-level wage changes of AI, software, and industrial robots for the US economy for the period covering 2011-2021. The objective of this study is to examine the impact of the accessibility of AI technologies on workers' wages and how this effect compares with earlier innovations, namely software and industrial robots. The findings indicate that while software and industrial robots have resulted in a labor displacement effect, characterized by a decline in wages, AI has had the opposite effect, leading to an increase in wages through a productivity effect, which has resulted in the creation of new job opportunities for labor.

Fossen and Sorgner (2022) examine the effects of emerging digital technologies on individual-level wage and employment patterns in the US economy between 2011 and 2018. The authors utilize a range of indicators to assess the effects of emerging digital technologies on the labor market, including the probabilities of computerization of occupations, the occupational effects of AI, the appropriateness of tasks for ML, and their within-occupation variance. Their findings indicate that labor-displacing technologies are related to a slowing of wage growth and a higher probability of occupational change and unemployment. Conversely, digital technologies that reinstatement effects, the measure of the occupational effects of AI in this study, are found to improve individual labor market outcomes. It is concluded that advances in AI do not displace human labor on average but rather reinstate it and that AI technologies generate new work tasks for human labor. The study also noted that, unlike previous technological advances, the next-generation digital technologies have affected high-skilled labor the most.

Bonsay et al. (2021) examined the relationship between AI (represented by high-tech exports), labor productivity, and unemployment with economic growth for the period covering 1988-2019 for 4 Asian countries that ranked high in the AI Readiness Index. The results show that AI, which facilitates technological progress in the economy, attracts and encourages foreign direct investment for expansion, especially technology transfer, job creation, and economic growth; helps open new markets to various free trade agreements; and increases growth through trade liberalization. Among the 4 Asian countries, Japan's more appropriate use of AI technology compared to other countries has both accelerated labor productivity and struck a balance to prevent technological unemployment. This supports the hypothesis, which asserts that AI-driven productivity gains can compensate for initial job losses. In high-income contexts, where technological adoption and human capital are robust, the compensatory effects of AI are expected to generate net employment growth. Conversely, in lower-income countries, the compensation mechanism may be weaker due to slower AI diffusion and limited capacity for innovation.

Frey and Osborne (2013), seeking an answer to the question of how sensitive jobs are to computerization, calculated the risk of automation of 702 occupations in their study. Consequently, the researchers determined that 47% of jobs in the US economy will be replaced by AI, which represents 47% of total employment in the US economy and is therefore at high risk of being automated. Frey and Osborne also examined the risk of automation in terms of wages and education level and found a strong negative correlation between the two variables. The researchers highlighted that unskilled workers can only be employed in non-automated roles or in positions that require creativity in response to new technologies unless they enhance their educational qualifications. However, for this to occur, employees must develop their social skills. Arntz et al. (2016) criticize Frey and Osborne's study for adopting an occupation-based approach rather than a task-based approach. Arntz et al. (2016), who focus on tasks within an occupation in relation to the fact that workers with the same occupation perform different tasks within the job, calculate the likelihood of jobs being subject to automation for 21 OECD countries and conclude that jobs can be automated at an average rate of 9%. In comparison to the findings of Frey and Osborne (2013), the authors conclude that jobs are considerably less likely to be automated, attributing this difference to the task-based approach. In addition to this result, it was found that the risk of automation of jobs performed by low-skilled workers is higher than that of jobs performed by high-skilled workers. Empirical findings from Frey and Osborne (2013) and task-based critiques by Arntz et al. (2016) further reinforce that the risk of automation is heterogeneous, depending on the nature of tasks performed. Therefore, the way to deal with potential inequalities that may arise from technological change in the future is to provide low-skilled workers with the necessary training. Wang et al. (2023), in their study calculating the probability of substitution of jobs in China by AI, concluded that 54% of jobs in China are at elevated risk of substitution in the short-term future. The aforementioned jobs are predominantly manual and routine, with workers in production, transportation, manufacturing, and the service sector being particularly vulnerable to substitution. The last group of low-risk jobs that can be substituted includes 38% of the jobs in China and are mainly managerial jobs such as unit supervisors, which require intuition, social intelligence, and social interaction. When the authors compare their results with the proportion of jobs at different risk levels in the US in Frey and Osborne's (2013) study, they find that the proportions of high-risk and low-risk jobs in China are larger than those in the US, while the proportion of medium-risk jobs in China is smaller than that in the US.

Guliyev (2023) employed the System-GMM approach to examine the impact of AI on unemployment across 24 technologically advanced countries over the 2005-2021 period. The results of Guliyev indicate a negative correlation between the unemployment rate and the implementation of AI. Mutascu (2021) investigated the effect of AI on employment for 23 technologically advanced countries for the period 1998-2016 by using Least Squares panel regression and the System-GMM method, considering actual and expected inflation levels. In contrast with the findings of most of the current literature, the results demonstrate that the impact of AI on unemployment is not linear. Furthermore, the rapid increase in the use of AI reduces unemployment at low inflation levels. Nguyen and Vo (2022) analyzed the effect of AI on unemployment for the period 2000-2019 for a total of 40 countries, 25 developed and 15 developing countries. They investigated this relationship in the context of varying inflation levels, a methodology like that employed by Mutascu (2021). The results obtained from the analysis show a non-linear relationship between AI and unemployment influenced by inflation level. In consequence, the impact of AI on unemployment is positive up to a specific threshold level of inflation. Conversely, the effects are reversed after this threshold level is reached, that is when the inflation level continues to increase. This result implies that AI can address unemployment when inflation is at the anticipated level. In this case, Nguyen and Vo reach the same conclusion as Mutascu. This nuanced relationship informs an integrated hypothesis: the net impact of AI on employment depends not only on its direct effects (substitution and job creation) but also on broader macroeconomic conditions. In high-income countries, supportive policy frameworks and robust demand can enhance the compensatory effects of AI, whereas in lower-income countries, the adverse effects may be more pronounced.

