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Artificial Intelligence and Labor Productivity Paradox: The Economic Impact of AI in China India, Japan, and Singapore

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ABSTRACT

Artificial intelligence is designed to generate technologies that potentially increase productivity and economic welfare. This study analyzes the relationship between GDP and high-technology exports, GDP per person employed, and unemployment rate in China, India, Japan, and Singapore. Recent concerns on technological unemployment claim that artificial intelligence disrupts the labor market which decreases employment over time. Using the multiple regression analysis, this study proved that Japan comparatively has better utilization of AI and labor productivity as all independent variables show significance to the GDP. Labor productivity in all countries is positively related to GDP. However, China and India showed signs of improper AI utilization as technological unemployment occurred. The unemployment rate in China is insignificant to its GDP, while India's unemployment rate is positively related to GDP, hence the jobless growth. In Singapore, the insignificance of high-tech exports to GDP is due to its lack of R&D investments these recent years. The results suggest that AI escalates growth through proper utilization trade liberalization, as exercised by Japan, as it helps the economy to be open and flexible to various free trade agreements which facilitates technological progress and enables the opening of new markets for growth and expansion, especially of artificial intelligence, which attracts and encourage foreign direct investments that will cater technology transfer, creation of new jobs, and economic growth.

1. Introduction[1]

Since the 1950s, there has been an idea formulated by the operational and manufacturing engineers around the world: a completely automated industry where machines will be as capable as any human in the labor force, making jobs go obsolete as technologies replace them in driving the economy (Ernst et al., 2018). The emergence of artificial intelligence dominates the world as it advances and improves the livelihood of diverse countries. It is potentially designed for innovation which influences demand-supply, employment and its implications to the human welfare, and competition which focuses not just on AI in opposition to human intelligence, but as well as the widening inequality across the globe. AI is shaping reality from a futuristic vision to what economies need, as being deployed in vital sectors such as finance, national security, criminal justice, transportation, health care, and smart cities (West & Allen, 2018).

The use of new technology paves the way for capital accumulation and production of cheaper goods, the enhanced international competitiveness of countries, and an enhanced quality for scientific research institutions (Çaliskan, 2015). Technological development is one of the factors that increase economic growth on larger scales, as it helps improve the overall market of a country that can possibly produce--way more than the amount humans can--in terms of size, quantity, and quality of its goods and services. The Solow-Growth Model argued that technological advancement is an exogenous factor to economic growth, as a result of Solow's study using the US data showing that technology increased economic growth (Solow, 1956). Additionally, Romer

(1990), who is one of the founders of R&D-based endogenous growth models, also proved the positive relationship of economic growth and productivity with R&D-based technologies.

Labor productivity in industries and services is the main driver of aggregate economic growth, most particularly in South Asia. The efficiency of workers indicates the economic state, as economies of scale are taken into consideration, and as countries are always in competition; labor productivity holds a significant place in gaining competitive advantage, among others. It was claimed by the growth principle in neo-classical theory that technological transformation leads to an increase in the capita per person and thus further stimulates savings and investments which then increases the real GDP (Caliskan, 2015).

Okun (1962) empirically proved the inverse relationship between the unemployment rate and the potential output, depending on the participation in the workforce, the duration of work, and the change in productivity (Soylu et al., 2018). Although their relationship may be affected by other economic variables in the short run, a variable that may result in structural change in this relationship, in the long run, is a technology and its effect on unemployment. Technological advancement may lead to the substitution of capital for labor, resulting in less response of GDP growth to the unemployment rate than what Okun's law proposed (Falatoon & Safarzadeh, 2017). Unemployment is an issue in the economy, especially a developing one. Therefore, the paradox between the rise of technology in the workplace and human capital is an inevitable occurrence that the world must be ready for.

In a broader sense, Artificial Intelligence impacts the world in both ways bringing benefits and detriments in every economic aspect. AI is harnessed to change lives and be ubiquitous in economies, shifting labor-intensive industries to technology/capital-intensive industries to uplift modernization and productivity. According to Somjai et al., (2020), the initial and subsequent impact of AI adoption is positively related to the economic indicators increasing capital investments, economic output, return on capital, and wages for the existing labor force. AI will continue helping the economy as predictive algorithms are leveraged to improve various sectors' efficiency in production and increase sales volume with the adoption of AI technologies. Nonetheless, many studies have shown AI's negative effect on employment wherein technological unemployment and job displacement have been prevalent. Consequences for labor markets will affect workers in terms of inequality, wage-push inflation, and tax base shrinkage. AI could also have a disruptive effect on the economy and its relationship with other countries as it may augment the gap globally (Szczepanski, 2019).

This paper aimed to analyze the relationship between the dependent variable which is the economic growth, and independent variables consisting of technological innovation (artificial intelligence), labor productivity, and unemployment. The authors also examined the possibility of artificial intelligence outweighing labor or human capital as the main driver of growth, and whether technological unemployment occurs when there is an increase in economic growth due to technological dominance in selected Asian countries namely China, India, Japan, and Singapore.

The objectives of this study include:

- To estimate the impact of high-technology exports on the Gross Domestic Product in the selected Asian countries.
- To formulate how GDP per hour significantly affects the Gross Domestic Product.
- To evaluate how the unemployment rate impacts Gross Domestic Product in possible relation to the deployment of AI that causes technological unemployment.

In this light, this research examined the four Asian countries which have consistently been taking places in the top rankings of the leading countries in AI for the past years as reported by varieties of online research databases such as the AI Readiness Index by (Oxford Insights, 2020) wherein the countries' scores in the latest report were 69.08 (China), 55.98 (India), 78.7 (Singapore), and 73.3 (Japan). There were also data on AI rankings in consideration to the implementation, innovation, and investment according to the AI Global AI Summit Report as seen in *Table 1* by (Tortoise Media, 2019). In consideration to these indices and data are the determinants of AI, generally including the AI implementation in public services such as healthcare, education, and transportation provided by the government. Secondly, innovation in which industries and infrastructures are widely developed by AI startups to sustain the economy, and lastly, investment in high R&D intensity products and services which is the high-technology exports.

Rank	Implementation				Innovation			Investment		
Country	Talent	Infrastructure	Operating Management		Research	Development		Government Strategy	Commercial	**FINAL RANK**

China	18	3	3		2	1		1	2	**2**
Singapore	2	4	39		16	15		30	6	**7**
Japan	26	16	17		6	7		12	8	**9**
India	2	59	33		27	11		36	10	**20**

Table 1. *The Global AI Index: How are the G20 countries performing? By Tortoise Media*

In this paper, the authors analyzed how artificial intelligence impacts an economy in the selected Asian countries which are China, India, Japan, and Singapore given that these were considered to top the rankings for artificial intelligence globally and in the Asian region. With this, the authors used these countries to draw conclusions about the effect of AI in the economy for the purpose of inferring proportions in the Asian economies from those representative countries used as the basis for other countries that are planning or are currently participating as high-tech intensive economies respectively. It is important to examine their current policies concerning innovation and weigh the impact of AI in the economy and how it could possibly be a threat to employment in the labor market, making thousands of people jobless and affecting their disposable income and purchasing power, which then will lead to a decrease in their personal consumption that will distress the economy's output and growth. Hence, the importance of this study concerns the whole population of each country, government sectors, businesses, and industries. The overall economy will be in its extremity once the emerging AI phenomena are uncontrolled and utilized in a manner that its disadvantages are neglected. This paper calls for an adequate optimistic outlook of artificial intelligence, at the same time determining these technologies' opportunities and risks, provided that the business sectors and policymakers consider the actions needed for AI not to subjugate laborers and to utilize and manage AI innovation properly in the economy.

1.1 Theoretical Framework

This section presents the theories that the authors used to analyze the fundamental relationship between technology, labor productivity, and employment to economic growth. Economist Robert Solow developed a theory on growth called the Exogenous Growth Model or commonly known as the Solow Growth Model (Solow, 1956).

Liu & Peters (2012) claimed that unemployment in the traditional Solow growth model does not influence the long-run growth rate and productivity level. To fill this gap, Bräuninger & Pannenberg (2002) used the Augmented Solow-Model proposed by Mankiw, Romer, and Weil (1992) for empirical analysis on unemployment and productivity growth.

