The Impact of Generative AI on Labor Market

Zheng, Dewei
Graduate School of Economics, Kyushu University

https://doi.org/10.15017/7343225

出版情報：経済論究. 180, pp.43-63, 2025-03-27. 九州大学大学院経済学会

The Impact of Generative AI on Labor Market

Dewei Zheng [†]

Abstract

Generative AI has emerged as a transformative force in the modern economy, offering significant potential to enhance labor productivity, bridge skill gaps, and create new opportunities for both low- and high-skilled workers. By adopting logistic growth models, this study illustrates how generative AI facilitates education and skill acquisition, driving productivity gains while adhering to the principles of diminishing returns. The integration of education and skills through generative AI amplifies Total Factor Productivity (TFP), especially in the early and middle stages of adoption. However, its impact varies depending on the degree of substitution or complementarity with human labor. Overall, while generative AI addresses current economic challenges, such as declining labor force growth, its long-term success depends on the balanced implementation, continuous upskilling, and careful management of substitution effects. Its ability to create synergy between skills, education, and technological adoption positions it as a critical driver for sustained economic growth in the age of automation.

Keywords: Generative AI, Labor, Economic Growth

1 Introduction

ChatGPT was released in November 2022, as a milestone of the era of generative AI. Meanwhile, several generative AI products have been brought up in our world because of large venture capital and other investments in this area. Compared to preceding technologies like smartphones, AlphaGO, and autonomous driving techniques, whose processes were often indistinguishable, generative AI has captured people's attention worldwide due to its broad utility, which can significantly impact, change, and reshape various aspects of life and work.

[†] Graduate School of Economics, Kyushu University

Generative AI as defined by Chui, Hazan, Roberts, Singla, and Smaje (2023) contains a series of foundation models which attempt to imitate human brains to establish expansive artificial neural networks. These foundation models can facilitate deep learning which in return endows many evolutional abilities in AI, processing significant large and diverse sets of unstructured data. It is also possible to perform multithreading tasks, including classification, editing, summarisation, answering questions, and creating new content, among other tasks. Generative AI has also unlocked new possibilities and significantly enhanced existing capabilities across diverse modalities such as images, video, audio, and computer code. As a new technology revolution, it leads to similar results to previous ones. The mechanism behind each technology revolution generates absolute gains for individual workers with high learning ability, and absolute losses for those with low cognitive ability. Consideration about labor replacement arises every time when new technologies have been developed. Acemoglu and Restrepo (2018) claims that we may be too much worried about comprehensive labor replacement occurring due to the new technology because jobs previously performed by labor are automated, while at the same time, labors could be complemented by other new technologies. And human labor has comparative advantages in dealing with new and more complex tasks. Employment and labor share cannot be disturbed even in the face of rapid automation if this comparative disadvantage is considerable and the creation of new tasks continues in the long run. In addition, learning externalities can potentially change the wage structure as it will facilitate more workers joining the skilled pool. (Caselli, 1999) The findings align with the experiment conducted by Noy and Zhang (2023) who conclude that generative AI positively impacts labour productivity by not only improving the quality of tasks and reducing time spent but also narrowing inequality among workers (the gap in skills and performance).

It is natural to feel anxiety about the potential for technological unemployment when new technologies are introduced into the production process. From the perspective of history, Mokyr, Vickers, and Ziebarth (2015) conducted a detailed analysis from the First Industrial Revolution to the present and concluded that fundamental economic principles remain consistently relevant because scarcity will continue to affect us, particularly the scarcity of time. Additionally, the law of comparative advantage strongly suggests that most workers will still be needed for meaningful tasks, even in an economy where robots and automation play a significant role in production. There is also evidence showing that generative AI as a new technology may not decrease working opportunities overall. Autor, Dorn, and Hanson (2015) did empirical research indicating that while technological change has a neutral effect on overall employment levels, it significantly alters the composition of occupations within sectors. It means both manufacturing and non-manufacturing sectors would experience employment decline in routine task-intensive production and clerical occupations. This shift implies that workers will need to adapt by developing skills suited to non-routine and cognitive tasks that are less susceptible to automation. We assume that generative AI will play an important role in helping workers adapt to the new demands created by technological advancements. Unlike traditional automation and robots, generative AI focuses on imitating human brains, making it more suitable to be regarded as the computerisation of information processing in knowledge-intensive sectors. As a result, generative AI can support workers in roles that require adaptability, innovation, and complex problem-solving.