A review of the literature reveals that the most crucial point to be highlighted regarding these studies is that the projected consequences of AI technologies, regarding employment, exhibit considerable variability. The most plausible explanation is that the studies employ different variables to represent AI, utilize different data sets, use different methodologies, and examine different countries.

The empirical context is still insufficient since the future outlook for the economic effects of AI is mostly discussed in conceptual terms or at the theoretical level. A significant factor in this deficiency is the variable used to represent AI. This is why there is not yet a consensus in the literature on the net impact of AI on employment. The lack of consensus can be attributed to two primary factors: the dearth of empirical studies in the literature and the discrepancies in methodology, period, country, and variable definitions across studies. The hypotheses that this study addresses, based on its theoretical background, are formulated on the basis of this variability. By employing a dynamic panel regression model with an AI index that broadly represents the technology, the study aims to empirically test whether the net effect of AI on employment is positive and under what conditions the compensatory mechanisms may mitigate displacement effects. This approach directly builds upon and extends the findings of (Acemoglu and Restrepo, 2018a, 2018b) among others, by linking theoretical predictions with observed labor market outcomes across diverse economic contexts. The empirical analysis, described in the subsequent section, will provide evidence of the impact of AI on employment in the selected countries, thereby addressing the gaps in the existing literature and clarifying the conditions under which AI leads to net employment growth or displacement.

3. Research Design

3.1. Data Description and Source

Although there are many studies on the economic effects of technology in the literature, there is a lack of empirical studies that investigate the impact of AI technologies on the economy. In this regard, this study aims to investigate the impact of AI on employment in selected economies. The study uses panel data from 29 countries (see Table A1) from 2017 to 2021. The period and countries have been determined based on AI Index Data prepared by Stanford University. Table 1 shows the variables used in empirical analysis.

Table 1. Variable Details

Type of Variable	Variables	Abbreviation	Definition of Variables	Source
Dependent Variable	Employment Rate	emp_rate	Employment to population ratio, 15+, total (%) (modeled ILO estimate)	World Bank
Independent Variable	Artificial Intelligence	ai	Artificial Intelligence Index	Stanford University-Human-Centered AI Institute
Control Variables	GDP	gdp	GDP (constant 2015 US$)	World Bank
	Population	popg	Population growth (annual %)	World Bank
	Labor Productivity	lp	Output per worker (GDP constant 2017 international $ at PPP) -- ILO modelled estimates	International Labour Organization
	Unemployment Rate	unemp_rate	Unemployment, total (% of total labor force) (modeled ILO estimate)	World Bank

The empirical measurement of the potential impact of AI on human labor represents a crucial area of research. To investigate this effect, as shown in Table 1, the variables of employment rate, AI index, GDP, population, labor productivity, and unemployment rate are included in the econometric analysis. The data used in the study were obtained from the World Bank (WB), the International Labour Organization (ILO), and the Stanford University Human-Centered AI Institute.

The employment rate, the dependent variable, is the ratio of a country's working population to the total working-age population. AI Index, comprising 23 indicators, has been prepared by Stanford University since 2017 and is included as an independent variable in the study. The following variables are included as control variables in the analysis: GDP, output per worker, which represents labor productivity, population growth rate; and unemployment rate.

3.2. Variable Description

Dependent variable: The employment rate, the dependent variable, is represented by the ratio of employed persons to the total population. The employment rate is proxied by employment to population ratio. ILO defines employment as persons aged 15 years and over of working age who, in a given reference period, engage in any activity to produce goods or provide services for the purpose of earning wages or making a profit. The employment rate is a key indicator of an economy's capacity to provide employment opportunities for individuals who are actively seeking work. A high employment rate is indicative of a robust labor market, where a notable size of the population in the country is employed.

Independent variable: In empirical studies that investigate the economic effects of AI, variables such as R&D expenditures, high-technology exports, information and communication technologies (ICT) exports, patent applications, and the number of robots have been used to proxy for AI. However, these variables are insufficient for representing AI. The rationale behind the utilization of the AI Index in this study is that it is believed to be an accurate proxy for AI.

The AI Index has been developed by Stanford University since 2017. AI Index consists of two categories which are R&D and Economy, covering 23 variables (see Table A2). AI index is calculated in absolute and per capita terms. As illustrated in Table A2, eight of the sixteen indicators in the R&D category and two of the seven indicators in the Economy category are derived through the calculation of identical variables on a per capita basis. This study uses the absolute value of the AI Index.

Control variables: The control variables used in the analysis are GDP, labor productivity, population, and unemployment. To represent labor productivity, output per worker is used. Labor productivity is defined as the total volume of output produced per worker in a given reference period. “Per worker” is measured as the number of working people or hours worked, while the total volume of output is measured in terms of GDP. The rate of growth of the population is used as a measure of population, and the rate of unemployment is used as a measure of unemployment. The unemployment rate is calculated by dividing the unemployed people by the labor force. ILO defines unemployment as individuals of working age who are unemployed in the reference period and who are also looking for work and are available for work.

3.3. Model Specification

The empirical studies on the relationship between AI and employment remain relatively limited, while various aspects of this area have been discussed in the existing literature. Considering this gap in the research, this study aims to contribute to the existing literature with an empirical model that examines the impact of AI on employment. Moreover, another research gap in this field is that the variables utilized to determine the effect of AI on employment are not entirely representative of AI. This study addresses this gap by using the AI Index to represent AI. To empirically examine the impact of AI on employment using a dynamic model, the first regression model is specified as follows:

$$\begin{aligned} emp\_rate_{i,t} = \beta_0 + \beta_1 emp\_rate_{i,t-1} + \beta_2 ai_{i,t} + \beta_3 lngdp_{i,t} + \beta_4 popg_{i,t} \\ + \beta_5 lp_{i,t} + \beta_6 unemp\_rate_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{1}$$

where i, t and β represent country, time and coefficient respectively. The term $emp\_rate_{i,t}$ demonstrates the employment rate, while $emp\_rate_{i,t-1}$ denotes a one-year lag of employment rate. $ai_{i,t}$ is the artificial index, $lngdp_{i,t}$ is the logarithm of GDP, $popg_{i,t}$ is the population, $lp_{i,t}$ is the labor productivity, $unemp\_rate_{i,t}$ is the unemployment rate, $\varepsilon_{i,t}$ is error term.

