



Retracted Article: Artificial Intelligence and Economic Growth: A Theoretical Framework

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The Editor in Chief, after consulting members of the editorial board, has retracted the article:

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from publication because it contains material that overlaps in the mathematical model with the following article:

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The corresponding author has requested that this paper is retracted from publication.

We received, peer-reviewed, accepted, and published this article in good faith based on the warranties of the corresponding author with respect to originality, publishing ethics and integrity.

The retracted article will remain online to maintain the scholarly record, but it will be digitally watermarked on each page as “Retracted”.

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Artificial Intelligence and Economic Growth: A Theoretical Framework

Lei Wang^{*}, Provash Kumer Sarker^{**}, Kausar Alam^{***}, Shahneoj Sumon[§]

Abstract

The growing adoption of Artificial Intelligence (AI) has sparked ubiquitous concerns worldwide. Artificial intelligence can affect economic growth and employment. The influence is assumed to be substantial because the adoption of AI technology may lead to increased productivity, lower wages, prices, and labor substitution. Artificial intelligence can affect global economic growth with its widespread adoption and diffusion. We mathematically examined the effects of AI on economic growth, reiterating how AI is unique as a production factor. The models show that AI capital lowers capital prices, increases wages, and augments productivity. Besides, AI capital positively affects the labor share and vice versa, provided that AI and labor are complementary. We improved a task-based model to show AI raises both labor share and wages by generating new tasks. We also present the potential policy implications of AI adoption. We conclude AI can contribute to economic growth. Labor-abundant countries should adopt labor-augmenting technology, while countries with an aging population can adopt capital-augmenting technology. However, caution should be exercised in ensuring that the models are leveraged optimally.

Keywords: artificial intelligence; automation; economic growth; Industry 4.0.

JEL classification: O40, J23.

1. INTRODUCTION

The world is undergoing a wave of technological innovation through artificial intelligence (AI). From industrial applications to personal assistants, AI is deployed in many aspects of daily life. As a factor of production (Wagner, 2020), AI is also implemented in the production of goods and services, which might affect economic growth and income (Acemoglu & Restrepo, 2019a). The continuation of this process will contribute to profound

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social and economic changes (Feijoo et al., 2020). Studies predict that AI will contribute to economic growth by raising productivity, while there are also concerns about job displacement. Besides, declining labor's economic share in recent years provokes research interests (Crafts & Mills, 2017). Notably, with rapid technology advancement, AI has become a focus of a recent economic investigation. AI may affect capital accumulation and labor force through increased productivity and labor efficiency. AI applies to any device or software as a computerized system that can sense its environment around, think, learn, and perform actions like humans. It means AI has "the capability of a machine to work as a human." This definition evokes two fundamental economic implications, i.e., productivity growth and employment.

This paper has concentrated on the effects of AI on economic growth, which stem from intelligent manufacturing in the coming decades. The extant literature shows many studies on the effects of technological advancement on economic growth and productivity. In more recent times, AI-related research includes the themes of automation, innovation, employment, social change, and its role in business models. However, the review of recent and key studies on the field suggests that many questions still require further research and investigation in the currently emerging academic field of economics on AI (Agrawal, Gans, & Goldfarb, 2019b). We take this opportunity to research the specific research question: Does AI increase economic growth? To answer the research question, we set the following specific objectives:

1. How will AI increase productivity if firms adopt AI as a factor of production? Is AI a different factor of production? How?
2. Is AI a substitute for or complementary to labor and/or human capital? What effects may it have on the cheap-labored emerging economies?
3. May the adoption of AI fail to materialize benefits, as predicted by the economic growth theory? Why?

As AI is a technological breakthrough (Denning & Lewis, 2017), it appears prudent to sharpen the economic tools proactively to use them when the dynamics further unfold. Therefore, this study examines the effects of AI on growth to understand the dynamics and make policy toolkits for the future. Compared to the literature, this paper's contribution mainly is testing AI as a production factor to examine how AI can reshape the production frontier and affect economic growth. This paper is the initial effort to research and develop a neoclassical production model incorporating AI as a production factor. We model AI as a capital-labor hybrid factor of production, assuming AI can amplify and transcend the existing labor and capital capacity to drive economic growth by intelligent automation, labor and capital augmentation, and innovation diffusion.

We structure the rest of the paper as follows. Section 2 contains the literature review and analysis of the current research and development in AI and economics. In Section 3, we define the methodological approach of the paper. In Section 4, we illustrate the economic intuition of technology and growth theory. We analyze all the existing theoretical models and develop the production function modeling the AI as capital, the growth rate of capital, labor, and augmenting technology in Section 5. In addition, we improved a task-based model to reflect the effect of new job creation by AI and compared the three different production functions. Finally, we conclude by summarizing the findings and presenting policy implications in Section 6.

2. REVIEW OF LITERATURE

The current paper reviews the key AI-relevant research studies, mainly from the recent five years, which address the development of AI economics and find gaps for future research. The extant literature contains a wide range of topics, including the effects of AI on competition (Varian, 2017), public policy (Goolsbee, 2019), economic policy (Agrawal, Gans, & Goldfarb, 2019a), innovation (Cockburn, Henderson, & Stern, 2019), international trade (Goldfarb & Trefler, 2017), inequality (Sachs, 2017), behavioral economics (Camerer, 2019), markets (Milgrom & Tadelis, 2019), economic growth (Aghion & Benjamin, 2019; Hamori & Kume, 2018; Lu, 2021), productivity growth (Brynjolfsson, Rock, & Syverson, 2017), society and firms (Makridakis, 2017) and political power (Horowitz, 2018). Some authors investigated AI's effects from a legal or ethical perspective (Muller, 2016; Russell, Hauert, Altman, & Veloso, 2015). However, the most in-depth debate concerns the impact on employment for the diffusion of robotization and automation (Acemoglu & Restrepo, 2020; Agrawal, Gans, & Goldfarb, 2018; Agrawal et al., 2019a; Arntz, Gregory, & Zierahn, 2017; Autor, 2015; Autor & Salomons, 2018; Chiacchio, Petropoulos, & Pichler, 2018; Dauth, Sudekum, & Woessner, 2017; Frey, Osborne, & Holmes, 2016; Grawtz & Micheals, 2018). We find exciting variations across the mentioned studies, as it is early to predict the AI's effects on employment and income while industries are steadily adopting. An emerging body of studies contributes to estimating AI's economic impact across time and space (Cockburn et al., 2019; Fujii & Managi, 2018; Keisnejr, Raffo, & Wunsch-Vincent, 2015). Even though they adopted different measurement techniques and definitions, they provide evidence for the fast-track scientific and technological research associated with AI dimensions.