In the short-run model with the production function assumed to be of Cobb-Douglas type:

$$Y = K^{a}L^{1-a} \; with \; 0 < \alpha < 1$$

Wherein: **Y** is the total of homogenous output; **K** is the capital; **L** is the labor
The labor function considering unemployment is presented as:

$$\boldsymbol{L = (1 - u)N}$$

Wherein: **1 – u** represents the employment rate; **u** is the unemployment rate; **N** is the number of people or the population

Labor supply in efficiency units is presented as:

$$\boldsymbol{N = H^{\beta}(E\bar{N})^{1-\beta}} \; with \; \boldsymbol{0 < \beta < 1}$$

Wherein: **N** is the number of labor workers; **H** is the human capital raised to $\boldsymbol{\beta}$ which represents its elasticity; **E** is the technological state; $\boldsymbol{\bar{N}}$ is the workforce

The contribution of **N** is the combination of human capital and technology with respect to the workforce.

Therefore, the production function is given as:

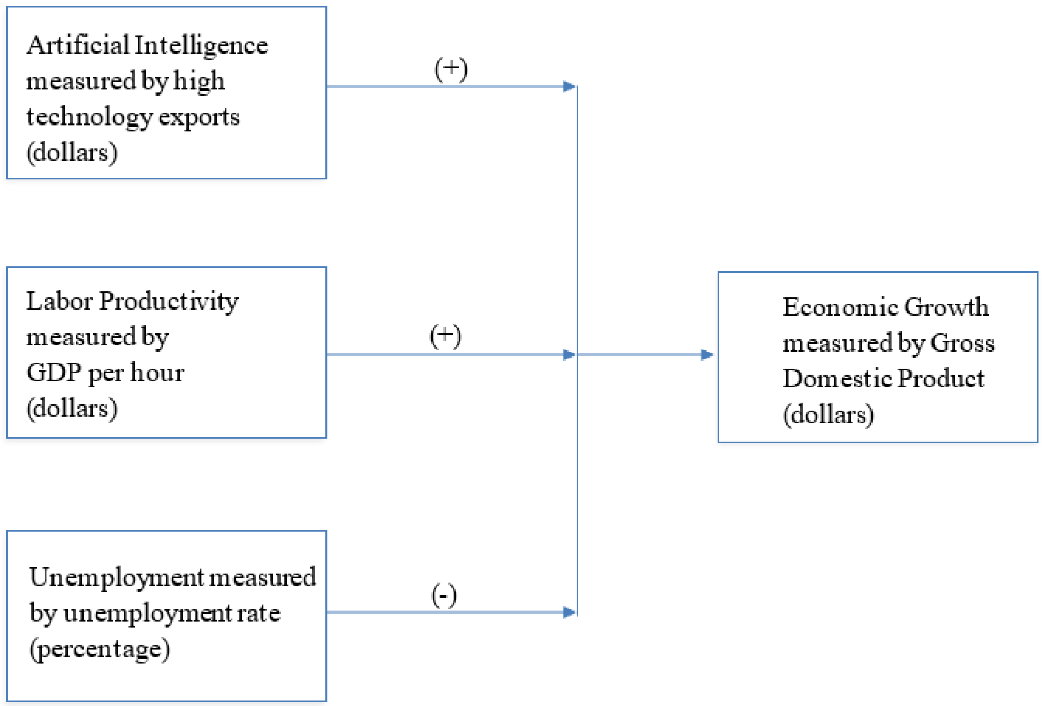
$$\boldsymbol{Y = (1 - u)^{1-a}K^{a}H^{\beta(1-a)}(E\bar{N})^{(1-\alpha)(1-\beta)}}$$

The exponent ***(1-a)*** indicates that human capital and technological state is a factor of labor.

1.2 Conceptual Framework

Through sustaining high R&D intensity products and services which are the high-technology exports per country, it is claimed to be positively related to economic growth. Labor productivity is positively related to economic growth as workers stay in their jobs longer, they become more productive through learning-by-doing, increasing the production in the country. According to Okun's law, to achieve a decline of one percent (1%) in the unemployment rate, then real GDP must grow approximately 2%. With that, Chand, et al., (2017) identified that the unemployment rate is negatively related to economic growth.

1.3 Simulacrum



2. Literature Review

2.1 Artificial Intelligence versus Labor Productivity as the main driver of economic growth

Raj and Seamans (2019) expounded how technological advances contribute to both the economic growth and concerns for human workers wherein computer algorithms may outweigh the functionality of humans. However, Acemoglu and Restrepo (2018, 2019, 2020) argued that the productivity effect of AI offsets the displacement effect on workers if labor demand is expanded through efficient production.

2.2 High-technology Exports on Economic Growth

Theoretical models from (Solow, 1956) and (Romer, 1986) study the link between innovation and economic growth. Solow stressed that labor force and capital are exogenously the main drivers of economic growth, hence the usage of Cobb-Douglas production function, which focuses on the interrelation between innovation, output, and productivity. In contrast, Romer's endogenous growth theory considered technological change as a factor of economic growth that is dependent on population growth working in the knowledge sector or R&D and capital accumulation.

According to the export-led growth hypothesis, strong export growth is considered an advantage in terms of capital formation that increases productivity, importation of capital goods, and competition with foreign industries that encourages resource allocation to export industries, concluding that high-tech exports have a significant role in progressive economies (Suryanto, 2016). Moreover, (Ekananda & Parlinggoman, 2017), was able to identify that high-tech goods exports positively affect the economic growth in countries with a relatively large and small portion of high-tech exports in terms of productivity using the random effect model. Another theory called the growth principle in neoclassical theory justified that technological transformation increases the real GDP, claiming that technological transformation is positively correlated with growth (Caliskan, 2015).

Kabaklarli et al., (2018) have observed that there exists a statistical significance between high-tech exports and economic growth in OECD countries. Economies of the Asia-Pacific region also made evident AI's potential as their main driver in the succeeding years (Haseeb et al., 2019). Afzal & Lawrey (2014) used Data Envelopment Analysis (DEA) to measure the efficiency of R&D expenditures as an input to knowledge generation in the ASEAN region including Singapore. Results showed that Singapore was the most efficient country during 2010. Singapore increased its FDC contribution for competition and innovation in science and technology, which led to being a developed industrial country brought about by the usage of high-technology and ventures in high-tech industries (Litsareva, 2017). On the other hand, Ho, et al., (2010) found the insignificance of GDP and AI and believed that aside from increasing Singapore's R&D investment, efficient exploitation of domestic R&D in the country must also be prioritized as it will help the country cope with the technological advances needed to boost the economy using R&D.

The productivity slowdown in Japan as a result of non-utilization of technology brought by R&D. As studied by Nakamura et al., (2019), the insufficient innovative technology deployed is what drove the economy down, although the R&D efficiency of Japan is yet another factor to be improved to sustain the economy. Studies from Haseeb et al., (2019) and Lu et al., (2018) have deduced that there is a positive relationship between the emerging Artificial Intelligence in Japan and its economic growth throughout the years.

Sultanuzzaman et al., (2019) analyzed the impact of export and technology in sustaining the economic growth of Asian countries including China, India, and Singapore. According to the data from China, researchers have concluded that higher education and technological innovation influences the trends and patterns in economic growth (Zhou & Luo, 2018). On the other hand, Sun & Heshmati (2012) highlighted the positive effect of high-tech export ratio to the efficiency level but is less significant due to problems arising from the high-tech sector such as being confined to low-cost labor upon producing high-tech exports, dependence on the international market due to high-tech exports' disparity - with ICT products accounting 90% of the total exports while other high-tech exports (aero, biotechnology, etc.) only has a minimal share.

Xing (2011) argued that recognizing China as the high-tech trade global leader is misleading and is in fact a myth as 75% of high-tech exports fall under computer and communication technology and 82% are assembled with imported parts and components that are from other country origins not identified, affirming that the current trade statistics for China's high-tech exports are greatly exaggerated.

According to Fayaz & Bhatia (2018), India needs to escalate its investment in R&D to increase its exports' technological intensity as economic growth heavily relies on R&D investments. Meanwhile, Kilavus & Topcu's (2012)'s study on exports in developing countries including India applying OLS and PSCE estimation, resulted in the high-tech manufacturing industry and investments being significantly related to growth performance. Malik & Velan (2020) investigated the dynamics of software exports, IT investments, and GDP in India, as a result, the indicated variables presented a long-run equilibrium relationship with each other, and the paper implied R&D investments' expansion to have a competitive edge in the global market. Rahman, et al., (2019) claimed R&D activities and patent applications show an insignificant effect on economic growth, instead, these R&D involvements are utilized through commercialization. Moreover, Gani (2009) stated that the strength of the positive influence of high-tech export values on GDP decreases when a country's technological performance index declines. Lower-middle income countries such as India need to seek foreign investment support through FDIs to help the country improve technological activities, alongside utilizing skilled workers.