The relationship between technological developments and productivity growth has long been a topic of debate, with a complex history. The complex relationship between these two variables has once again been the subject of debate in recent years, largely due to the rapid advancement of AI technologies. Furthermore, the question of whether technological advancements (in this study—AI) are labor-friendly remains unsolved. In light of this, the potential for labor productivity to influence the relationship between AI and employment could not be ignored in this study. Accordingly, an interaction term is incorporated into Eq. (1), wherein the variables of AI and labor productivity are interacted. So, in the second model, the impact of interaction of AI and labor productivity on employment will be examined through the application of the following econometric equation:

$$emp_{rate_{i,t}} = \beta_0 + \beta_1 emp_{rate_{i,t-1}} + \beta_2 ai_{i,t} + \beta_3 lngdp_{i,t} + \beta_4 popg_{i,t} + \beta_5 lp_{i,t} + \beta_6 unemp_{rate_{i,t}} + \beta_7 ai * lp_{i,t} + \varepsilon_{i,t} \quad (2)$$

In the model presented in Eq. (2), the interaction between the ai and lp means that the partial effect of AI on employment is contingent on the value of labor productivity. To determine the statistical significance of this partial effect, it is necessary to examine the joint effect of these two independent variables on the dependent variable, rather than the individual significance of the independent variables subject to the interaction term. Table 2 presents the results of the chi-squared test of the joint effect of the AI and LP variables. The results of this test indicate that the null hypothesis (H0 = β2 = β5 = 0) is rejected when the probability value is less than 0.05. This suggests that the interaction term, which comprises AI and labor productivity variables, is jointly significant with respect to the employment rate. Given that these variables are jointly significant, it is appropriate to proceed with the analysis of the interaction term.

Table 2. Results of The Chi-square Test of The Variables of ai and lp

test ai lp		
(1)	ai = 0	chi2 (2) = 85.21
(2)	lp = 0	Prob > chi2 = 0.0000

Balanced panel data analysis is conducted on 29 countries for the period covering 2017–2021. The purpose of the study and the availability of the data were considered in the econometric model. Given that the employment rate will be influenced by values from the previous period, a dynamic panel data model was employed. The examination of labor market dynamics can yield a more precise and extensive insight into employment patterns and the factors influencing them (Zhao et al., 2022; Guliyev, 2023).

4. Empirical Analysis and Results

4.1. Descriptive Statistics

The data analysis was conducted using Stata 15.0 software, and the descriptive statistics of the variables are represented in Table 3. Table 3 presents the number of observations, mean, standard deviation, minimum, and maximum values of the series of variables. The data set contains 145 observations for each variable and is therefore a balanced panel data set. In panel data sets, it is essential to consider the mean value to ascertain the central tendency of the variable in question. In this case, the mean value of the dependent variable, employment rate, is 57.24%, with a data range spanning from a minimum of 41.33% to a maximum of 68.58%. The mean value of the independent variable, the AI index, is 13.74, with a minimum value of 0.557 and a maximum value of 78.16. It is evident that the data exhibits a greater degree of dispersion than the mean value. This may be caused by differences in the degree of economic and technological advancement across countries, as well as the varying rates of adoption of AI technologies. Although 23 of the 29 countries included in the study are developed countries and 6 are developing countries, the significant disparity between countries in terms of AI merits attention. This conclusion is essentially consistent with the observable facts. Similarly, in the labor productivity data set, while the mean value is 95.421, the minimum and maximum values are distributed between 18.541 and 219.127.

Table 3. Descriptive Statistics

Variables	Observations	Mean	Standard Deviation	Minimum	Maximum
emp_rate	145	57.24	6.185	41.33	68.58
ai	145	13.74	15.83	0.557	78.16
lngdp	145	27.70611	1.134337	26.03897	30.64354
popg	145	0.508	0.674	-4.170	1.939
lp	145	95.421	36.250	18.541	219.127
unemp_rate	145	6.209	3.120	2.400	17.22
ai*lp	145	1243830	1674209	31035.32	9775330

Multicollinearity, referring to a situation where two or more variables in a regression model are highly correlated, is one of the key assumptions of the Classical Linear Regression Model. In accordance with this assumption, there should be no issue of multicollinearity between the explanatory variables. The phenomenon of multicollinearity arises from the reciprocal relationships that exist between explanatory variables. Consequently, the most logical and easy way to identify multicollinearity is to examine the correlation coefficient. Many researchers concur that a threshold value of 0.9 represents an optimal demarcation for the multicollinearity problem (Asteriou and Hall, 2007). The matrix illustrating the relationships between the variables employed in the model and the corresponding correlation coefficients is presented in Table 4.

Table 4. Correlation Matrix

	emp_rate	ai	lngdp	popg	lp	unemp_rate	ai*lp
emp_rate	1.0000						
ai	0.1568	1.0000					
lngdp	-0.0340	0.7378*	1.0000				
popg	0.0952	0.0564	-0.1067	1.0000			
lp	0.2339*	-0.1186	-0.3313*	-0.0206	1.0000		
unemp_rate	-0.6842*	-0.1687*	0.0001	0.0168	-0.1176	1.0000	
ai*lp	0.1946*	0.8065*	0.5283*	0.0266	0.3219*	-0.1594	1.0000

Note: * explains the significance at 5%.