We only emphasized the effects of AI on economic growth in this paper. We start with the economic perspectives of AI as an emerging technology. Romer (1986) shows that technical progress is the key driver of economic growth. Any newly emerging technology causes significant uncertainty, especially regarding its effect on economic growth and changing economic and social structures or the policy challenges it creates (European Commission, 2019). As technology advances, it may substantially affect the economy concerning productivity, growth, inequality, market power, innovation, and employment.

To consider the empirical evidence of labor productivity, Grawtz and Micheals (2018) find that only industrial robotic automation increased labor productivity growth by 0.36 percentage points across 17 countries between 1993 and 2007. This finding supports that AI-led automation and robotization will stimulate productivity, resulting in increased growth. While other authors (Aghion & Benjamin, 2019) also state that the past automation aspects of production, ranging from the steam engine through electricity to computer chips, have been vital for economic growth since the industrial revolution. They also state that AI may be deployed in the intelligent production of goods and services, potentially affecting economic growth and income shares. To interpret the correlation between technology and economic growth, we study the historical connection between economic growth and technological advancements.

Dating back to the 21st century, we observe that information technology has been credited with overall positive effects on production (Jorgenson, Ho, & Stiroh, 2008; Oliner, Sichel, & Stiroh, 2007). Cockburn et al. (2019) find that AI and other forms of advanced automation, including robots and sensors, can be perceived as a general-purpose technology (GPT), enabling lots of follow-on innovation that ultimately leads to productivity growth. Notably, the first study of robots on firm-level production growth shows that industrial robots'

use significantly enhances a higher level of labor productivity among the 3,000 manufacturing firms surveyed (European Commission, 2016). More empirically, Grawtz and Micheals (2018) mention that only industrial robotic automation in the industries increased productivity by 0.36 percentage points across 17 countries between 1993 and 2007. In addition, Acemoglu and Restrepo (2019a) report a net positive impact of AI technologies linked to increased productivity.

However, if this theory is correct, this leads to a lack of corresponding increases in productivity despite recent AI advances. Recent studies show that productivity growth has declined in advanced economies in the past two decades (Gal & Witheridge, 2019). Besides, growth has slowed by a 1.7 percent average annual growth rate in the past decade across advanced economies. A large proportion of this economic downturn—almost half - is due to decreased job productivity growth (Gordon, 2018). It implies that despite having technological development, advanced economies failed to gain productivity in those two decades. Therefore, it provokes a question what fails technology to enhance productivity? To answer the question, we elaborate on the proximate causes of such failure in the following paragraph.

We first note implementation lags to account for the loss in productivity. Brynjolfsson et al. (2017) argue that the lack of complementary investments causes a notable lag between the commercialization of innovative ideas and technological progress. As authors argue, these lags are visible with general-purpose technology (GPT), citing historical examples of electrification and the integrated circuit. Another proximate cause is a strategic management failure. Bloom, Sadun, and Reenen (2012) show that better information technology management can explain the difference in productivity between US and UK firms. However, labor participation may also partly explain the decline. To the extent AI innovations lead to changes in occupations, it will be necessary for the labor force to learn new skills to enable continued employment or transition to new employment. Notably, one particular concern with AI is evident that the changes will happen so quickly that there will be sustained periods in which large segments of the population are not working (Acemoglu & Restrepo, 2018; Goolsbee, 2019). These sped up transformations and the potential disruptions to the workforce require essential policies to support workers and labor productivity. Getting the full potential from AI investments requires an organizational redesign to employ a management strategy to catalyze technology transformation.

We consider the past technological innovations in the industrial revolutions, which automated many jobs and later led to widespread displacement, triggering the Luddite riots (Mokyr, 1990). Regarding automation's effects on labor, Frey et al. (2016) claim that about 66 percent of all jobs in developing countries are vulnerable to automation. However, there is evidence that induced automation increased economic growth as well. Growiec (2019) mentions that the output is increasingly produced in automated processes that will increase growth in a digital economy. Other researchers find that rapid technological progress in AI has been predicted to contribute to mass unemployment, raised inequality, and higher productivity growth through automation (Thomas & Naude, 2018).

Conversely, Roubini (2015) and Stiglitz (2014) argue that more efficiency and productivity created by robots and computers could balance the threats on the rise of unemployment with robots or AI. The degree to which new technologies will require the complementary input of skilled human labor is the primary determinant of AI's effect on employment and income inequality. However, Berg, Buffie, and Zanna (2018) mentioned that

even the modest changes in complementarity could produce vast differences in labor market outcomes requiring follow-up investigations.

In this research, we are particularly interested in the causes of productivity growth and how AI adoption may affect economic growth in the future. After a comprehensive review of the existing literature, we find AI technology can displace jobs and affect economic growth. We examine how AI can contribute to economic growth.

3. METHOD

We employ the model to examine how AI, as a capital-labor hybrid factor of production, can significantly affect growth by intelligent automation, labor and capital augmentation, and innovation diffusion. This paper develops a theoretical model with mathematical and economic intuition to study such effects of AI on economic growth. To map AI's impact on growth, we consider applying AI technology like machine learning, neural networks, industrial robotics, advanced analytics, 3D printing, data analytics, quantum computing, and nanotechnology to produce goods and services and innovate industry 4.0 concepts. We assume a closed economy with one enterprise, homogeneous labor, and full employment. Under these assumptions, the neoclassical production function is as follows.

$$Y = AF K^\alpha L^{1-\alpha}$$

where (Y) is the output, (A) is the determinant level of technology, (F) is the total factor productivity, (K) is the traditional capital, and (L) is the labor force. The α and $(1-\alpha)$ refer to the output elasticities of labor and capital, respectively. These values are constants determined by existing technology, where the value of α is $0 < \alpha < 1$.