2.3 Labor productivity and its Impact on Economic Growth

Artificial intelligence can increase the productivity of some workers, but it can also replace employed people and will transform almost all occupations to some degree. Although, Singapore was known to attract labor-intensive industries in which focus on the provision of education for its population that will help them learn skills to them employable in various industries (Shaimerdenova & Zamor, 2017). Capital productivity helps increase the quality of labor through the continuous improvements of different machinery and equipment (Korkmaz, 2017). According to Maitra (2016), human capital investment and employment greatly contribute to increases in economic growth.

The government of Singapore prioritized and developed a vibrant education system and raised its level of science and technology to promote a vibrant knowledge-based economy. Maitra (2016) examined the role of human capital investment in promoting economic growth of developed and developing countries and it is found that in the variation of economic growth both the human capital investment and labor force have a significant causal effect.

Technical progress and advances in productivity play a vital role because it is the ultimate source of economic growth in Japan. According to Oh and Sim (2016), cross-country correlations show a connection among capital accumulation, economic growth, and the long-term employment relationship that is significant in the labor market. The researchers also used an endogenous growth model because the sectoral and aggregate productivities are endogenously determined by migration decisions, human capital accumulation, and technology investment. It was also established that inefficient allocation of labor productivity in Japan is one of the causes of the economic slowdown, thus efficiency and utilization and reallocation are, in fact, major contributors to economic growth (Nakamura et al., 2019).

China is dependent on technological advancements and innovations, and it is no wonder that its economy is growing quickly and steadily. Although, education, engagement in technological advancements, and optimal utilization and allocation of the factors of production which are labor and capital productivity offer great potential for high-speed growth (Chang-wen et al., 2016). Investments, the level of GDP per capita, and population growth are the factors most significant to economic growth in China, shown in the Solow Model. They find that capital accumulation is most important to growth along with structural change and a slower population growth rate (Assbring, 2012).

Understanding the drivers of economic growth is beneficial for low-income countries like India (Panagariya et al., 2014). According to the 2013 World Development Report: there are essentially four main forces that contribute to the increase in an economy's per capita GDP: the capital per unit of labor, fertility decline, technological progress, and increase in labor productivity. Meanwhile, the manufacturing sector is considered as one of the major sources of growth because it offers a large scope of capital accumulation and economics of scale and embodied and disembodied technological progress, which all of them are directly related to productivity growth regardless of geographic location and country (Aggarwal, 2018).

The ICT revolution has increased global trade in services and the process of globalization has driven the expansion of trade in services. Arguments have been raised that manufacturing may not be driving enough growth but the shifting of labor towards IT-enabled services can also encourage productivity and economic growth. The most dynamic sector of the Indian economy is the emergence of services (Panagariya et al., 2014). According to Ronit & Divya (2014), exports in India comprise a minor part of the GDP. Thus, it does not affect its economy’s growth because of the country’s large domestic market; instead, India’s growth in GDP increases its export sector’s growth, since international market demand for India is affected by its domestic industries’ demand growth.

2.4 Unemployment on Economic Growth

As the world advances, workers move between employment, unemployment, and not-in-the labor force, and worker movements, which determine aggregate labor market indicators such as unemployment, employment, and labor participation rates (Kakinaka & Miyamoto, 2011). According to Todaro & Smith (2012), the investment in human resources can improve the quality of the living standard of a country and could have a more positive effect on GDP.

Okun (1962) discussed the relationship between economic growth and unemployment rate; and according to Okun’s law, to achieve a decline of one percent (1%) in the unemployment rate, then real GDP must grow approximately 2%. If the unemployment rate decreases by 1%, then GNP will increase to 3% (Misini, 2017). Chand et al., (2017) identified that the unemployment rate is negatively related to economic growth. Endogenous growth allows unemployment to reduce its long-run productivity growth (Liu & Peters, 2012). Singapore has made its city-state shift to a more advanced and developing country status by the beginning of the last decade, but since 1997, the number of unemployed has consistently outnumbered job vacancies available, and this gap had widened over the years (Tat & Toh, 2014). High unemployment causes economic activity to decline as public income decreases (Ștefănescu-Mihăilă, 2015). According to Hui (2013), even increasing the minimum wage has a low bargaining power to workers, hence it does not help with unemployment.

Japan has achieved phenomenal economic development to become the first country to move from less developed to developed economy status in the post-WWII era (Zang & Baimbridge, 2012). Oh & Sim (2016) stated that rapid economic growth may tend to reduce unemployment or add fuel to unemployment. The existing literature on Japanese labor markets indicates that regional disparities in unemployment rates have decreased over time (Kondo, 2015). Moreover, Kyo (2018) also stated that there is indeed a negative correlation between the components of economic growth and unemployment.

In China, the high and sustained GDP growth rate of around 10% over the past 30 years is accompanied by increasing unemployment rates and decreasing labor force participation rates. (Liu, 2012). The rapid growth and economic development in China were paradoxically brought by the increasing unemployment rate which equates to a dramatic decrease in the labor force (Liu, 2012). Economic growth is essential in understanding its relationship with unemployment, which is an important macroeconomic indicator that reflects the lapses of an economy to fully utilize its human resources (Karikari-Apau & Abeti, 2019). The unemployment rate’s insignificance to economic growth in China and other countries has been studied by Daly and Hobijn (2010), deducing that the Okun’s Law might not be applicable to countries including China, given that there is an unusual rise in unemployment, labor productivity remained to be surging because of the efficient hours per worked in the labor force. On the other hand, Lal (2010) also concluded that the Okun’s Law claim does not support countries that are highly developing such as China, since its government is constantly solving its unemployment issues and because of political stability and good governance.

Moreover, unemployment in India has been a consistent issue for years. Full-time job opportunities are decreasing day by day due to part-time and casual work (Chand, et al., 2017). Although the Indian economy is the third-largest economy in the world, the unemployment rate is very high and it also differs every year due to its large labor force caused by the young working population of the country (Kumar & Murali, 2017). Despite the growth of GDP, jobless growth becomes more integral based on the findings of the periodic labor force survey of 2017-18, proving the fact that GDP growth is not an automatic transformation process for employment in the economy (Paruchuru et al., 2020). One of the main causes of jobless growth in India over the years is prevailing job losses, which according to Madhavan (2018), have risen between 2016 to 2017 for as much as 1.5 million jobs lost. Moreover, rigid labor laws in India that lead to corporate houses being reluctant in employing people has also been an issue. Policy paralysis concerning labor reforms has failed to reap demographic dividends and engage foreign investors in funding entrepreneurs' manufacturing facilities expansion (Jha & Mohapatra, 2020).

2.5 Technological Unemployment brought by Artificial Intelligence

AI and automation's complexity enhances productivity made by human capital, and with this, arises the fear of technological unemployment as AI disrupts the labor market and possibly replaces laborers in the world that leaps to continuous modernization. Moreover, contrasting perspectives on AI versus the labor force, such as the Doomsayer's perspective, which predicts politics and economic disasters, emphasized that technology may obstruct employment, but it also helps augment the efficiency of human capital. Optimists and unifying perspectives claim technology may partly affect the labor market but not as a whole since AI may increase employment for specific skills that may be needed to automate the said technological change. Hence, it creates new latitudes through "creative destruction" (Frank et al., 2019).

2.6 Statement of Hypothesis

- H_0: High-technology exports have no significant effect on the country's Gross Domestic Product.
  H_1: High-technology exports have a significant effect on the country's Gross Domestic Product.
- H_0: An increase in GDP per person employed indirectly affects a country's Gross Domestic Product.
  H_1: An increase in GDP per person employed directly affects the country's Gross Domestic Product.
- H_0: The unemployment rate is inversely related to the country's Gross Domestic Product.
  H_1: The unemployment rate is directly related to the country's Gross Domestic Product.

2.7 Synthesis:

This research paper aimed to determine the relationship between economic growth and variables namely: high-technology exports, labor productivity, and unemployment. Technological progress has been pervasive for the past years, and it can be seen how it is most likely to be uncontrolled once it dominates economies without proper and improved government policies being imposed to adapt and contain the fast-growing innovation. As stated by Solow (1956), economic growth is driven by key inputs such as human capital, physical capital, and knowledge.