In Table 4, a positive correlation is observed between emp_rate and ai, popg, and lp. Conversely, a negative correlation is observed between emp_rate and lngdp and unemp_rate. While the correlation between ai and lngdp and popg is positive, the correlation between ai and lp and unemp_rate is negative. Finally, a positive correlation is observed between ai*lp and all variables except unemp_rate.

4.2. Empirical Methodology

Dynamic models are distinguished from static models by the inclusion of lagged values of variables in their specifications. However, since the dependent variable whose lagged value is added to the model as an independent variable violates the exogeneity assumption, an endogeneity problem is possible in the model. In this case, when the model is estimated with the OLS method, the unit, time, and endogeneity effects will be neglected. Furthermore, if the Random Effects estimator is applied, the correlation of an independent variable in the model as the lagged form of the dependent variable with unobserved effects will again violate the assumption of the estimator used (Baltagi, 2021). Estimators such as OLS and Fixed Effects are known to be biased and inconsistent in the presence of dynamic effects and simultaneities in the model specification (Levine et al., 2000; Hasan et al., 2009; Hasan and Tucci, 2010; Baltagi, 2021; Zhao et al., 2022). Although the fixed effects estimator can be used in dynamic models since it allows independent variables and unit effects to be correlated, it should be employed with caution since it may result in dynamic panel bias, also referred to as Nickell bias. According to Nickell (1981), this bias occurs when N (unit cross-section) exceeds T (time cross-section) (Yerdelen-Tatoglu, 2020). In the data set used in this study, given that the unit cross-section is N=29 and the time cross-section is T=5 (i.e., N>T), it would not be appropriate to employ the OLS or fixed effects estimator.

One of the important problems that can arise in dynamic panels is the phenomenon of endogeneity bias. Static models are constrained in their capacity to incorporate the variables that may give rise to an endogeneity effect. Endogeneity bias is defined as the effect of the past on the present, and this problem arises from the correlativity between the dependent variable and the error term. There are some techniques suggested in the literature for addressing the endogeneity problem. The best option among these techniques is considered to be the use of instrumental variables (Bascle, 2008; Semadeni et al., 2014).

Anderson and Hsiao (1982) initiated the development of the first differences method for the use of endogenous instruments in panel data. Subsequently, Arellano and Bond (1991) developed the GMM estimator as a more efficient estimator than the first difference estimator. However, the GMM estimator may result in a bias problem in unbalanced panel data. In response, Arellano and Bover (1995) developed the System-GMM to address this issue, and Blundell and Bond (1998) extended the System-GMM to accommodate short panels with a large cross-section (N) (Roodman, 2006). Accordingly, the optimal estimator for addressing the endogeneity issue is the System-GMM. In light of the aforementioned explanations, the System-GMM is the most appropriate for this study. The empirical model is presented in Eq. (1), Eq. (2), and the findings are presented in the next section.

4.3. Analysis of Empirical Results

To investigate the impact of AI on employment, this study employs System-GMM, proposed by Blundell and Bond, as it offers several advantages over other alternative approaches. The fundamental criterion for the System-GMM is that N is larger than T. This study covers 29 countries over a period of 5 years, thereby rendering it an appropriate candidate for the proposed estimator. Also, System-GMM is an optimal approach for analyzing panel datasets, facilitating the identification and addressing of potential issues such as over-identifying constraints, measurement errors, endogeneity biases, and autocorrelation. In order to reap these benefits, the System-GMM is utilized. Table 5 presents the estimation results of System-GMM.

Table 5. Estimation of Results of System-GMM

Variables	(1)	(2)
L.emp_rate	-0.0574(0.486)	-0.0602(0.464)
ai	0.0298***(0.000)	0.0480***(0.000)
lngdp	-0.113(0.258)	-0.0861(0.390)
popg	0.764***(0.000)	0.766***(0.000)
lp	2.95e-05***(0.000)	3.39e-05***(0.000)
unemp_rate	-1.361***(0.000)	-1.361***(0.000)
ai*lp		-2.13e-07**(0.029)
Constant	68.43***(0.000)	67.45***(0.000)
Observations	116	116
Instruments	10	11
AR (1) (p-value)	0.0453	0.0480
AR (2) (p-value)	0.434	0.435
Sargan (p-value)	0.0930	0.107
Wald Test (p-value)	0.0000	0.0000

Note: ***, ** and * explain the significance at 1%, 5% and 10% respectively, whereas the values are in parentheses contains P-values.

Table 5 demonstrates that the impact of a one-unit increase in the previous year's employment rate on the current year's employment rate is not statistically significant, suggesting that, within the short time span of our dataset, past employment levels do not have a strong direct influence on current employment. This may be partly due to the relatively stable nature of employment rates in our sample and the dynamic characteristics of the labor market captured by our control variables. The independent variable, AI, is statistically significant at the 1% level. In this case, a one-unit increase in AI is associated with a 0.0298-point increase in the employment rate. The positive sign of this significance coefficient indicates that AI has a positive effect on employment and an increase in AI adoption is associated with higher employment levels. This suggests that AI, rather than leading to outright job losses due to automation, exhibits a job-creation effect in the observed sample of countries. One possible explanation for this result is that AI enhances productivity and innovation, which in turn drives economic expansion and job creation, particularly in sectors where AI complements human labor. This finding aligns with the compensation mechanism in labor economics, where productivity gains foster new economic opportunities that counterbalance potential labor displacement. Among the control variables included in the model, GDP is not found to be statistically significant at any level. This suggests that, after accounting for AI adoption and other labor market factors, variations in GDP alone do not exhibit a direct impact on employment. A plausible explanation is that the effect of GDP on employment operates indirectly through factors such as capital investment, labor market regulations, or structural economic shifts, which are not directly captured in this specification. However, the population growth rate, labor productivity, and unemployment rate are found to be statistically significant at the 1% level. Accordingly, a one-unit increase in the population growth rate increases the employment rate by 0.764 points. Higher population growth is associated with rising employment levels. This is an expected result as a growing population generally translates into an expanding labor force and increased economic activity. A one-unit increase in labor productivity increases the employment rate by 0.0000295 points. Although the observed change is relatively minor, it is nonetheless evident that labor productivity exerts a positive impact on employment. The effect of another control variable, the unemployment rate, on employment is statistically significant at the 1% level and a one-unit increase in the unemployment rate decreases employment by 1.3 points. It confirms that as unemployment rises, employment decreases, which is an expected relationship reflecting labor market equilibrium conditions.