To study how AI functions differently from labor and capital, we improve the production model by integrating the artificial intelligence capital, AI capital-augmenting technology, and AI labor-augmenting technology and examined its impact on labor share, wages, and capital prices.

$$Y = K^\alpha \left(L \frac{e-1}{e} + A \frac{e-1}{e} \right)^{\frac{e(1-\alpha)}{e-1}}$$

where (K) is the traditional capital, (L) is labor; (A) is AI capital, including the effects of other endogenous variables, (e) is the elasticity of substitution between labor (L) and AI capital (A), and $e \geq 0$.

Sophisticatedly, we add the elasticity of substitution between labor and AI capital to the neoclassical production and task-based model to account for the effects of new job creation. The implication of the task-based model is to exhibit the effect of generating new tasks. Examining the effects in sequence, we associate the model with the economies, which have the cost-competitive advantage of labor. We also compare three production functions based on the technology effects on factors to advocate optimal production function.

4. DISCUSSION

We study to gain a more nuanced understanding of AI's impacts on economic growth. We start with such intent from a fundamental analysis of how automation may affect productivity through innovation induced by AI in the future. We find that the most recent

literature review is limited to theoretical debates or speculative forecasts about the potential effects of AI while AI adoption is still growing and takes time to get reflected in the real economy. The only empirical evidence available is about sweeping technological change or is confined to robots' industrial applications. Therefore, we emphasize developing the conceptual framework to study the impact of AI on economic growth and present a mathematical interpretation of the concept. We will illustrate the theory of growth and model development, respectively, in the following two sections.

4.1 Technology and Growth Theory

For over two centuries, technological innovations have been the key drivers of economic growth (Brynjolfsson & McFee, 2017). Wright and Schultz (2018) find that advances in technological automation increase productivity significantly. To understand how technological changes drive growth, we adopt the perspective of the economic theory of a firm to explore the changes that AI brings to the firm. The underlying proposition of growth theory is that a sustained growth rate of output per capita, in the long run, requires advances in technological knowledge as new goods, new markets, or new processes. The driver of growth, thus, is technological change. The source of rising productivity growth by new technologies dates back to the 1960s. Simon (1965) explained the macroeconomic implications of computerization. His analysis was based on "factor price frontier"- the combinations of factor prices that allow a cost-minimizing firm to achieve a cost per unit of output under highly formalized assumptions. The following equation can summarize the factor rewards.

$$w\alpha_L + (1 + r)\alpha_K = 1$$

where w = wage rate, α_L = labor input coefficient, r = real interest rate, α_K = capital input coefficient and the price of output is normalized to 1. A combination of capital and labor produces the output; the model assumes constant returns to scale and a single good, which can be used for either new capital or consumption. Under competition, the factor prices will rise until the cost becomes equal to the price at 1; therefore, in equilibrium, innovative technology will raise either wage rates or interest rates, or both. However, the author defends that technological change will affect the unit inputs by decreasing the coefficient value of labor and/or capital input so that at current factor prices, the cost of production with the new technology will be less than 1.

$$\omega_0\alpha_L^* + (1 + \gamma_0)a_L^* < 1$$

where subscripts 0 denote actual factor prices, and asterisks denote the new technology with innovation. This paper also considers the endogenous technology model for productivity growth an essential economic toolkit for growth management. The endogenous technology model explains that knowledge is a produced input, and its growth is proportional to the inputs into the production process. Aghion and Howitt (1998) explain that the AK model assumes that learning by doing induces technological progress that contributes to raising the marginal product of capital, which offsets the propensity for the marginal product to diminish if technology remains the same. The production function of the model is $Y = AK$, where the marginal product of capital is equal to the constant (A). The model shows the growth in the form as follows.

$$\delta K_t / \delta_t = \phi(\lambda Y_t)^\beta$$

Here Y_t is output at time t , K_t is technological knowledge, a fraction (λ) of the output is employed to inventive inputs, $\delta K_t / \delta t$ is knowledge growth, and its growth is a function of innovative inputs. To simplify it, we assume that output is produced with labor and that labor grows at a constant growth rate, i.e., n . Therefore, if $\beta > 1$ corresponds to increasing returns to inventive inputs, then the growth rate of output tends to infinity (Romer, 1986, 1990).

Baumol's cost disease is another potential source of rising productivity growth. Baumol emphasized the potential for low productivity-growth industries to have rising costs and the potential to slow aggregate economic growth (Baumol, 1967; Baumol, Blackman, & Wolff, 1985; Baumol & Bowen, 1965). However, they used old-method (Laspeyres) output indexes to analyze; therefore, the calculations produced a biased output. However, because of the substitution parameters, the impact could raise rather than lower aggregate productivity growth.

The potentials for accelerating economic growth have emerged at intervals in economic literature. We found two ways to explore AI-effects on economic growth if firms integrate artificial intelligence into production as an additional production factor. The first way is to improve the neoclassical production function (see, e.g., Autor & Dorn, 2013; Hanson, 2001; Lankisch, Prettnner, & Prskawetz, 2019; Prettnner & Strulik, 2017), and the second way is to extend the task-based model (Acemoglu & Restrepo, 2019b; Zeira, 1998). The following two sections illustrate the rationale for improving AI-enabled production function and model artificial intelligence capital and labor augmenting technology in the production function.

5. THEORETICAL MODELS OF ARTIFICIAL INTELLIGENCE

We examine almost all published theoretical AI models based on these three aspects. First, what approaches were employed to represent AI in an economic model? Second, how is AI as a factor of production different from labor and capital? Third, in which aspects (substitution, complementarity, and productivity) will AI have impacts, and what is the empirical evidence of these effects of AI? As far as the current state of formal theoretical modeling of AI in growth is concerned, a recent uttering of papers includes the following research.