2.7.1 High-technology Exports on Economic Growth

The majority of these studies claim that high-tech exports are significantly related to economic growth, given that exports are one of the drivers of the Gross Domestic Product, and technology, according to various economic theories and models, increases growth over time (Suryanto, 2016). The literature used in this paper provided a broad inclusion of AI technologies deployed for the past years in the global economies. However, in a wider perspective, colluding the possible technological unemployment and labor to capital-intensive shift among industries, complications and gaps still exist because of the limited and intellectual areas that AI can be deployed into.

2.7.2 Labor Productivity on Economic Growth

By boosting productivity, it results in improved economic growth. Labor productivity is known as the value that each worker makes or creates according to per unit of his or her input. It has been proven that labor productivity is significantly related to economic growth. Although for some, technological advancements may disrupt labor productivity. Moreover, labor productivity also grows with an increase in technology which results in a positive correlation with economic growth (Korkmaz, 2017).

2.7.3 Unemployment on Economic Growth

A low unemployment rate is ideal for a country as it promotes productivity and production, which essentially increases GDP. In addition to the relationship between economic growth and unemployment, according to Atkinson (2019) in their study, several other studies find no evidence for job loss. Hence, an increase in technological innovation will not affect or increase unemployment in a country. The studies about unemployment and GDP were linear and had similar, accurate results. The authors, however, fell short on the studies regarding unemployment in Japan and Singapore and used the few resources available.

3. Research Method

3.1 Study Design

This paper is designed to study the economic impact of artificial intelligence on four countries in Asia namely China, India, Japan, and Singapore. These countries are four of the top Asian countries that have been consistently leading in AI Readiness for the past years. The authors examined how AI will affect the economy and some of the industries in these respective countries and learned what will be its economic implications to each country. This quantitative and time-series research study contains the positive and negative relationship between economic growth (in dollars) and the three independent variables: artificial intelligence, labor productivity, and unemployment. However, this study has used high-tech exports (in dollars), as a proxy of artificial intelligence. Labor productivity, on the other hand, uses GDP per hour (in dollars), and unemployment, measured by unemployment rate (in percentage).

3.2 Study Site

This paper estimated the relationship of artificial intelligence, labor productivity, and unemployment with economic growth and possibly examine if AI outweighs human capital or labor productivity. This is a cross-country study in which the selected Asian countries are specifically China, India, Japan, and Singapore. The following countries were deliberately chosen since these countries are reported to consistently be in the top countries in utilizing Artificial Intelligence rankings for the past years and are known to be technologically inclined, therefore, these are the countries with readily available data that could provide a proper estimation as to the effect of this paper's independent variables to the dependent variables, as well as to accurately compare the deployment of AI to the labor productivity and its effects to each country.

3.3 Data Collection Procedure

The authors gathered online data resources from a peer-reviewed scholarly literature platform which includes academic journals, research articles, and databases from statistical websites. The data for GDP and high-technology exports were gathered from The World Bank. The data for GDP per hour were gathered from Our Word In Data by the University of Oxford. The data for the unemployment rate were gathered from Index Mundi, Knoema, and Macrotrends. The period covers from 1988 up until 2019.

3.4 Data Analysis/Mode of Analysis

The authors used the regression analysis statistical method to measure and estimate the relationships and associations between the dependent and independent variables based on a theoretical or empirical concept. The authors followed the similar approach used by (Ustabas & Ersin, 2016) who analyzed the effects of R&D and high-tech exports on economic growth. The regression analysis method is the tool applied to measure the indicated variables and their relationship. The econometric model of this paper is hereby presented as:

$$\boldsymbol{logGDP_i = \beta_0 + \beta_1 HTE_i + \beta_2 GDPperHour_i + \beta_3 UE_i + \varepsilon}$$

Wherein $i = 1, 2, 3, 4$

Moreover, *1* represents **China**, *2* represents **India**, *3* represents **Japan**, and *4* represents **Singapore**.

The log indicates the growth rate of GDP, and the response variable $\boldsymbol{Y}$ denotes the GDP, which is the measurement used for economic growth. Moreover, $\boldsymbol{\beta_0}$ represents the intercept, which refers to the value of Y (GDP) is when X is equal to 0. $\boldsymbol{\beta_1 HTE}$ stands for the regression coefficient or the slope (parameter) which in this case is the value of artificial intelligence technology measured by high-technology exports, $\boldsymbol{\beta_2 GDPperHour}$ denotes the labor productivity measured by the GDP per hour, and $\boldsymbol{\beta_3 UE}$ is the unemployment measured by the unemployment rate. These regression coefficients refer to the change in variable Y when variable X changes in one unit. Lastly, $\boldsymbol{\varepsilon}$ on the other hand signifies the error term.

This regression analysis statistical technique is used to analyze a wide variety of gathered data to estimate the relationship and the direction that a dependent variable will change as a result of a change in the independent variables (Barnes, 1998). This method helps measure the degree of dependence of the variables to each other and how the independent variables impact the topic of interest which is the dependent variable; it also produces a regression equation that represents the relationships of the variables (Allen, 1997).

3.5 Regression Diagnostics

An ordinary least squares regression (OLS) is a statistical model that estimates the relationship of explanatory variables and outcome variables by minimizing the sum of square errors, wherein an error is the distinction between actual and predicted outcome variable values.

There are various tests in examining the assumptions of linear regression, which consist of the *stationarity testing* that states that the value of the variable does not change with time, used test in economics Augmented Dickey-Fuller (ADF) test which is the unit root test for stationarity. However, it is known that the results from the traditional unit root test might be altered if the evaluated time series have structural breaks. Further, *cointegration tests* identify if the presence of correlation between many time series in the long term, and with that, the usage of the Johansen cointegration test to investigate the effects of the independent variables on the dependent variables in the long run.

In addition to this, structural breaks affect the cointegration test results, and the estimated models could also be subject to biased parameter estimates. Therefore, parameter instability testing upon the estimation of the models is necessary. The *stability test* is used to know regression coefficients' stability between two periods, implying that a change in the parameter indicates structural change. Chow test is used in the regression analysis (Ustabas & Ersin, 2016).

Moreover, *multicollinearity* is known as the correlation between two independent variables, it is detected by the Variance Inflation Factor which estimates how much the variance of a coefficient is multicollinearity inflated. Furthermore, heteroskedasticity occurs when the standard errors of variables are non-constant. To *test for heteroskedasticity*, the Breusch-Pagan test is used to test if the variance of errors in regression is dependent on the independent variables' values. *Durbin-Watson autocorrelation* test measures the correlation in the residuals from a regression analysis. On the other hand, the Breusch-Godfrey test is used to test *serial correlation* to detect autocorrelation of a variable and its lagged version, hence it measures the relationship of past values to its current values.

Normality of residual refers to an assumption running in a linear model; if residuals are normally distributed or not. Lastly, *specification error tests* that use RESET tests, whether the model is misspecified in terms of the error of inclusion or omission of variables, functional forms, and structures. Ramsey Reset test identifies if a significant non-linear relationship exists in a regression model (Montgomery, 2012).

4. Results and Discussion

This paper estimated the impact of high-technology exports on the Gross Domestic Product in the selected Asian countries. Furthermore, the authors also determined how GDP per hour affects the Gross Domestic Product even in the presence of AI in the workplace. And lastly, this paper evaluated how the unemployment rate impacts Gross Domestic Product in possible relation to the deployment of AI that causes technological unemployment.