In the last rows of Table 5, the results of the sequence correlation and over-identification tests are reported. In the autocorrelation test proposed by Arellano and Bond (1991), the null hypothesis, "There is no second-order autocorrelation," is tested for the residuals in the first-difference model. As a result of this test, there should be no second-order autocorrelation for the GMM estimator to be efficient (Arellano and Bond, 1991). Arellano and Bond emphasized the importance of testing the exogeneity of instrumental variables, even when they are weakly exogenous, after GMM estimation. The results of Model (1) suggest that the AR (1) rejects the null hypothesis, whereas the AR (2) model accepts the residuals do not exhibit second-order autocorrelation. Arellano and Bond also proposed the Sargan test as a means of testing the exogeneity of the instrumental variables and stated that if the instrumental variables used in the model are exogenous, the Sargan test will prove that the residuals (error term) will be uncorrelated with the independent variable. The Sargan (1958) test for over-identifying restrictions is employed to determine whether the instruments are well-identified and whether over-identifying restrictions are valid. The null hypothesis is that the overidentifying restrictions are valid, in other words, instrumental variables are exogenous, i.e. valid. This signifies an acceptance of the null hypothesis, which asserts the validity of the instrumental variables employed in the model. The validity of the instruments is assessed using the Sargan test, which in this case indicates that the overidentifying restrictions are valid. Although the Hansen test is often recommended for evaluating instrument validity, it can be overly conservative in panels with a short time dimension and a limited number of instruments. As noted by Roodman (2006), the Hansen test may yield excessively strict results under these conditions, and similar concerns regarding instrument weakness and overidentification tests are discussed by Blundell and Bond (1998). Therefore, given the data structure (N > T) and the constraints on the instrument count, the Sargan test results to provide a more reliable assessment of instrument validity in the model. In Model (1), the Sargan test yields a probability value that indicates the acceptance of the null hypothesis. This demonstrates that the instrumental variables employed in the model are exogenous and, thus, valid. Considering this evidence, it can be reasonably concluded that the model setting is appropriate. Another point that is taken into consideration to ensure that the results obtained from the estimators are not biased is the number of instrumental variables used. In this instance, the number of instrumental variables must be equal to or less than N (cross-section). Because the number of instruments in the model may exceed N as it increases with T (Yerdelen-Tatoglu, 2020). As evidenced in Table 5, the numbers of instruments are less than N. Finally, the Wald test statistic, which is employed to evaluate the overall significance of the model, has a probability value of less than 0.05, thereby indicating that the model as a whole is statistically significant.

The estimation results of the second model, including the interaction term obtained by the System-GMM method are shown in Table 5. According to the compensation mechanism, if AI adoption substantially increases labor productivity, it can create additional jobs by expanding output (offsetting the jobs lost to automation); if productivity gains are small, AI may primarily displace workers. The AI therefore interacted with labor productivity to test this interplay. The inclusion is theoretically motivated by the idea that AI’s impact on employment depends on productivity gains and the interaction term examines the contingent effect of AI on employment when labor productivity increases. In theory, the net effect of AI on employment is conditioned on productivity – for instance, AI-driven automation accompanied by high productivity might eventually require fewer workers per unit output (thereby dampening employment gains), whereas, in contexts of lower productivity, labor demand might be more directly boosted through AI’s complementarity (Acemoglu and Restrepo, 2018a; Bessen, 2018). This nuance is captured by the interaction term. It is clarified in the study that the partial effect of AI on employment is not constant but varies with the level of productivity. Consistent with theory, a positive coefficient for AI and a negative coefficient for the ai*lp term are shown in the estimates, suggesting that employment is generally promoted by AI, although this positive effect diminishes at higher productivity levels (where more output can be produced with fewer workers). This result accords with the theoretical expectation that the compensation effect (through productivity-led output expansion) has limits – i.e. as productivity rises, the incremental employment benefit of AI diminishes (Piva and Vivarelli, 2017). This phenomenon reflects a dual mechanism in technological adoption. On one hand, AI has the potential to create new job opportunities and improve existing ones by increasing output and fostering innovation. On the other hand, as productivity improves, the drive for cost reduction may lead firms to automate tasks previously performed by workers, thereby dampening the net positive effect on employment. This dynamic is particularly evident in developed economies, where high technological adaptation and scale economies are prevalent (Acemoglu and Restrepo, 2018a; Gries and Naudé, 2018).

An examination of the other variables in Model (2) reveals that the probability value of the first-order lagged term of the employment rate, that is, the effect of a one-unit increase in the previous year's employment rate on the current year's employment rate, is not statistically significant at any level. This indicates that the employment rates of the current period are not related to the level of previous periods. GDP is not significant at any level, while population growth rate, labor productivity, and unemployment rate are statistically significant at a 1% level. Accordingly, a one-unit increase in the population growth rate increases the employment rate by 0.766 points, while a one-unit increase in labor productivity increases the employment rate by 0.0000339 points. Although the increase is minimal, it is nonetheless evident that labor productivity exerts a beneficial influence on employment. The effect of another control variable, the unemployment rate, on employment is statistically significant at the 1% level and a one-unit increase in the unemployment rate decreases employment by 1.361 points.