Zeira (1998) used an automation model and found that fractions of the tasks are automated, and an increase in automation increases capital share, productivity, and growth. Hanson (2001) used the neoclassical model and reported that labor and computer capital complement each other, while extensive use of smart machines robustly stimulates innovation and increases productivity. However, the model does not consider the effect of new job creation. Peretto and Seater (2013) use the endogenous model and find that growth is an endogenous technology outcome. Employing a theoretical model on an aggregate level, Sachs, Benzell, and LaGarda (2015) defend that labor is a substitute for AI, and new workers will be worse off because of the productivity increase of robots if savings fall. The authors also mention that the consumption of AI products will increase. Hemous and Olsen (2016) use a theoretical model with 'directed technical change' and find that AI is a perfect substitute for low-skilled workers and income inequality effect on low-skill laborers. Russell and Norvig (2016), using the Cobb-Douglas model, find that labor and AI capital complement each other, and the extensive use of AI-powered machines promotes economic growth. The utility model proposed by Kavuri and McKibbin (2017) indicate that AI can affect production and consumption. AI can increase the productivity and consumption of AI goods because of price

effects. [Aghion, Jones, and Jones \(2017\)](#) employ the CES production function and conclude that AI replaces particular tasks with machines. If the automated sector's productivity increases, then its share in GDP declines because of price effects. [Agrawal et al. \(2018\)](#) recently used an innovation-based growth model and showed how AI could enhance prediction accuracy and increase economic growth. A task-based model by [Acemoglu and Restrepo \(2019a\)](#) shows that AI creates new jobs, while labor has competitive advantages in newly created jobs. They also mention that labor and capital are perfect substitutes, and the extent of substitution is determined by the relative prices of labor and capital.

Some studies adopt the two-level adopted CES production function to interpret economic growth's effects on wages and labor structure ([DeCanio, 2016](#)). The author focuses on the substitution effects of AI capital for a particular production factor and pays attention to the elasticity of substitution between artificial intelligence capital and two production factors (labor and capital). Therefore, based on the previous research, we intend to employ the neo-classical production function incorporating AI as a capital-labor hybrid factor of production, focusing crucially on emerging economies that may severely affect productivity and employment.

5.1 Modeling Artificial Intelligence in Production Function

After reviewing the existing models, we propose that AI be incorporated into a production function as a production factor. First, we take the neoclassical model to examine the effects of AI technology on production. The neoclassical theory defines economic growth as the function of three factors: labor, capital, and technology. Technology factors can boundlessly contribute to economic growth, even if an economy has limited capital and labor resources. We utilize the neoclassical production function as we consider limited resources and technology aspects in manufacturing goods and services. We assume a closed economy with one enterprise, and all labor force is homogeneous and fully employed. Under these assumptions, the neoclassical production function is as follows.

$$Y = AF K^\alpha L^{1-\alpha}$$

where (Y) is the output, (A) is the determinant level of technology, (F) is the total factor productivity, (K) is the traditional capital, and (L) is the labor force. The α and $(1-\alpha)$ refer to the output elasticities of labor and capital, respectively. These values are constants determined by prevailing technology, where the value of α is $0 < \alpha < 1$.

Now we extend the production function incorporating the technology impact induced by artificial intelligence. We study two types of artificial intelligence effects. One is complementary to labor (complementarity effect), and the other substitutes for labor (substitution effects). Considering the technology, the production function of the enterprise is as follows.

$$Y = K^\alpha \left(L^{\frac{e-1}{e}} + A^{\frac{e-1}{e}} \right)^{\frac{e(1-\alpha)}{e-1}} \quad (1)$$

where (K) is the traditional capital, (L) is labor; (A) is artificial intelligence capital including the effects of other endogenous variables, (e) is the elasticity of substitution between labor (L) and artificial intelligence capital (A) and $e \geq 0$, $Y = K^\alpha \min(L, A)$, when $0 < e < 1$, AI capital is complementary to labor, while $e = 1$, $Y = K^\alpha L^\beta A^{1-\alpha-\beta}$, when $e > 1$, AI capital is a substitute for labor. When (e) positively tends to infinity, $Y = K^\alpha (L + A)^{1-\alpha}$. The total labor force (including AI capital) of the enterprise is as follows.

$$Z = L^{\frac{e-1}{e}} + A^{\frac{e-1}{e}}$$

Suppose the enterprise profits π , the labor's wage is ω , the rent for traditional capital is R_k , and the rent for artificial intelligence capital is R_A . Thus,

$$\pi = Y - \omega L - R_k K - R_A A$$

The labor wage when the enterprise maximizes profits is:

$$\omega = \frac{\partial Y}{\partial L} = (1 - \alpha) K * Z^{\frac{1-e\alpha}{e-1}} * L^{\frac{1}{e}} \quad (2)$$

The rent for traditional capital is:

$$R_k = \frac{\partial Y}{\partial K} = \alpha * K^{\alpha-1} * Z^{e(1-\alpha)} \quad (3)$$

The rent of artificial intelligence capital is

$$R_A = \frac{\partial Y}{\partial A} = (1 - \alpha) K * Z^{\frac{1-e\alpha}{e-1}} * A^{\frac{1}{e}} \quad (4)$$

There is no arbitrage condition $R_k = R_A$, therefore,

$$K = \frac{\alpha}{1 - \alpha} Z * A^{\frac{1}{e}} \quad (5)$$

Substituting the [equation \(5\)](#) into (2), (3), and (4), we get:

$$\omega = v * L^{\frac{1}{e}} * Z^{\frac{1-\alpha}{e-1}} * A^{\frac{\alpha}{e}} \quad (6)$$

where $v = \alpha^\alpha (1 - \alpha)^{1-\alpha}$. Thus,

$$R = R_k = R_A = v * Z^{\frac{1-\alpha}{e-1}} * A^{\frac{\alpha-1}{e}} \quad (7)$$

Proposition 1.0:

a) The gradual accumulation of artificial intelligence capital (A) increases wages (ω) and lowers traditional capital rent (R_k).

b) At α , we assume that the share of traditional capital to be fixed. When the value of elasticity of substitution between (A) and (L) is $0 < e < 1$, AI capital becomes complementary to labor, and it increases the share of labor but decreases the share of AI capital. Conversely, when $e > 1$, labor and AI capital substitute each other, AI capital reduces the labor share and AI capital share itself. However, when $e = 1$, the labor share and AI capital share remain constant.

All proofs are attached in the [Annex](#).