4.1 Results

4.1.1 China

Regression Equation for China:

$$\boldsymbol{logGDP_1 = \beta_0 + \beta_1 LOGHTE_1 + \beta_2 LOGGDPper\mathrm{Hour}_1 + \beta_3 UE_1 + e}$$

Diagnostic Tests	**Results**	**Interpretation**
ADF Unit Root Test	All p-values < 0.05	No presence of unit root
VIF Multicollinearity Test	All values < 5	No presence of multicollinearity
Durbin Watson	Value is near 2	No presence of autocorrelation
Ramsey RESET Test	P-value > 0.05	No presence of misspecification
Breusch-Godfrey Serial Correlation Test	Due to the Cochrane-Orcutt procedure, no presence of autocorrelation was detected	
Normality of Residual	P-value > 0.05	Residuals are normally distributed
Breusch-Godfrey-Pagan Heteroskedasticity Test	P-value > 0.05	No presence of heteroskedasticity
Chow Breakpoint Test	P-value > 0.05	No breakpoint detected during 2004
Johansen Cointegration Test	One p-value < 0.05	One cointegrating equation

Table 2. Diagnostic Tests of China

Presented in *Table 2* the authors used the Augmented Dickey-Fuller test for determining stationarity. The time series of all the variables in China, namely gross domestic product, high-technology exports, GDP per hour, and unemployment rate are all stationary at their second differences, having probabilities that are less than 0.01. Therefore, we can reject the null hypothesis that all series have a unit root, concluding that the time series' statistical properties do not change over time. In China's case, the uncentered VIF for high technology exports, GDP per hour, and unemployment rate are 1.41, 5.24, and 1.29 which are all less than 10, therefore we reject the null hypothesis that there exists multicollinearity detected in the model. The Ramsay Reset test is used as a specification test for a regression model. The p-value for China's f-statistics is 73%, which means that we fail to reject the null hypothesis of correct specification at a 5% level of significance. Therefore, the functional form and model is proven to be correct, and it does not suffer from omitted variables. Meanwhile, we accept the null hypothesis for the normality of residual diagnostic that verifies that the residuals are normally distributed in this model, given that the p-value of the Jarque-Bera test is at 59% which is greater than the 5% significance level. In checking for heteroskedasticity in the model, the Breusch-Pagan Godfrey test was used, and it showed that the chi-square probability of the observed R-squared is 0.2710 (27%) which is greater than 0.05 (5%) level of significance, therefore we accept the null hypothesis that there is no heteroskedasticity in the model and the variance of the residual term is constant. The chow breakpoint test was used to determine if the coefficients are different for split data sets. In China's case, at the breakpoint year for 2004, the p-value of the f-statistic is 16%. Accordingly, we accept the null hypothesis stating that there is no breakpoint detected in the model at a 5% level of significance. Furthermore, the cointegration test result using the Johansen test indicated that there is one cointegrating equation(s) with a p-value of 0.0003 at 0.05 level.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.025531	0.006363	4.012472	0.0005
DLOGHTE	0.012994	0.008805	1.475832	0.1525
DLOGLP	0.770643	0.073419	10.49656	0.0000
DC_UE	0.489118	0.621594	0.786877	0.4388
AR(1)	0.672775	0.198424	3.390586	0.0023
SIGMASQ	3.54E-05	1.32E-05	2.683815	0.0127
R-squared	0.937297	Mean dependent var		0.087503
Adjusted R-squared	0.924757	S.D. dependent var		0.024138
S.E. of regression	0.006621	Akaike info criterion		-7.005649
Sum squared resid	0.001096	Schwarz criterion		-6.728103
Log likelihood	114.5876	Hannan-Quinn criter.		-6.915176
F-statistic	74.74143	Durbin-Watson stat		1.924148
Prob(F-statistic)	0.000000			
Inverted AR Roots	.67			

Table 3. Regression Results of China

The regression results for China in *Table 3,* as variables were all first differenced, showed that high-technology exports (DLOGHTE) with a p-value of 0.1525 has an insignificant relationship to economic growth at a level of significance. Whereas labor productivity, measured by GDP per hour (DLOGLP) with a p-value of 0.00 is a significant determinant of economic growth at a 1% level of significance, indicating that a 1% increase in GDP per hour leads to a 0.7706 increase in GDP. The unemployment rate (DC_UE) is also shown to have an insignificant relationship with economic growth, with a p-value of 0.4388 at a level of significance. The model was proven significant at a 10% significance level with its zero (0) F-statistic value.

4.1.2 India

Regression Equation for India:

$$logGDP_2 = \beta_0 + \beta_1 LOGHTE_2 + \beta_2 LOGGDPperHour_2 + \beta_3 UE_2 + \varepsilon$$

Diagnostic Tests	Results	Interpretation
ADF Unit Root Test	All p-values < 0.05	No presence of unit root
VIF Multicollinearity Test	All values < 5	No presence of multicollinearity
Durbin Watson	Value is near 2	No presence of autocorrelation
Ramsey RESET Test	P-value > 0.05	No presence of misspecification
Breusch-Godfrey Serial Correlation Test	P-value > 0.05	No presence of serial correlation
Normality of Residual	P-value > 0.05	Residuals are normally distributed
Breusch-Godfrey-Pagan Heteroskedasticity Test	P-value > 0.05	No presence of heteroskedasticity
Chow Breakpoint Test	P-value > 0.05	No breakpoint detected during 2005

Johansen Cointegration Test	Two p-values < 0.05	Two cointegrating equation

Table 4. Diagnostic Tests of India

Table 4 showed the ADF test for stationarity in India's data made evident that the time series of all the variables: gross domestic product, high-technology exports, GDP per hour, and unemployment rate are all stationary at their second differences, having probabilities that are less than 0.01. We conclude that the null hypothesis that all series have unit root is rejected. Variation Inflation Factors were used to detect severe multicollinearity in the model containing Singapore's data. The uncentered VIF for high technology exports is 1.98 GDP per hour is 6.94, and the unemployment rate is 3.09, which is all less than 10. Therefore, we reject the null hypothesis that there exists multicollinearity detected in the model. In testing for misspecification in the regression model of India using Ramsay Reset, presented that the p-value off-statistics is 95%, which means that we fail to reject the null hypothesis of correct specification at a 5% level of significance. Therefore, the functional form and model are proven to be correct. Breusch-Godfrey test was used to determine any existing correlation in the model. The p-value of the F-statistic is 83%, which gives evidence that there exists no serial correlation in the residuals of the mean equation. The residuals for India's model are proven to be normally distributed since the p-value of the Jarque-Bera test is at 54% which is greater than the 5% significance level. The Breusch-Pagan Godfrey test was used in checking for heteroskedasticity in the model, and the results showed that the chi-square probability of the observed R-squared is 0.5053 (51%) which is greater than the 5% level of significance, therefore we accept the null hypothesis that there is no heteroskedasticity in the model and the variance of the residual term is constant. In India, at the breakpoint year of 2005, the p-value of the f-statistic is 45%, which means we reject the null hypothesis stating that there is no breakpoint detected in the model at a 5% level of significance and that there is a detected structural break at the specified breakpoint in India's data. The Cointegration test result using the Johansen test indicated that there are two cointegrating equations with 0.0121 and 0.0245 p-values at 0.05 level.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.034903	0.004149	8.412789	0.0000
DLOGHTE	-0.003528	0.010641	-0.331556	0.7431
DLOGLP	0.537486	0.068962	7.793956	0.0000
DI_UE	5.790782	2.625526	2.205570	0.0372

R-squared	0.459243	Mean dependent var	0.062368
Adjusted R-squared	0.391648	S.D. dependent var	0.015943
S.E. of regression	0.012435	Akaike info criterion	-5.805085
Sum squared resid	0.003711	Schwarz criterion	-5.614770
Log likelihood	85.27119	Hannan-Quinn criter.	-5.746904
F-statistic	6.794076	Durbin-Watson stat	1.957691
Prob(F-statistic)	0.001782	Wald F-statistic	24.39453
Prob(Wald F-statistic)	0.000000		

Table 5. Regression Results of India

As presented in *Table 5*, the regression results for India, as variables were all first differenced, showed that high-technology exports (DLOGHTE) with a p-value of 0.7431 does not affect the country's economic growth at a 10% level of significance. Meanwhile, labor productivity which is measured by GDP per hour (DLOGLP) with a p-value of 0.00 is a significant determinant of economic growth at a 1% level of significance, indicating that a 1% increase in GDP per hour leads to a 0.5375 increase in GDP. The unemployment rate (DI_UE) is shown to have a positive relationship with economic growth, with a p-value of 0.0372 at a 5% level of significance, wherein for every 1% increase in the country's unemployment rate, GDP still increases at 5.7908. The model was proven significant at a 10% significance level with its zero (0) F-statistic value.