Following estimation, the results are tested for the weakness of the variables to ensure the validity of the instruments and models. The AR (2) and Sargan's tests produce insignificant statistics, indicating that the estimation results in the model are unbiased. The probability value of the autocorrelation test for AR (2) errors is greater than 0.05, indicating that the null hypothesis is accepted and that the residuals do not exhibit 2^{nd} autocorrelation. The Sargan test result shows that the null hypothesis is accepted, i.e., the over-identifying restrictions are valid, in other words, the instrumental variables are exogenous. This supports the interpretation that the estimated coefficients are free from endogeneity bias. Finally, the number of instruments is less than N, and the probability value of the Wald test statistic is less than 0.05, thereby indicating that the model as a whole is significant.

Our empirical results indicate that the overall effect of AI on employment is positive. However, previous studies have often emphasized that AI tends to automate low-skilled jobs, potentially resulting in job losses (Frey and Osborne, 2013; Wang et al., 2023). The positive impact observed in our analysis can be attributed mainly to the specific characteristics of our dataset and the model specification. High technological adaptation and economies of scale, which are prevalent, particularly in advanced economies, can not only compensate for potential job displacement but also stimulate the creation of new employment opportunities.

5. Discussion, Conclusion, and Policy Recommendations

A review of the existing literature reveals a lack of clarity regarding the impact of the proliferation of AI technologies on employment. If these technologies merely substitute for labor, they will have a negative impact, whereas, in the absence of labor displacement, they will have a positive impact. (Martens and Tolan, 2018). The advent of AI has the potential to enhance employment opportunities in several ways. Firstly, it can facilitate the creation of new roles or enhance the value of existing roles through the introduction of new technologies. Secondly, it can complement existing labor, allowing for the optimization of existing processes and the introduction of new efficiencies. One of the results of the model estimations shown in Table 5 of the previous section indicates that AI has a net positive effect on employment, suggesting that, at least in the short run, AI technologies play a complementary and creative role in labor markets. This positive effect is likely driven by compensatory mechanisms inherent in developed economies where higher labor productivity, economies of scale, and technological adaptation can foster the creation of new jobs or transform existing roles. In the analysis, the inclusion of macroeconomic controls such as labor productivity and GDP appears to capture these compensatory effects, resulting in a net employment-enhancing outcome. These results contribute to the current debate on the future of work, suggesting that AI does not necessarily lead to mass displacement of labor but can, under certain conditions, reinforce employment growth. The other result of the model estimations is that the coefficient on the variable representing the interaction between AI and labor productivity is negative. The negative coefficient of the ai*lp interaction term suggests that while AI can enhance employment through productivity gains and innovation, its job-creation effect is moderated by the level of labor productivity. In environments characterized by high productivity, the cost-saving incentives associated with AI may lead to greater automation and a subsequent reduction in labor demand, thereby mitigating the overall positive impact on employment. In high-productivity environments, where firms are likely to adopt AI technologies primarily as instruments for further reducing production costs and increasing efficiency, the focus may shift from complementing human labor to substituting it, particularly in routine, low or moderately skilled tasks. This substitution effect can partially offset the positive, employment-enhancing impacts of AI.

While the existing literature is limited in quantity, several empirical studies have reached conclusions regarding both positive and negative effects. The importance of empirical studies in terms of reflecting real-life experiences has encouraged us to examine this issue empirically. This study makes a distinctive contribution to the literature in several ways. Firstly, it uses a variable that is widely considered to be fully representative of AI. Secondly, it covers the recent years when AI has become popular. Furthermore, the interaction between AI and labor productivity in the analysis contributes to an enhancement of the theoretical framework. It quantifies the condition that sufficient productivity gains are crucial for the positive employment effect of AI to materialize. This nuance contributes to the literature by emphasizing that the balance between displacement and job creation can vary depending on productivity dynamics. The finding that AI has a positive effect on employment is consistent with the results of several previous studies, including those conducted by Fossen and Sorgner (2022), Fossen et al. (2022), Acemoglu and Restrepo (2018a, 2018b), Guliyev (2023), Mutascu (2021), and Nguyen and Vo (2022). Specifically, the results provide empirical support for the task-based framework of Acemoglu and Restrepo (2018a, 2018b) and related theories, indicating that AI-driven automation has been accompanied by the creation of new tasks and roles for labor (consistent with the job creation effect) and productivity improvements that ultimately compensate for displacement.

Fossen and Sorgner (2022) posit that AI will create new jobs for human labor and increase wages through its productivity effect. Acemoglu and Restrepo (2018a) advance the argument that AI will create new jobs and tasks in which labor has a comparative advantage, or that new versions of existing jobs and tasks will emerge. Guliyev (2023), Mutascu (2021), and Nguyen and Vo (2022) present evidence indicating that AI has a negative effect on the unemployment rate. In this instance, it is evident that there are existing studies in the literature that align with the findings of the analysis presented in this study.