5.1.1 AI Capital-augmenting Technology

Adopting capital-augmenting AI technology is an ideal phenomenon for the capital-intensive industry. In industry 4.0, enterprises increasingly adopt AI technology to promote productivity and profitability. We assume the enterprises use machine learning, big data, neural network to innovate the production process for sustainable productivity, cost savings, low carbon emission, minimum waste, and energy optimization. Thus, the production function will be:

$$Y = K^\alpha \left(L^{\frac{e-1}{e}} + T_A A^{\frac{e-1}{e}} \right)^{\frac{e(1-\alpha)}{e-1}} \quad (8)$$

Here T_A is the AI capital-augmenting technology, which creates a demand for investment in technology. The total labor force (including AI capital-augmenting technology) of an enterprise is as follows.

$$Z_A = L^{\frac{e-1}{e}} + T_A A^{\frac{e-1}{e}}$$

Likewise, applying the equilibrium condition, we get,

$$K = \frac{\alpha}{1-\alpha} T_A^{\frac{e-1}{e}} Z_A^{\frac{1}{e}} A^{\frac{1}{e}}$$

The wage,

$$\omega = v \left(T_A^{\frac{(1-e)\alpha}{e}} \right) (L^{\frac{1}{e}}) (Z_A^{\frac{1-\alpha}{e-1}}) A^{\frac{\alpha}{e}} \quad (9)$$

The rent for capital,

$$R = R_K = R_A = v \left(T_A^{\frac{(1-e)(1-\alpha)}{e}} \right) (Z_A^{\frac{1-\alpha}{e-1}}) A^{\frac{\alpha}{e}} \quad (10)$$

Proposition 2.0:

a) When the elasticity of substitution between is $0 < e < 1$, it means AI capital complements labor, and AI capital-augmenting technology increases wages. Conversely, when $e > (1/\alpha) > 1$, it means AI capital substitutes labor and vice versa, and AI capital-augmenting capital technology lowers wages.

b) If $e > 1$, it means AI capital and labor are substitutes to each other, and AI capital-augmenting technology uplifts the price of capital. Conversely, if the elasticity of substitution (e) is $0 > e > 1$, AI capital complements labor, and AI capital-augmenting technology raises the labor share, even reducing the share of AI capital.

All Proofs are attached in the [Annex](#).

5.1.2 AI Labor-augmenting Technology

AI technologies can substantially complement human workers and may create more employment opportunities. This technology adoption practically promotes labor-intensive industries, which substantially demand data scientists, machine learning engineers, domain experts, and software developers. We assume the enterprises invest the capital in improving labor-augmenting technology (T_L). The production function is as follows-

$$Y = K^\alpha \left((T_L L)^{\frac{e-1}{e}} + A \frac{e-1}{e} \right)^{\frac{e(1-\alpha)}{e-1}} \quad (11)$$

Here T_L is the AI labor-augmenting technology, which increases the demand for labor. The total labor force (including AI labor-augmenting technology) of the firm is

$$Z_L = (T_L L)^{\frac{e-1}{e}} + A \frac{e-1}{e}$$

Likewise, applying the equilibrium condition, we get

$$K = \frac{\alpha}{1-\alpha} Z_L A^{\frac{1}{e}} \quad (12)$$

The wage,

$$\omega = v \left(T_L \frac{(1-e)}{e} \right) (L^{\frac{1}{e}}) (Z_L^{\frac{1-\alpha}{e-1}}) A^{\frac{\alpha}{e}} \quad (13)$$

The rent for capital,

$$R = R_K = R_A = v \left(Z_L^{\frac{(1-\alpha)}{e-1}} \right) A^{\frac{\alpha-1}{e}} \quad (14)$$

Proposition 3.0

a) Labor-augmenting technology raises the price of capital. When $0 > e > \alpha$, AI capital is complementary to labor, labor-augmenting technology lowers wages. When $e > 1$, artificial intelligence capital and labor substitute each other, labor-augmenting technology increases wages.

b) When $0 < e < 1$, AI capital is complementary to labor, labor augmenting technology lowers labor share but increases the share of AI capital, and the share of traditional capital remains unchanged. When $e > 1$, AI capital and labor substitute each other, labor-augmenting technology raises labor share. However, it reduces the share of AI capital, and the share of traditional capital remains unchanged. When $e = 1$, both labor share and the share of AI capital are fixed.

All proofs are attached in the [Annex](#).

5.1.3 Task-based Model

Technological innovation can lead to the creation of new tasks, jobs, and new industries. The world economy already has an AI industry that helps businesses adopt and apply AI

technology. However, the neoclassical model overlooks the effects of new job creation through technological advancement. Therefore, to communicate this effect, we improved a model after reviewing the task-based approach developed by Zeira (1998); Acemoglu and Restrepo (2019a). We assume assuming the interval of a task (j) is [N-1, N] where N is the new task, and the increasing value of (N) means the automation creates new demand for employment and thus new tasks. When the value of N-1 gets higher as N becomes higher, it shows the replacement of old tasks. The underlying economic insight is that the development of automation creates new jobs while eliminates some other jobs. We study the impact of creating new tasks on wages, capital prices, labor share, and capital share in the following part. We improve the production function of the enterprise by integrating a task-based model as follows.

$$Y = K^\alpha \left[\int_{N-1}^I (T_{Aj} \cdot Qj)^{\frac{e-1}{e}} dj + \int_I^N (T_{Lj} \cdot Lj)^{\frac{e-1}{e}} dj \right]^{\frac{(1-e)}{\alpha}} \quad (15)$$

where T_A and T_L capital-augmenting and the labor-augmenting technology, respectively. Q_j , L_j is the capital and labor invested in task j. (I) indicates the frontier of AI possibilities, a higher (I) means advanced artificial intelligence. We assumed that AI capital works in a smaller interval, while workers work in a large one because the low-skilled workers are more easily replaced by AI capital. Finally, workers mainly engage in more complex tasks, such as innovative ones. Under such an assumption, the output of an enterprise can be represented by the following model. Thus, the total labor force, including AI capital and labor augmenting technology of an enterprise, is.

$$Z = \int_{N-1}^I (T_{Aj} \cdot Qj)^{\frac{e-1}{e}} dj + \int_I^N (T_{Lj} \cdot Lj)^{\frac{e-1}{e}} dj \quad (16)$$

The profit:

$$\pi = Y - R_K K - R_C \int_{N-1}^I Q dj - \omega \int_I^N L dj \quad (17)$$

In order to maximize profit, wages are:

$$\omega = (1 - \alpha) L^{\frac{1}{e}} T_L^{\frac{e-1}{e}} K^\alpha Z^{\frac{(1-e)\alpha}{e}} \quad (18)$$