4.1.3. Japan

Regression Equation for Japan:

$$\boldsymbol{logGDP_3 = \beta_0 + \beta_1 HTE_3 + \beta_2 GDPperHour_3 + \beta_3 UE_3 + \varepsilon}$$

Diagnostic Tests	**Results**	**Interpretation**
ADF Unit Root Test	All p-values < 0.05	No presence of unit root

VIF Multicollinearity Test	All values < 5	No presence of multicollinearity
Durbin Watson	Value is near 2	No presence of autocorrelation
Ramsey RESET Test	P-value > 0.05	No presence of misspecification
Breusch-Godfrey Serial Correlation Test	P-value > 0.05	No presence of serial correlation
Normality of Residual	P-value > 0.05	Residuals are normally distributed
Breusch-Godfrey-Pagan Heteroskedasticity Test	P-value > 0.05	No presence of heteroskedasticity
Chow Breakpoint Test	P-value > 0.05	No breakpoint detected during 2004
Johansen Cointegration Test	Two p-values < 0.05	Two cointegrating equations

Table 6. Diagnostic Tests of Japan

The authors used the Augmented Dickey-Fuller test for determining stationarity as presented in *Table 6*. The time series of all the variables in Japan namely gross domestic product, high-technology exports, GDP per hour, and unemployment rate are all stationary at their second differences, having probabilities that are less than 0.01. Therefore, we can reject the null hypothesis that all series have a unit root, concluding that the time series' statistical properties do not change over time. The uncentered VIF for high technology exports, GDP per hour, and unemployment rate are 1.18, 2.79, and 1.11 which are all less than 10, therefore we reject the null hypothesis that there exists multicollinearity detected in the model. The Ramsay Reset test is used as a specification test for a regression model. The p-value for Japan's f-statistics is 39%, which means that we fail to reject the null hypothesis of correct specification at a 5% level of significance. Therefore, the functional form and model is proven to be correct, and it does not suffer from omitted variables. We accept the null hypothesis for the serial correlation LM test up to 2 lags since f-statistics is at 41%. On the other hand, we accept the null hypothesis for the normality of residual diagnostic that verifies that the residuals are normally distributed in this model, given that the p-value of the Jarque-Bera test is at 67% which is greater than the 5% significance level. In checking for heteroskedasticity in the model, the Breusch-Pagan Godfrey test was used, and the results showed that the chi-square probability of the observed R-squared is 0.5643 (56%) which is greater than the 0.05 (5%) level of significance, therefore we accept the null hypothesis that there is no heteroskedasticity in the model and the variance of the residual term is constant. The chow breakpoint test was used to determine if the coefficients are different for split data sets. In Japan's case, at the breakpoint year or 2004, the p-value of the f-statistic is 10%. Accordingly, we accept the null hypothesis stating that there is no breakpoint detected in the model at a 5% level of significance. Furthermore, the cointegration test result using the Johansen test indicated that there are two cointegrating equations with 0.0074 and 0.0332 p-values at 0.05 level.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.005232	0.002309	-2.266159	0.0317
DJ_HTE	2.84E-13	1.26E-13	2.248079	0.0329
DJ_LP	0.027856	0.003088	9.022128	0.0000
DJ_UE	-1.800530	0.401884	-4.480221	0.0001
R-squared	0.854354	Mean dependent var		0.011916
Adjusted R-squared	0.838171	S.D. dependent var		0.019821
S.E. of regression	0.007974	Akaike info criterion		-6.705457
Sum squared resid	0.001717	Schwarz criterion		-6.520426
Log likelihood	107.9346	Hannan-Quinn criter.		-6.645141
F-statistic	52.79360	Durbin-Watson stat		1.590237
Prob(F-statistic)	0.000000			

Table 7. Regression Results of Japan

Table 7 presented the regression results for Japan, as variables were all first differenced, it showed that high-technology exports (DJ_HTE) with a p-value of 0.03 has a significant relationship to economic growth at a 5% level of significance. The estimation suggests that a 1% increase in high-technology exports leads to a 2.84E-13 percent increase in Japan's GDP. Whereas labor productivity, measured by GDP per hour (DJ_LP) with a p-value of 0.00 is also a significant determinant of economic growth at a 1% level of significance, indicating that a 1% increase in GDP per hour leads to a 0.0278 increase in GDP. The unemployment rate (DJ_UE) is shown to have an indirect relationship with economic growth, with a p-value of 0.0001 at a 1% level of significance, wherein for every 1% increase in the country's unemployment rate, GDP decreases at -1.8005. The model was proven significant at a 10% significance level with its zero (0) F-statistic value.

4.1.4 Singapore

Regression Equation for Singapore:

$$logGDP_4 = \beta_0 + \beta_1 HTE_4 + \beta_2 GDPperHour_4 + \beta_3 UE_4 + \varepsilon$$

Diagnostic Tests	**Results**	**Interpretation**
ADF Unit Root Test	All p-values < 0.05	No presence of unit root
VIF Multicollinearity Test	All values < 5	No presence of multicollinearity
Durbin Watson	Value is near 2	No presence of autocorrelation
Ramsey RESET Test	P-value > 0.05	No presence of misspecification
Breusch-Godfrey Serial Correlation Test	Due to the Cochrane-Orcutt procedure, no presence of autocorrelation was detected	
Normality of Residual	P-value > 0.05	Residuals are normally distributed
Breusch-Godfrey-Pagan Heteroskedasticity Test	P-value > 0.05	No presence of heteroskedasticity
Chow Breakpoint Test	P-value < 0.05	Breakpoint detected during 2004
Johansen Cointegration Test	One p-value < 0.05	One cointegrating equation

Table 8. Diagnostic Tests of Singapore

Depicted in *Table 8* is the ADF test for stationarity, and the time series of all the variables in Japan namely gross domestic product, high-technology exports, GDP per hour, and unemployment rate are all stationary at their second differences, having probabilities that are less than 0.01. Therefore, we conclude that the null hypothesis that all series have unit root is rejected. The uncentered VIF for high technology exports is 2.06, GDP per hour is 2.45, and the unemployment rate is 1.18, which are all less than 10, therefore we reject the null hypothesis that there exists multicollinearity detected in the model. In testing for misspecification in the Singapore regression model using Ramsay Reset, it presents that the p-value of f-statistics is 91%, which means that we fail to reject the null hypothesis of correct specification at a 5% level of significance. Therefore, the functional form and model is proven to be correct, and it does not suffer from omitted variables. The residuals for Singapore's model are proven to be normally distributed since the p-value of the Jarque-Bera test is at 63% which is greater than the 5% significance level. Hence, we accept the null hypothesis for the normality of residual diagnosis. The Breusch-Pagan Godfrey test was used in checking for heteroskedasticity in the model, and the results showed that the chi-square probability of the observed R-squared is 0.3748 (37%) which is greater than the 5% level of significance, therefore we accept the null hypothesis that there is no heteroskedasticity in the model and the variance of the residual term is constant. In Singapore, at the breakpoint year of 2004, the p-value of the f- statistic is 2%, which means we reject the null hypothesis stating that there is no breakpoint detected in the model at 5% level of significance and that there is a detected structural break at the specified breakpoint in Singapore’s data. The Cointegration test result using the Johansen test indicated that there are three cointegrating equations at 0.05 level with p-values of 0.000, 0.0018, and 0.0202.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.043071	0.008660	4.973766	0.0000
DS_HTE	1.59E-13	1.99E-13	0.799207	0.4317
DS_LP	0.011742	0.002307	5.090830	0.0000
DS_UE	-3.591918	0.846761	-4.241949	0.0003
AR(1)	0.580077	0.166052	3.493350	0.0018
SIGMASQ	0.000288	0.000104	2.768136	0.0105

R-squared	0.775433	Mean dependent var	0.057565
Adjusted R-squared	0.730520	S.D. dependent var	0.036412
S.E. of regression	0.018902	Akaike info criterion	-4.913888
Sum squared resid	0.008932	Schwarz criterion	-4.636342
Log likelihood	82.16526	Hannan-Quinn criter.	-4.823415
F-statistic	17.26511	Durbin-Watson stat	2.260891
Prob(F-statistic)	0.000000		

Table 9. Regression Results of Singapore

Presented in *Table 9*, the regression results for Singapore, as variables were all first differenced as well, showed that high-technology exports (DS_HTE) having a 0.43 p-value assumes that high-technology exports do not affect economic growth with a given confidence level. In contrast, labor productivity, measured by GDP per hour (DS_LP) with a p-value of 0.00 is proved to have a significant relationship of economic growth at a 1% level of significance, which indicates that a 1% increase in GDP per hour leads to a 0.0117 increase in Singapore's GDP. The unemployment rate (DS_UE) is shown to have a negative impact on economic growth, with a p-value of 0.0003 at a 1% level of significance, stating that for every 1% increase in the country's unemployment rate, GDP falls at roughly -3.5919. The model was proved to be significant and correct at a 10% significance level with its zero (0) F-statistic value.