In their analysis of the occupational impact of AI on the US economy, Fossen and Sorgner (2022) conclude that, on average, advances in AI do not displace human labor but rather reinstate it. This finding aligns with the idea that AI technologies lead to the creation of new tasks for labor. Fossen et al. (2022) found that for the US economy, AI increases wages through productivity effects by creating new jobs for labor and showed that the effects due to productivity and the creation of new jobs and tasks are greater than the displacement effects of AI. In this case, the results of this study, which indicate a positive impact of AI, are consistent with the interpretation by Fossen and Sorgner that AI transforms occupations and can enhance human productivity. Moreover, the findings of our study demonstrate that the overall impact of AI on employment is positive when the effects of productivity and job creation are greater than the effects of substitution. This finding aligns with the conclusions of Fossen et al. (2022), who reported that AI can counteract labor displacement by creating new job roles, particularly in sectors with robust innovation ecosystems. Acemoglu and Restrepo (2018a, 2018b) put forth a task-based theory, the AR Model, which conceptualizes automation, AI, and robotics technologies as a takeover of tasks previously performed by human labor. They conclude that these technologies can lead to the creation of new tasks, which in turn can result in an increase in employment and wages. They posit that the most effective means of counteracting the effects of automation is by creating new labor-intensive jobs that reintroduce labor in new roles and responsibilities, thereby increasing the overall share of labor and offsetting the impact of automation and AI technologies. In this case, if newly created jobs and tasks or transformed existing jobs go hand in hand with these technologies, the growth process will be balanced and there is no need to paint a pessimistic scenario for labor. However, automation technologies that displace workers will tend to reduce employment and wages if their productivity effects are limited. This is expected to occur if the displacement effect is larger than the productivity effect. Guliyev (2023) analyzed the impact of AI on unemployment in technologically advanced countries and found evidence of a negative relationship between the two variables, indicating that AI has the effect of reducing the unemployment rate. The author concludes that AI is capable of transforming the workforce by generating new jobs, automating routine tasks, and enhancing productivity. Furthermore, the author emphasizes that AI technologies can free labor from routine tasks, enabling it to engage in more complex and creative tasks that necessitate human capabilities such as critical thinking and problem-solving. This shift in focus is likely to enhance the overall work experience and increase job satisfaction. Moreover, AI can support firms in making more informed decisions by offering data-driven insights and analytics into their business models, which can lead to increased profitability and growth. Furthermore, the expansion of AI-driven technologies can facilitate job creation by creating new job roles and expanding existing ones. In a similar vein, Mutascu (2021) examined the influence of AI on unemployment in technologically advanced countries. He investigated this effect by considering actual and expected inflation levels in the analysis. The findings indicate that when inflation is low, the extensive utilization of AI has the potential to mitigate unemployment, provided that the tendency to increase wages is counterbalanced by expansion and the generation of new employment opportunities. Nguyen and Vo (2022) also analyzed the effect of AI on unemployment under various inflation levels, as in Mutascu. The results of the analysis indicate that AI has a positive effect on unemployment up to a certain threshold level of inflation. Beyond this threshold level, the effects are reversed. This finding suggests that AI effectively addresses unemployment issues when inflation is at the expected level. In this context, the conclusions reached by Nguyen and Vo (2022) and Mutascu (2021) are identical.

It can be posited that AI will transform all jobs, tasks, and professions, at least to some extent. This is because AI can increase the productivity of certain types of labor, while simultaneously eliminating the necessity for others. As with other technologies, AI has the potential to change the demand for certain types of labor and to enhance the skill requirements of those engaged in such work. It is evident that the impact of AI on the labor market will vary depending on the specific nature of the work. In some instances, AI may complement or strengthen certain forms of labor, while in others, it may pose a competitive challenge to existing roles. It is therefore inaccurate to assert that technological change will inevitably result in unemployment. For example, robots have the potential to compete with human labor, especially within the manufacturing sector. This could result in a reduction in wages and employment opportunities. Conversely, ML has the potential to enhance the productivity of those engaged in the software sector, while also creating new avenues for investment and production. Because of the evolution of technology, the skills required for human labor will also change. Consequently, AI will create new employment opportunities, even if it results in the substitution of some jobs or tasks. Because creative destruction has always existed and will continue to exist.

As the use of AI technologies becomes widespread, they will also have an impact on economic policies, and the policies of countries will be shaped according to this technology. In addition to monetary and fiscal policies, governments' supervision and intervention systems will change in market regulations. In this regard, it is important to see how politicians will respond and react to both the advantages and obstacles associated with the advent of AI. So, preparations need to start now to manage the transition to such a technological innovation.

The most crucial policies to be implemented are those that focus on the supply of human capital and the supply of AI capabilities within this human capital. Because the most important problem that prevents the spread of AI is the lack of AI skills. To overcome this, it is especially useful to design education and training policies. In addition to educational policies, companies that invest in AI should also adopt the principle of enhancing employee efficiency in utilizing AI technologies. This can be achieved by modifying work environments to align with these technologies and modifying perspectives. In order to reap the full benefits of technology, it is essential to adopt a human-centered approach in all fields (Petropoulos and Kapur, 2022). Furthermore, it is crucial for policymakers to design strategies that harness the positive aspects of AI while mitigating potential adverse effects. In particular, policies should focus on human capital development by investing in education and continuous training programs that equip workers with the skills needed to complement AI technologies; and on sector-specific interventions by tailoring support for industries at higher risk of automation-induced job losses through targeted retraining and upskilling initiatives; and on strengthening social safety nets to provide support during transitional periods as labor markets adjust to technological changes. Additionally, innovation and investment incentives are essential to encourage firms to adopt AI in ways that enhance productivity without excessively substituting human labor, for instance, through measures that promote human-AI collaboration. By integrating these detailed policy measures, future research and policy formulation can better address the challenges and opportunities presented by AI-driven technological change, ensuring a balanced and inclusive growth process.

The impact of AI may depend on several factors, including the elasticity of labor demand and supply, the qualifications of the labor force, the adoption of AI technologies, and other variables. Given the current lack of clarity regarding the definitive impact of AI, there is no basis for fear or pessimistic speculation about its potential consequences. It is neither advisable to imagine negative outcomes nor to ignore the potential for job displacement due to automation, especially during the transitional phase, nor is it constructive to indulge in utopian fantasies about the impending perfection of AI. This dual outcome underscores the complex nature of AI's impact on employment. It is important to note that, in addition to our study’s results indicating a positive effect, potential negative effects should not be overlooked; an important reason for emphasizing this is that our dataset spans a relatively short period of time. This period, which coincides with significant economic shocks -including those associated with the COVID-19 pandemic- may have temporarily influenced employment dynamics in certain sectors. Therefore, a longer-term analysis might reveal a more pronounced pattern of job displacement or creation resulting from AI and digitalization. While our results suggest that AI currently augments employment, they also serve as a cautionary note that the balance between AI’s compensatory and substitution effects may shift over time or across different labor market segments. It is too early to make any exact assessments at this stage. Future research should consider expanding the temporal scope of the analysis and examining sector-specific impacts, particularly focusing on retraining and upskilling processes for low-skilled workers. It is therefore recommended that national economies adopt a comprehensive approach to all potential implications and implement the necessary policies in a considered manner.