The rent of traditional capital is

$$R_K = \alpha Z^{\frac{e(1-\alpha)}{e-1}} K^{\alpha-1} \quad (19)$$

The rent of artificial intelligence capital is

$$R_C = (1 - \alpha) Q^{\frac{1}{e}} (T_A)^{\frac{e-1}{e}} K^\alpha Z^{\frac{(1-e)\alpha}{e}} \quad (20)$$

Under no arbitrage $R_k = R_C$

$$K = \frac{\alpha}{1-\alpha} Q^{\frac{1}{e}} T_A^{\frac{1-e}{e}} Z \quad (21)$$

Substituting equation (16) into equations (18) and (19) gives,

$$\omega = \alpha^\alpha (1-\alpha) L^{\frac{1}{e}} Q^{\frac{1}{e}} T_L^{\frac{e-1}{e}} A^{\frac{1-e}{e}} Z^{\frac{1-\alpha}{e-1}} \quad (22)$$

$$R = \alpha^\alpha (1-\alpha) Q^{\frac{\alpha-1}{e}} T_A^{\frac{(1-e)(1-\alpha)}{e}} Z^{\frac{1-\alpha}{e-1}} \quad (23)$$

While improving the new production function, propositions 1.0 and 2.0 still hold. We made the following proposition for the task-based model.

Proposition 4.0:

- a) If the value of (N) gets higher, AI creates new tasks, wages, and capital prices go up.
- b) If the value of (I) gets higher, the share of labor decreases while the share of AI capital increases, and the share of traditional capital remains at α .

The underlying economic assumption of proposition 4.0 is that AI's development creates new tasks and widens the work interval of labor. The new tasks create new demand for labor and hence raise wages and the share of labor. Conversely, a higher (I) means AI replaces many jobs. When the work interval of labor diminishes, or as it may happen, fewer jobs are available to humans, lowering labor share. After all, if technology progress can create new tasks, new tasks' positive effect can outweigh the adverse impact of substitutive AI on labor.

All Proofs are attached in the [Annex](#).

5.2 Growth Perspectives

We assume the labor (L) is a constant, and artificial intelligence capital (A) tends positively to infinity to explore the equilibrium path of long-term economic growth trajectory. We employed the following three production functions to analyze the growth rates of per capita GDP, per capita traditional capital, and per capita artificial intelligence capital, respectively, from a closed, single-firm, and full employment economy perspective.

5.2.1 AI capital

We suppose that the enterprise invests capital in improving AI capital.

$$Y = K^\alpha \left(L^{\frac{e-1}{e}} + A^{\frac{e-1}{e}} \right)^{\frac{e(1-\alpha)}{e-1}}$$

We assume (L) is constant, and AI capital (A) tends to have positive infinity. Thus, the equation yields to

$$Y = K^\alpha * A^{1-\alpha} \quad (24)$$

Now we consider the savings. For example, the savings rate is (s), and the households invest a part of the savings (ρ) in traditional capital. Therefore, $(s-\rho)$ is invested in AI capital, and the depreciation rate is δ . Thus,

$$K^* = \rho sY - \delta K \quad (25)$$

$$A^* = (1 - \rho)sY - \delta K \quad (26)$$

We define the change in the variable of interest (i) as growth, i.e., $g_i = i^*/i$, where $i = Y, y, K, c, A, a$. Here the lower-case alphabets refer to per capita output (y), traditional capital (c), and artificial intelligence capital (a), respectively. Because the capital has no differences, the growth rate of traditional capital and AI capital must be the same, $g_K = g_A$, or we can also say $K^*/K = A^*/A$. By substituting into the [equation \(25\)](#) and [\(26\)](#), we get

$$\rho = \frac{K}{K + A} \quad (27)$$

Because (L) is a constant and (A) tends positively to infinity, we can derive the following equation:

$$K = \frac{\alpha}{1-\alpha} Z A^{\frac{1}{e}}$$

To:

$$K = \frac{\alpha}{1-\alpha} A \quad (28)$$

Now, we substitute the [equation \(28\)](#) to [equation \(27\)](#), and we get $\alpha = \rho$. Therefore,

$$g_K = g_A = v s - \delta \quad (29)$$

where $v = \alpha^\alpha (1 - \alpha)^{1-\alpha}$

Given the [equation \(24\)](#), we get:

$$G_y = \alpha G_k + (1 - \alpha) G_A = v s - \delta \quad (30)$$

Here we define the population growth rate as (n), per capita output as $y = \frac{Y}{L}$, per capita traditional capital $c = \frac{K}{L}$, and per capita AI capital as $a = \frac{A}{L}$. [Equations \(29\)](#) and [\(30\)](#) imply that

$$g_y = g_k = g_a = v s - (n + \delta)$$

In the long-run balanced growth trajectory, the wage price is

$$\omega = v L^{\frac{1}{e}} Z^{\frac{1-\alpha}{e-1}} A^{\frac{1}{e}} \cong v L^{\frac{1}{e}} A^{\frac{1}{e}}$$

and the capital price (R) will be

$$R = v Z^{\frac{1-\alpha}{e-1}} A^{\frac{\alpha-1}{e}} \cong v; \text{ Where } v = \alpha^\alpha (1 - \alpha)^{1-\alpha}$$

5.2.2 AI capital-augmenting technology

Now we assume that enterprise invests capital in improving AI capital-augmenting technology (T_A). Thus, the resultant production function will be:

$$Y = K^\alpha \left[L^{\frac{e-1}{e}} + (T_A A)^{\frac{e-1}{e}} \right]^{\frac{e(1-\alpha)}{e-1}} \tag{31}$$

Similarly, we get:

$$Y \approx T_A^{1-\alpha} K^\alpha A^{1-\alpha} \tag{32}$$

Applying the equilibrium condition, we get:

$$K = \frac{\alpha}{1-\alpha} A$$

Since $K^*/K = A^*/A$, we also have:

$$g_k = g_p = v s T_A^{1-\alpha} - \delta \tag{33}$$

where T_A is the is AI capital augmenting technology.