4.2 Discussions

4.2.1 China

4.2.1.1 High-technology exports and economic growth

Findings from Sultanuzzman, et al., (2019), Zhou & Luo (2018), and Sun & Heshmati (2012) which argued that high-tech exports positively impact economic growth in China go against the authors' findings which states that GDP and high-tech exports in China have an insignificant relationship. Xing (2011) argued that recognizing China as the high-tech trade global leader is misleading and is in fact a myth as 75% of high-tech exports fall under computer and communication technology and 82% are assembled with imported parts and components that are from other country origins not identified, affirming that the current trade statistics for China's high-tech exports are greatly exaggerated. To accurately measure China's high-tech trade position, the value-added approach should be utilized, as well as the detailed country distribution of value chains. He also pointed out that assembling the imported parts and components into finished products does only need low-skill labor, thus the question about considering assembling high-tech product parts as advanced technology and automation remain. The inconsistency of the trade statistics based on global supply chains is alarming, especially as it inflates the export value due to incorrectly crediting entire values of assembled high-tech products to China, hence the significance of high-technology exports of China in its GDP may be fictitious.

4.2.1.2 Labor productivity and economic growth

Results also show that economic growth and labor productivity are positively related in China. Given the fact that China is an economy that witnesses fast economic growth and rapid transformation in the economic structure and is an example of a developed country that has a strong economy, education, engagement in technological advancements and innovations, and optimal utilization and allocation of the production factors such as labor and capital productivity offer great potential for further development and high-speed growth (Chang-wen et al., 2016).

According to Assbring (2012), investments, the level of GDP per capita, and population growth are the factors most significant to economic growth in China which are shown by using the Solow Model. The result shows that the model augmented with both human capital and structural change best explains economic growth in China. They find that capital accumulation is most important to growth along with structural change and a slower population growth rate.

4.2.1.3 Unemployment and economic growth

The unemployment rate's insignificance to economic growth in China and other countries has been studied by Daly and Hobijn (2010) of the Federal Reserve Bank of San Francisco, deducing that the Okun's Law might not be applicable to countries including China, given that there is an unusual rise in unemployment, labor productivity remained to be surging because of the efficient hours per worked in the labor force. On the other hand, Lal (2010) also concluded that the Okun's Law claim does not support countries that are highly developing such as China, since its government is constantly solving its unemployment issues and because there is political stability and good governance in terms of maintaining its country's growth. The rapid growth and economic development in China were paradoxically brought by the increasing unemployment rate which equates to a dramatic decrease in the labor force (Liu, 2012). Another reason behind the positive but statistically insignificant relationship between the unemployment rate and GDP is because of China's reputation globally, making foreign investors interested in investing in the country that further uplifts its economic growth. Thus, Karikari-Apau & Abeti (2019), argued about the significance and indirect relationship between GDP and unemployment rate in China do not conform to the regression analysis findings in this paper.

4.2.2 India

4.2.2.1 High-technology exports and economic growth

Rahman, et al., (2019) claimed R&D activities and patent applications show an insignificant effect on economic growth, instead, these R&D involvements are utilized through commercialization. Moreover, Gani (2009) stated that the strength of the positive influence of high-tech export values on GDP decreases when a country's technological performance index declines. Lower-middle

income countries such as India need to seek foreign investment support through FDIs to help the country improve technological activities, alongside utilizing skilled workers.
According to Ronit and Divya (2014), exports in India comprises a minor part of the GDP, thus it does not affect its economy's growth because of the country's large domestic market, instead, India's growth in GDP increases its export sector's growth, since international market demand for India is affected by its domestic industries' demand growth.

In conclusion, the results of the regression findings in this paper are in opposition to studies by Fayaz & Bhatia (2018) and Kilavuz & Topcu (2012) claiming that R&D investments provide an impact to grow technological intensity and growth performance in India. The results also disagree with Malik & Velan (2020) who deduced that R&D investments give a competitive edge to the country and thus technological advancements have a long-run relationship with economic growth.

4.2.2.2 Labor productivity and economic growth

According to the findings, there is a positive relationship between economic growth and labor productivity in India. According to the 2013 World Development Report: there are essentially four main forces that contribute to the increase in an economy's per capita GDP. These are capital per unit of labor, fertility decline, technological progress, and increase in labor productivity. Meanwhile, the manufacturing sector is considered as one of the major sources of growth because it offers a large scope of capital accumulation and economics of scale and embodied and disembodied technological progress, which all of them are directly related to productivity growth regardless of geographic location and country (Aggarwal, 2018).

In a developing economy, labor productivity in primary sectors is relatively much lower than in non-primary sectors like manufacturing industries. However, the nature of manufacturing and services has altered when the breakthrough of globalization and information and communication technology (ICT) services have entered. The ICT revolution has fueled up global trade in services and the process of globalization has driven the expansion of trade in services. Arguments have been raised that manufacturing may not be driving enough growth but rather shifting of labor towards IT-enabled services can also encourage productivity and economic growth. The most dynamic sector of the Indian economy is the emergence of services (Panagariya et al., 2014).

4.2.2.3 Unemployment and economic growth

According to the regression analysis findings, India's unemployment rate has a positive relationship to economic growth. One of the main causes of jobless growth in India over the years is prevailing job losses, which according to Madhavan (2018), have risen between 2016 to 2017 for as many as 1.5 million jobs in the BFSI, IT, and Telecom sectors due to consolidation. Another factor is the excess in capital and labor which in turn are invested in automation and robots that serve as labor substitutes, which justifies the direct relationship between India's GDP and unemployment rate. One case would be in Suzuki Motors India Ltd.., where 5000 robots were used in its Manesar and Gurugram plants. Rigid labor laws in India that lead to corporate houses being reluctant in employing people have also been an issue. Policy paralysis concerning labor reforms has failed to reap demographic dividends and engage foreign investors in funding entrepreneurs' manufacturing facilities expansion (Jha & Mohapatra, 2020).

Over the years, as technology took part in driving India's economy, there is also job-deficient growth, rising farm distress, and youths concerned for job reservations in the public sector. Overall job scenario might be caused by artificial intelligence (AI) displacing human labor in the services sector, making labor demand for predictable jobs shrink, and one way to cope is to upskill to improve job prospects.

This concludes that the literature findings based on Chand, et al., (2017) and Kumar & Murali (2017) stating that India's unemployment rate and GDP has a strong negative correlation with each other and claiming that unemployment impacts India's growth and development do not conform with the authors' findings in this paper.

4.2.3 Japan

4.2.3.1 High-technology exports and economic growth

In Japan's case, the findings of this paper are positively aligned with the study of Nakamura et al., (2019), implying the positive and significant relationship of Japan's economic growth and high-tech exports as innovative technology deployed is believed to be what drives the economy to grow, hence R&D efficiency of Japan is another factor to be improved to sustain the economy. Studies from Haseeb et al., (2019) and Lu et al., (2018) also conform with this paper's findings as they have deduced that there is a positive relationship between the emerging Artificial Intelligence in Japan and its economic growth throughout the years.

4.2.3.2 Labor productivity and economic growth

Similar to the findings from China and India, Japan's labor productivity implicitly has a significant relationship with its economic growth and is considered as one of the main drivers of Japan's economy. As stated by Oh & Sim (2016), technical progress and advances in productivity play a vital role because it is the ultimate source of economic growth in Japan, showing the connection between capital accumulation, economic growth, and the long-term employment relationship that is significant in the labor market. Nakamura et al., (2019) also established that inefficient allocation of labor productivity in Japan is one of the causes of the economic slowdown, thus efficiency and utilization, and reallocation are in fact major contributors to economic growth.

4.2.3.3 Unemployment and economic growth

The findings of this paper concerning the relationship of the unemployment rate of Japan to the economic growth conform to the Okun's Law discussed by Okun (1962) in which he emphasized the negative relationship between unemployment and GDP. For every 1% increase in Japan's unemployment rate, its GDP decreases by 1.8 which is close to 2%, hence the validity of Okun's Law in Japan is still transparent. Moreover, Kyo (2018) also stated that there is indeed a negative correlation between the components of economic growth and unemployment.