As a branch of information technology, it will also play an important role in improving labor productivity–not simply by automating existing processes, but by transforming the current production model. (Dedrick, Gurbaxani, & Kraemer, 2003) China has been experiencing an ageing and fertility-declining society in the context of flourishing generation AI. China has to shoulder considerable stress and face different obstacles and challenges for its economic development due to huge changes in demographics. Luo, Su, and Zheng (2021) use the PDE (Population Dynamics Equation) model to estimate the trend of the population change in China from 2015 to 2050. Their findings reveal that the total population would decline to 1.40-1.44 billion by 2030 and 1.29-1.40 billion by 2050. While the elderly would increase to account for 20% by 2033, which indicates that China has stepped into a super-aged society. Along with the continuous rapid population decline and ageing process, the gradually increasing life expectancy would aggravate the welfare burden financially and the shortage of care services. In fact, there are five main characteristics in an increasingly ageing society: (1) the process of population ageing is deepening; (2) the composition of the elderly is changing, from the young-old to the oldest-old; (3) the labour force will shrinking rapidly; (4) the total dependency ratio is increasing and the pressure of care for the elderly will become one of the most intractable social problems; (5) the size of each household keeps small and the number of elderly people living alone is increasing (Bai & Lei, 2020).

(Romer, 1990) find that the application of robots induces considerable negative employment effects for blue-collar workers but less than for workers with high education experience. Compared to previous studies, this study highlights how generative AI influences labor productivity through both education and skill acquisition. This dual-channel approach extends beyond previous studies, which often emphasized one-dimensional effects such as task automation or productivity improvements in isolation. The analysis underlines a synergistic relationship between generative AI, education, and skill acquisition, suggesting that the combination of these factors can amplify productivity. This idea contrasts with earlier studies that primarily discussed generative AI as a substitute for human labor without exploring its complementary effects. Another notable finding is how generative AI can reduce the skill gap between low- and high-skilled workers by enhancing learning capabilities and providing personalized educational tools.

The remaining parts of this study are structured as follows: Section 2 introduces a bundle of related previous research. The model is outlined in Section 3. Section 4 is our conclusion and discussion. Key proofs are covered in the appendix.

2　Literature Review

Based on the Harrod-neutral process, Nelson and Phelps (1966) establish a model to explain the positive relationship between technology in practice and education attainment.　The economy gains more technological progress with a higher rate of return to education.　From the perspective of the development of the U.S., educational investments have general effects on the economy, politics and society.　Human capital plays a central role in boosting the economy, both in general and in the specific period of economic growth in the U.S. Additionally, investments in human capital can help alleviate economic disparities.　Under the Tinbergian assumption, technological progress tends to widen the economic gap between skill groups due to its inherently skill-biased nature.　However, this widening disparity can be countered by increasing the supply of human capital, as a more educated and skilled workforce can adapt to and benefit from technological advancements.　(Acemoglu & Autor, 2012) Our model is also developed based on this assumption.　We hypothesise that the effect of generative AI (ρ) positively influences education levels, with its impact following a sigmoid pattern. One of the main differences between their study and ours is that we believe generative AI influences labor productivity through two channels: former education and skill acquisition in the workplace. Additionally, education influenced by generative AI will further impact the process of skill acquisition. Romer (1990) made arguments on the importance of increasing human capital, consistent with economic theory, which suggests that productivity gains do not inherently improve by simply increasing capital unless paired with human capital and technology innovation.　He also discussed how labor scarcity may drive technological change and productivity growth, as it encourages firms to invest in labor-saving technologies.　According to the study conducted by Zarifhonarvar (2024), which provides a profound understanding of the changes caused by generative AI technologies.　The study finds that ChatGPT has full effects on 32.8% of occupations, while partial effects on 36.5% and no effect on the remaining 30.7%.　Lots of jobs would be displaced, especially for the routine ones, which can lead to a rise in the unemployment rate and induce a larger income gap.　On the other hand, Generative AI may bring up new employment opportunities, particularly in high-skilled and value-added jobs, which in turn improve labour productivity and boost the economy.

Based on the study conducted by Noy and Zhang (2023), it shows that the generative AI, ChatGPT, helps College-educated professionals improve their writing tasks to midlevel.　Not only does it improve low-ability workers' performance, but also it reduces the effort and time they spend on it, which reduces the unequal situation in the workplace.　However, their experiment only explains the direct effect on worker productivity, and it is difficult to capture the indirect ones of the dynamic and complex labour market.　For instance, generative AI can equip a new employee who does not have any programming work experience well and quickly, which in return ensures his basic performance in elementary code issues. Although it may decrease the demand for basic programmers, the scarcity of expertise could not be influenced. How labour skills can be best complemented by generative AI would be a mystery. If we refer to history, it is apparent that computerisation once significantly reduced routine work such as assembly line work, data management, payroll processing etc.. On the other hand, it increases the demand for workers who can program, design systems or address troubleshooting technical issues. Thus, these changes have contributed to a larger wage gap.