We define the growth rate of AI capital augmenting technology as $G_{T_A} = g$. The following equation implies that:

$$K = \frac{\alpha}{1-\alpha} Z_L A^{\frac{1}{e}}$$

$$g_Y = (1-\alpha)g + \alpha g_k + (1-\alpha)g_A \tag{34}$$

Or,

$$g_Y = (1-\alpha)g + v s T_p - \delta \tag{35}$$

Thus, we get

$$g_k = g_A = v s T_A^{1-\alpha} - (n + \delta) \tag{36}$$

In the balanced growth trajectory, the wage price (ω) and capital price (R) are:

$$\omega = v T_A^{\frac{(1-e)\alpha}{e}} L^{\frac{1}{e}} Z_A^{\frac{1-\alpha}{e-1}} A^{\frac{\alpha-1}{e}} \tag{37}$$

$$R = v A_A \frac{(1-e)(1-\alpha)}{e} Z_A^{\left(\frac{1-\alpha}{e-1}\right)} A^{\frac{\alpha-1}{e}} \approx v A_A^{1-\alpha} \tag{38}$$

5.2.3 AI labor-augmenting technology

If the firm invests the capital in improving labor-augmenting technology (T_L), all else is held constant; the production function is as follows:

$$Y = K^\alpha \left((T_L L)^{\frac{e-1}{e}} + A \frac{e-1}{e} \right)^{\frac{e(1-\alpha)}{e-1}} \quad (39)$$

As (L) is a constant, and (A) tends to positive infinity, $Y = K^\alpha A^{1-\alpha}$. Similarly, we have:

$$g_y = g_k = g_a = vs - (n + \delta) \quad (40)$$

In the balanced growth trajectory, the wage-price (ω) and capital price (R),

$$\omega = v \left(A_L \frac{e-1}{e} \right) (L^e)^{\frac{1}{e}} (Z^{\frac{1-\alpha}{e-1}} A^{\frac{\alpha}{e}} \approx v A_L^{\frac{e-1}{e}} (L^e)^{\frac{1}{e}} A \quad (41)$$

$$R = v Z^{\frac{1-\alpha}{e-1}} A^{\frac{\alpha-1}{e}} \approx v \quad (42)$$

Now, given the production function $Y = K^\alpha \left((A_L L)^{\frac{e-1}{e}} + A \frac{e-1}{e} \right)^{\frac{e(1-\alpha)}{e-1}}$, where labor (L) is a constant, and AI capital (A) tends positively to infinity. In the long run, economic growth reaches steady-state equilibrium and growth rate per capita output, per capita traditional capital, and per capita, AI capital will yield to $vs-(n-\delta)$. Until reaching such a state, the savings rate determines the level of capital and output, thus, economic growth. By contrast, a higher population growth rate or depreciation rate leads to slower economic growth. Thus, we see that technological progress can lead to sustained output per worker output in a steady-state. Once the economy reaches a steady-state, the growth rate of output per worker depends only on technological progress. We modeled the technological progress here as labor augmenting, meaning that it does not cause the actual number of workers to increase but more units of output per worker.

5.3 Comparison of the Models

We compare the production function models shown in the paper. Production function types (I), (II) and (III) refer to AI capital, AI capital augmenting, and AI-labor augmenting technology, respectively in the production functions.

Table no. 1 – Comparison of production functions

Factors→	Production function type I		Production function type II			Production function type III		
	(A)	(L)	(A)	(L)	(T _A)	(A)	(A _L)	(L)
Substitution effect on wage	+	+	-	-	-	-	+	+
Complementary effect on wage	+	-	+	+	-	-	+	-
Substitution effect on capital share	+	-	+	-	+	-	+	-
Complementary effect on capital share	+	-	+	-	+	-	+	+

Notes: (+) means when the factor increases, the wages increase too. (-) means when the factors increase, the wages decrease. The same applies to capital share as well. A, L, A_L, T_A refers to AI capital, labor, AI labor-augmenting technology, and AI capital-augmenting technology.

Table no. 1 shows the conclusion drawn from proposition 1.0 to 3.0. From both propositions, the production function signifies that higher AI capital leads to a higher labor share when AI capital complements labor. By contrast, higher labor-augmenting technology results in lower labor share. When AI capital and labor substitute, labor-augmenting technology positively affects labor share, while the effect of AI capital is negative. If AI's productivity is much higher than humans, it is not wise for humans to compete with AI by improving productivity. In sum, assuming AI innovates jobs, it is optimal to develop complementary artificial intelligence, particularly in emerging economies.

6. CONCLUSION AND POLICY IMPLICATIONS

In the present study, we investigated the AI implications considering the critical insights of AI technologies with the probable impacts on the future of production possibility, employment, and the respective policymaking for many economies. To examine the effects of AI on economic growth, we have developed a theoretical framework and explored the effects of artificial intelligence on capital, wages, and economic growth. The model shows that an increase in AI capital results in lower capital prices, a higher wage, and increased productivity. Because of the price and productivity effects, AI capital becomes complementary to labor and will raise one sector's productivity. As shown by the task-based model, the technological acceleration by AI capital-augmenting technology will add reciprocity to workers, increase efficiency, and improve wages. However, AI as a substitute for labor will replace many workers with machines. This AI automation will replace many jobs, lower wages, and labor share. Thus, the substitution effect may polarize the labor market, which is alarming for cheap-labored economies. To mitigate that concern, policymakers and practitioners can improve labor-augmenting technology to gain workers' competitive advantages and create more jobs that will promote wages and welfare. However, many economies may not obtain the AI benefits due to the failure of adopting and integrating the AI with productive economic sectors. Reflecting on these facts and proposed models, we conclude that economies confronting technological advancement should adopt AI technology. Based on the proposed models, we present the following policy implications.

1). Labor-abundant countries should employ AI labor-augmenting technology in production function (III) if AI capital substitutes labor.

2). Countries with major aging populations must optimally employ AI capital-augmenting technology in replacing repetitive jobs and creating new ones (I and II).

3). Concurrently, both models should be integrated based on the economic context and potential optimal leverage of combined integration.

Summing up, to materialize the expected merits of AI and de-risk undesirable effects, policymakers across the world should foster economic growth by complementing AI and labor while optimally leveraging AI capital with the pace of technological progress.

The study's main limitation is the lack of empirical examination of the effects, and future research studies may contribute to the existing literature by empirically examining the effects of AI on economic growth. Besides, the comparative case studies of emerging and developed countries can also contribute to the literature by providing cutting-edge insights on AI.