4.2.4 Singapore

4.2.4.1 High-technology exports and economic growth

It was found that R&D investment in Singapore has a weak and insignificant impact on the economic growth according to its lower estimated elasticity values, and because of the recent phenomenon concerning Singapore's lower level of R&D capital investment as compared to the other OECD nations, which opposes the claims by Kabarkli, et al., (2018) who observed the statistical significance between GDP and high-tech exports OECD countries in Singapore. Other opposing claims from Litsareva (2017) and Afzal & Lawrey (2014) stated that high-technology exports became a strong driver for competition and innovation, and R&D expenditures that account for a developed knowledge economy in Singapore. On the other hand, Ho, et al., (2010) acknowledging GDP's insignificance with high-tech exports, believed that aside from increasing their R&D investment, efficient exploitation of domestic R&D in the country must also be prioritized as it will help the country cope with the technological advances needed to boost the economy using R&D.

4.2.4.2 Labor productivity and economic growth

Results show that productivity has a significant and positive relationship with economic growth in Singapore. Over the last three decades, investment in human capital and employment contributed to economic growth in Singapore. It is found that both human capital investment and labor force have significant and positive effects on the variation of economic growth (Maitra, 2016). According to Shaimerdova & Zamor (2017), Singapore attracted labor-intensive industries to which they focused on providing education for the population that equips them with fundamental and basic skills to be qualified in attending to the labor market. The direction and nature of the significant causal effect of the investment in human capital and labor force participation in the economic growth of Singapore have been established and it appears that budgetary allocation for human capital formation is effectively utilized which contributes to economic growth (Maitra, 2016).

4.2.4.3 Unemployment and economic growth

According to (Chand et al, 2017), the unemployment rate is negatively related to economic growth in Singapore, which is aligned to the regression results of this paper. Singapore has made its city-state shift to a more advanced developing country status by the beginning of the last decade, but since 1997, the number of unemployed has consistently outnumbered job vacancies available, and this gap had widened over the years and affected the economic growth (Tat & Toh, 2014). With this, high unemployment causes economic activity to decline as public income decreases (Ștefănescu-Mihăilă, 2015). And according to Hui (2013), even increasing the minimum wage has a low bargaining power for workers, hence does not help with unemployment, and does not further improve economic growth because of lack of workers.

5. Conclusion and Policy Implications

5.1 Conclusion

This research paper empirically estimated and examined how artificial intelligence, labor productivity, and unemployment impacts economic growth and determines if technological unemployment has been prevalent in the tech-intensive economies of the selected Asian countries.

The data used in this research paper were high-technology exports as a proxy variable for AI, GDP per hour to measure labor productivity, and the unemployment rate to measure unemployment. The dependent variable used is a gross domestic product as a variable of economic growth. The authors used multiple regression analysis to determine the relationship of each independent variable to the dependent variables for each country.

5.1.1 China

Results revealed that in China, high-technology exports and unemployment rate are insignificant to the GDP. Meanwhile, GDP per hour positively impacts China's GDP. The insignificance of high-tech exports may be due to the inconsistency of the trade statistics based on global supply chains as it inflates export value due to incorrectly crediting entire values of assembled high-tech products imported to China from other countries, hence the significance of high-technology exports of China to its GDP is factitious. On the other hand, unemployment's insignificance can be explained by the claim that Okun's Law does not support countries that are highly developing such as China, since its government is constantly solving its unemployment issues and because there is political stability and good governance in terms of maintaining its country's growth and since China's reputation globally makes foreign investors interested in investing in the country that further uplifts its economic growth.

5.1.2 India

In India's case, high-technology exports show no significance to its GDP, however, GDP per hour positively impacts GDP, and the unemployment rate does impact GDP, but they exhibit a positive relationship. Exports in India comprises a minor part of the GDP, thus it can be drawn that it does not affect its economy's growth because of its large domestic market, instead, India's growth in GDP increases its export sector's growth, since international market demand for India is affected by its domestic industries' demand growth. Over the years, as technology took part in driving India's economy, there is also job-deficient growth, rising farm distress, and youths concerned for job reservations in the public sector, hence overall employment insignificance might be caused by artificial intelligence (AI) displacing human labor in the services sector, making labor demand for predictable jobs shrink.

5.1.3 Japan

On the other hand, findings from Japan's regression analysis indicated that high-technology exports, GDP per hour, and unemployment rate all have significance to Japan's GDP. High-tech exports and GDP per hour are revealed to have a positive impact, meanwhile, the unemployment rate and GDP are inversely related. The positive and significant relationship between Japan's economic growth and high-tech exports as innovative technology is deployed is believed to be what drives the economy to grow, helping improve its growth through the years.

Japan's economy holds a strong grasp in accelerating its artificial intelligence involvement and labor productivity, shaping a great balance in order to efficiently utilize both capital-intensive and labor-intensive production that prevents its economy from experiencing technological unemployment as compared to the other Asian countries examined. It is well-known that Japan is one of the largest and highly-developed economies globally, achieving high economic growth rates that are led by factors such as high standard of education, high rates of plant and equipment investment and R&D, proper labor governance, accessibility to technologies, a large domestic market, and trade liberalization. Automation and robotics in Japan are known to either displace or enhance human labor, thus it is important to secure benefits from AI to experience the latter. Aside from the productivity growth brought by AI, empirical evidence according to Acemoglu & Restrepo (2017), IMF staff calculations based on Japan's data found that increase in AI density in manufacturing is linked to local gains in employment and wages.

5.1.4 Singapore

Singapore's findings showed that high-technology exports do not affect GDP, and GDP per hour positively affects GDP, and unemployment rate and GDP have an indirect relationship. It was found that R&D investment in Singapore has a weak and insignificant impact on the economic growth according to its lower estimated elasticity values, and because of the recent phenomenon concerning Singapore's lower level of R&D capital investment as compared to the other OECD nations.

Furthermore, we accept the null hypothesis stating that their high-technology exports and unemployment rate is insignificant to the GDP in China. We, therefore, reject the null hypothesis that labor productivity is not related to China's GDP. In India, we accept the null hypothesis that high-tech exports are insignificant to the GDP, and we reject the null hypothesis of insignificance between GDP per hour, unemployment rate, and GDP. On the other hand, we reject all null hypotheses for Japan since all independent variables impact the GDP. Lastly, we accept the null hypothesis that Singapore's high-tech exports do not affect GDP and accept the alternative hypothesis that GDP per hour and unemployment rate are significant to GDP.

5.2 Policy Implications

The policy implications of this paper suggest that other economies being involved in artificial intelligence utilization should focus on developing high standards of an educational system that covers a wide range of skills aligned to the new job creation rooted in technology and leverage this transformation to further enhance people's livelihood and income, as the continuous shift towards technological change is inevitable. Focusing on one or few particular areas of study in terms of education, especially non-technology related degrees, may be one of the common practices even in the 21st century, but as AI progresses, workers will be challenged or forced to shift to jobs complimentary to the new technologies, especially for non-tech graduates and workers who might seek tech-job due to occupation shortage.

Japan's economic growth is driven by both technology and labor productivity, considering a balance between the two. Japan's technological advancement is in fact brought about by the youth of Japan since government spending on education takes up a substantial percentage of their GDP. Accordingly, as compared to other neighboring countries, education in Japan is more advanced and familiar with technology, which is one of the factors contributing to Japan's success in balancing employed people in tech and other industries and the country's artificial intelligence acceleration. Furthermore, a significant amount of education investment from the government will effectively mitigate technological unemployment as many high-technology and skilled jobs are being unfilled nowadays due to the lack of tech and advanced skills.

Aside from this, approaches similar to Japan's that can benefit other economies in terms of strengthening innovation and technology while diligently controlling its labor force is the creation of policies that allows and maximizes diffusion and adoption of foreign technologies by creating labor laws that will decrease unemployment rate and will help attain healthy inflation-adjusted compensation growth that will stimulate demand, and providing educational and infrastructural needs. Secondly, the practice of the private sector in adopting technology and being receptive to new advancements will help establish a strong and competitive foundation in AI expansion.

To escalate AI's contribution to growth, trade liberalization as exercised by Japan, can also be considered as this helps the economy to be open and flexible to various free trade agreements which facilitates technological progress and enables opening of new markets for growth and expansion especially of artificial intelligence, which attracts and encourage foreign direct investments that will cater technology transfer, creation of new jobs, and economic growth.

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