6. Limitations and Future Research Directions

The principal limitation of the study is that the subject is of such contemporary interest that the data available for analysis are insufficient to represent the full range of applications of AI. Another notable limitation of the study is the omission of potentially influential variables such as institutional factors and educational attainment. Although the model incorporates key controls like economic growth, population increase, and labor productivity, data constraints for the selected time period and countries precluded the inclusion of robust measures for education and related institutional indicators. This omission may limit the model's ability to fully capture the multifaceted dynamics affecting employment in the context of AI. Future research leveraging more comprehensive datasets should consider these factors to enhance the model’s explanatory power and provide a more nuanced understanding of the interplay between technology and labor markets.

As further empirical studies are conducted, the potential for AI to substitute, complement, or create new jobs and tasks for human labor, labor demand, income inequality, and so forth will become more apparent. The impact of these effects can be more effectively evaluated in comparison to previous technological revolutions, and the distinctive attributes of AI technologies will facilitate an understanding of the differences. The issue can be examined in greater detail by focusing on AI-based applications, or it can be researched with a comprehensive data set. Furthermore, it is evident that an investigation into the influence of these technologies on employment, disaggregated by occupation, sector, skill level, and demographic characteristics such as gender, age, disability status, and migrant status, would give a more overall understanding. Given the far-reaching effects that AI is predicted to have, it is imperative that the issue be examined in greater detail with a range of parameters. When the findings of this study are considered alongside future research, it is thought that the effects of AI technologies on employment can be discussed more clearly.

Despite its limitations, it is anticipated that this study will make a notable contribution to the existing literature on the economics of AI, which is a current and significant field of study. Furthermore, it will encourage further research in this area. As the number of studies on this subject increases, it will become evident that there are numerous gaps in the existing research and that new areas of study will emerge.

Declaration of Research and Publication Ethics
This study which does not require ethics committee approval and/or legal/specific permission complies with the research and publication ethics.

Researcher’s Contribution Rate Statement
First Author: Study conception and conceptualization, Investigation, Reviewing of literature, Writing – original draft, Data collection, Analysis, and interpretation of results.
Second Author: Study conception and conceptualization, Investigation, Writing – review & editing, Supervision.

Declaration of Researcher’s Conflict of Interest
There is no potential conflicts of interest in this study.

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APPENDIX

Table A1. List of Countries

Australia	Denmark	Israel	Poland	Switzerland
Austria	Finland	Italy	Portugal	The Netherlands
Belgium	France	Japan	Russia	Türkiye
Brazil	Germany	South Korea	Singapore	United Kingdom
Canada	India	Malaysia	Spain	United States of America
China	Ireland	Norway	Sweden	

Table A2. Stanford AI Index Variables and Definitions

Variables	**Definitions**
	Research and Developments
Number of AI Journal Publications	Number of published AI journal publications in a given country.
Number of AI Journal Citations	Number of published AI journal citations in a given country.
Number of AI Conference Publications	Number of published AI conference publications in a given country.
Number of AI Conference Citations	Number of published AI conference citations in a given country.
Number of AI Repository Publications	Number of published AI repository publications in a given country.
Number of AI Repository Citations	Number of published AI repository citations in a given country.
Number of AI Patent Applications	Number of published AI patent applications in the given country.
Number of AI Patent Grants	Number of published AI patent grants in the given country.
Number of AI Journal Publications PC	Number of published AI journal publications in a given country in per capita terms.
Number of AI Journal Citations PC	Number of published AI journal citations in a given country in per capita terms.
Number of AI Conference Publications PC	Number of published AI conference publications in a given country in per capita terms.
Number of AI Conference Citations PC	Number of published AI journal citations in a given country in per capita terms.
Number of AI Repository Publications PC	Number of published AI repository publications in a given country in per capita terms.
Number of AI Repository Citations PC	Number of published AI repository citations in a given country in per capita terms.
Number of AI Patent Applications PC	Number of published AI patent applications in the given country in per capita terms.
Number of AI Patent Grants	Number of published AI patent grants in the given country in per capita terms.

Table A2. Continue

Economy	
Total AI Private Investment	Total amount of private investment funding received for AI startups.
Number of Companies Funded	Total number of newly funded AI companies in the given country.
AI Hiring Index	The AI hiring rate is calculated as the percentage of LinkedIn members with AI skills on their profile or working in AI-related occupations, who added a new employer in the same period the job began, divided by the total number of LinkedIn members in the corresponding location. This rate is then indexed to the average month in 2016; for example, an index of 1.05 in December 2021 points to a hiring rate that is 5% higher than the average month in 2016.
Relative AI Skill Penetration	The AI skill penetration rate shows the prevalence of AI skills across occupations, or the intensity with which LinkedIn members use AI skills in their jobs. It is calculated by computing the frequencies of LinkedIn users' self-added skills in a given area from 2015-2021, then reweighting those figures by using a statistical model to get the top 50 representative skills in that occupation.
AI Talent Concentration	The AI Talent Concentration is calculated using the counts of AI talent at the country level vis-a-vis the counts of LinkedIn members in the respective countries etc. A LinkedIn member is considered AI talent if they have explicitly added AI skills to their profile and/or they are occupied in an AI occupation representative.
Total AI Private Investment PC	Total amount of private investment funding received for AI startups in per capita terms.
Number of Companies Funded PC	Total number of newly funded AI companies in the given country in per capita terms.

Source: Zhang et al., 2022