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ANNEX

Proof of Proposition 1.0:

Changes in wage (ω) and capital rent (R)

(a) from equation (6),

$$\omega = v * L^{\frac{1}{e}} * Z^{\frac{1-\alpha}{e-1}} * A^{\frac{\alpha}{e}}$$

where $v = \alpha^\alpha (1 - \alpha)^{1-\alpha}$. We can differentiate

$$\ln \omega = \ln v \left(L^{\frac{1}{e}} \right) + \ln Z^{\left(\frac{1-\alpha}{e-1} \right)} + \ln A^{\left(\frac{\alpha}{e} \right)}$$

Accordingly,

$$\frac{\partial(\ln \omega)}{\partial A} = \frac{1}{eZA} \left[A^{\frac{e-1}{e}} + \alpha L^{\frac{e-1}{e}} \right] > 0$$

Similarly,

$$\frac{\partial(\ln R)}{\partial A} = - \left[\frac{(1-\alpha)}{eZA} \right] L^{\frac{e-1}{e}} < 0$$

(b) The traditional capital shares:

$$\alpha_k = \frac{RK}{Y} = \alpha$$

(c) The labor share:

$$\alpha_L = \frac{\omega L}{Y} = (1 - \alpha) \left[\frac{L^{\frac{e-1}{e}}}{L^{\frac{e-1}{e}} + A^{\frac{e-1}{e}}} \right]$$

$$\alpha_A = \frac{RA}{Y} = (1 - \alpha) \left[\frac{A^{\frac{e-1}{e}}}{L^{\frac{e-1}{e}} + A^{\frac{e-1}{e}}} \right];$$

Therefore, we can say:

$$\text{If } 0 < e < 1, \left[\frac{\partial(\alpha_L)}{\partial A} \right] > 0, \left[\frac{\partial(\alpha_A)}{\partial A} \right] < 0;$$

$$\text{If } e > 1, \text{ then } \left[\frac{\partial(\alpha_L)}{\partial A} \right] < 0, \left[\frac{\partial(\alpha_A)}{\partial A} \right] > 0;$$

while we assume $e = 1$, α_L , α_A , αK to be constant.

Proof of Proposition 2.0:

(a) from equation (9):

$$\text{The wage, } \omega = v T_A \left(A_L^{\frac{(1-e)\alpha}{e}} \right) \left(L^{\frac{1}{e}} \right) \left(Z_A^{\frac{1-\alpha}{e-1}} \right) A^{\frac{\alpha}{e}}$$

From the above equation, we derive that,

$$\frac{\partial(\ln \omega)}{\partial T_A} = \left[\frac{e-1}{eZ_A T_A} \right] \left[(1-e)\alpha + (1-e\alpha) \left(\frac{T_A A}{L} \right)^{\frac{e-1}{e}} \right]$$

So, when $0 < e < 1$, $\frac{\partial(\ln \omega)}{\partial T_A} > 0$; when $e > \frac{1}{e} > 1$, $\frac{\partial(\ln \omega)}{\partial T_A} < 0$;

(b) from equation (10):

$$\text{The rent for capital, } R = R_K = R_A = vA \left(A_L \frac{(1-e)(1-\alpha)}{e} \right) \left(Z_A \frac{1-\alpha}{e-1} \right) A \frac{\alpha}{e}$$

From the above equation, we get the following

$$\frac{\partial(\ln R)}{\partial T_A} = \left[\frac{L \frac{e-1}{e}}{e Z_A T_A} \right] \left[(1-e)\alpha + (1-e\alpha) \left(\frac{T_A A}{L} \right)^{\frac{e-1}{e}} \right]$$

when, $e > 1$, $\frac{\partial(\ln R)}{\partial T_A} > 0$;

we also prove that:

$$\alpha_L = \frac{\omega L}{Y} = (1-\alpha) \frac{L \frac{e-1}{e}}{L \frac{e-1}{e} + T_A A \frac{e-1}{e}}; \quad \alpha_A = \frac{RA}{Y} = (1-\alpha) \frac{(T_A A) \frac{e-1}{e}}{L \frac{e-1}{e}} + T_A A \frac{e-1}{e}$$

when $0 < e < 1$, $\frac{\partial(\alpha_L)}{\partial T_A} > 0$; $\frac{\partial(\alpha_A)}{\partial T_A} < 0$; when $e > 1$, $\frac{\partial(\alpha_L)}{\partial T_A} < 0$, $\frac{\partial(\alpha_A)}{\partial T_A} > 0$;

Proof of Proposition 3.0:

(a) from equations (17) and (18),

$$\frac{\partial(\ln \omega)}{\partial T_L} = \frac{1}{e Z_L T_L} \left[(e-\alpha)(T_L L)^{\frac{e-1}{e}} + (e-1)A \frac{e-1}{e} \right]$$

$$\frac{\partial(\ln R)}{\partial A_L} = \frac{1-\alpha}{e Z_L} T_L^e L^{\frac{e-1}{e}} > 0$$

Thereby, when $0 < e < \alpha$, $\frac{\partial(\ln \omega)}{\partial T_L} < 0$; when $e > 1$, $\frac{\partial(\ln \omega)}{\partial T_L} > 0$;

(b) from equations (10), (11) and (12):

$$\alpha_L = \frac{\omega L}{Y} = (1-\alpha) \left[\frac{T_L L^{\frac{e-1}{e}}}{T_L L^{\frac{e-1}{e}} + A \frac{e-1}{e}} \right]$$

$$\alpha_A = \frac{RA}{Y} = (1-\alpha) \left[\frac{A \frac{e-1}{e}}{T_L L^{\frac{e-1}{e}} + A \frac{e-1}{e}} \right]$$

When $0 < e < 1$, $\frac{\partial(\alpha_L)}{\partial T_L} < 0$, $\frac{\partial(\alpha_A)}{\partial T_L} > 0$; when $e > 1$, $\frac{\partial(\alpha_L)}{\partial T_L} > 0$, $\frac{\partial(\alpha_A)}{\partial T_L} < 0$.

Proof of Proposition 4.0:

a) $\frac{\partial(\ln \omega)}{\partial N} = \frac{\partial(\ln R)}{\partial N} = \frac{1-\alpha}{(e-1)Z} \left[N \left(\frac{e-1}{e} \right) - (N-1) \frac{e-1}{e} \right] > 0$;

b) $\frac{\partial(\ln \alpha_L)}{\partial I} = -\frac{1}{N-1} < 0$, $\frac{\delta(\ln \alpha_A)}{\partial I} = \frac{1}{I-N+1} > 0$;