Webb (2019) developed a new method to measure the impact of different technologies on various occupations, using historical case studies and focusing on three types of technologies: robots, software, and artificial intelligence. The results reveal that robots primarily impact low-skill occupations, software affects middle-skill occupations, and AI influences high-skill occupations. Jack reached a similar conclusion, suggesting that low-skilled workers are substitutable by IT, while high-skilled workers are complementary to it. However, AI is likely to have a broader impact across different occupations compared to the other two technologies. Jorgenson (2001) reached a similar conclusion, suggesting that low-skilled workers are substitutable by IT, while high-skilled workers are complementary to it. However, AI is likely to have a broader impact across different occupations compared to the other two technologies.

Furthermore, the significant effect of artificial intelligence is observed not only in labor demand but also in labor supply. As AI continues to develop, it will create new products and services, which will affect labor demand. Simultaneously, AI can enhance the efficiency of producing well-educated and more productive workers, thus influencing labor supply. In the case of generative AI, we view it as an advanced tool to assist in skill development. Rather than simply replacing workers, it reduces the skill gap between low- and high-skilled workers by enhancing learning abilities and facilitating skill. Unlike traditional automation, which primarily substitutes repetitive tasks, generative AI helps low- and mid-skill workers acquire knowledge and skills previously accessible only to high-skilled workers by facilitating on-demand learning and offering sophisticated assistance.

A set of researchers has been complemented to claim the effects of generative AI on the respect of labour. The revolution of generative AI technology has the potential to create new demands from the perspective of service. Consistent with many other studies, for instance, Frey (2019) put forward his reviews on an important question that the supply of new jobs can be reallocated to the workers being replaced by technological innovation. Technological advancements, such as generative AI, have the potential to create additional income and derive demand for new services. He also emphasized that readjusting, increasing human capital, and providing sustained training are essential to reallocate displaced low-skilled workers to new roles. Generative AI could play a significant role here, as its support can help less-skilled workers improve their problem-solving abilities and customer interactions, enabling them to perform more like high-skilled workers. For instance, as the product support is improved, customers could ask for personal customisation services, which gives workers new responsibilities and contents of their work Brynjolfsson, Li, and Raymond (2023). According to the work conducted by Acemoglu and Restrepo (2018), they claim that the task-based framework, unlike standard models of directed technological change that focus on factor-augmenting technologies, suggests that as a production factor becomes cheaper, it not only expands the range of tasks assigned to that factor but also creates incentives for developing technologies to utilize it more intensively. These economic incentives imply that by lowering the effective labour cost in the least complex tasks, automation discourages additional automation, thereby generating a self-correcting mechanism that promotes stability. For instance, generative AI can be introduced to handle basic customer inquiries, reducing the need for human agents in these areas. Automation in simple tasks (e.g., answering FAQs) makes human agents focus on more complex interactions requiring emotional intelligence and firms develop AI tools to assist human agents with data analysis or customer sentiment tracking, enhancing their productivity instead replacing them entirely.

3 Equation

This study considers generative AI as a form of 'augmented intelligence' that boosts the capabilities of human labor. The main function of it is not simply to replace workers but instead empowers them, narrowing the skill gap between low- and high-skilled occupations by enhancing learning abilities, facilitating skill acquisition, and supporting continuous professional growth. Generative AI also holds promise for continuous upskilling and reskilling. By offering personalized training experiences and providing feedback that adapts to individual learning styles, generative AI could help workers remain relevant in fast-changing industries. This technology could support companies by providing employees with up-to-date knowledge, reducing the need for frequent external training. Moreover, it has the potential to improve productivity in knowledge-intensive sectors by allowing workers to leverage AI as a collaborative tool, generating new ideas and solutions that might otherwise require highly specialized expertise.

We adopt Logistic growth to imitate the influence of Generative AI on the improvement of labour skills, which describes how their skills are enhanced rapidly at first, but the growth rate slows down as their skills approach the same level as mature ones or reach the limit of dealing with more complicated and professional work. Once employees have access to Generative AI, it could equip them with fundamental knowledge and skills to address basic working requirements and provide better services at a considerable speed. The most important thing is to strengthen the ability to learn skills that are completely new and unfamiliar to them. Generative AI has its own limitations in learning skills, especially when employees' problem-solving abilities grow up to a certain level that requires more professional and practical training. Therefore, the growth rate of learning skills is retarded and Generative AI adoption benefits gradually reach a certain level. The efficiency of employees could not be improved further.

Aparicio, Aparicio, Aparicio, and Costa (2024) set up a logistic growth model to illustrate how individuals obtain education and skill acquisition with diminishing returns. Based on this fundamental setting, we expand the model and establish connections with the Total Factor Productivity growth rate to explain the role education and skill acquisition play in productivity growth.

3.1 Education dynamics

$$\frac{dE(t)}{dt} = \rho \cdot (1 - E(t)) \tag{1}$$

This logistic growth model indicates the change in education level over time. Education level $E(t)$ grows over time, but the growth rate slows down as $E(t)$ approaches 1 (a maximum normalised education level). Parameter ρ represents the influence of generative AI both on learning working skills and on increasing the education level via personalised learning, student support, accessibility etc. Particularly in this equation, the interpretation aligns well with the role of ρ as a growth rate parameter, which determines how quickly the education level evolves over time.

No matter the impact of generative AI on skill acquisition or education, we assume it aligns with a sigmoid function ideal for modelling a system where growth is rapid in the early stage and slows down as it approaches a saturation point. Skill acquisition and knowledge attainment typically follow a pattern where progress is slow in the initial stages, accelerates after a foundational level of

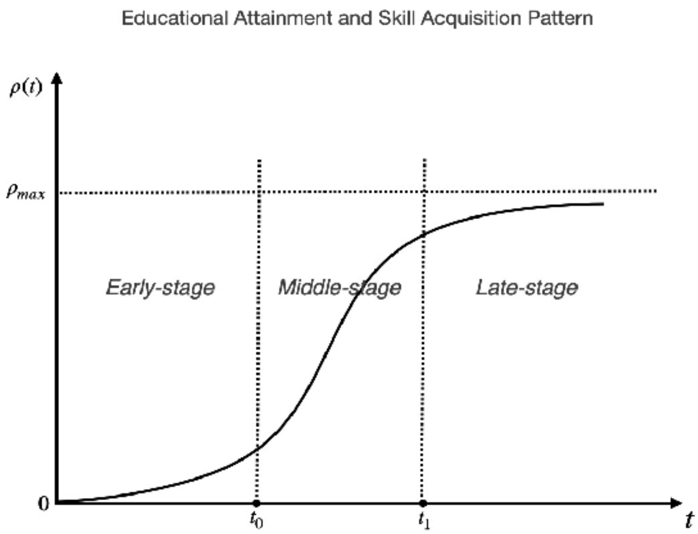

Fig. 1: Educational Attainment and Skill Acquisition Pattern
Source: Author's own work

knowledge and experience is achieved, and eventually stagnates as it approaches the maximum potential level. It makes sense to consider the process of learning following this mechanism in reality.

$$\rho(t)=\frac{\rho}{1+e^{-\gamma(t-t_0)}} \tag{2}$$

Where: t

- ρ is the maximum potential impact of generative AI (the upper limit),
- γ is a scaling parameter indicating how quickly the effect of AI grows initially, which controls the steepness of the curve.
- t_0, t_1 are the inflection points (the time at which generative AI's impact switches from different speeds).

$$\rho(t)=\frac{\rho}{1+e^{-\gamma(t-t_0)}} \tag{3}$$

Earlystage : $t \ll t_0 \Rightarrow \rho(t) \approx 0$

Middlestage : $t_0 < t < t_1 \Rightarrow \rho(t)$ grows rapidly

Latestage : $t \gg t_1 \Rightarrow \rho(t) \approx \rho$ maximum

As the above figure shows: at the early stage, the impact of generative AI is minimal because the process of educational attainment and skill acquisition is slow due to a lack of foundational knowledge. Training and experimentation with the technology might occur, but its influence on education and skills remains limited; At the middle stage, individuals are building upon the foundational knowledge acquired earlier, making faster and exponential progress by providing personalized learning, realistic virtual simulations, and automating repetitive educational tasks. This stage represents the transformative potential of generative AI in enhancing educational and experiential outcomes. At the late stage, growth slows significantly due to diminishing returns, reaching the natural upper bound of educational attainment and skill acquisition. The primary focus shifts to maintaining and optimizing the systems influenced by generative AI, rather than achieving further significant improvements.

The implications for generative AI in education and skill acquisition are that generative AI can tailor learning paths to individual needs, automate routine tasks and boost experience, accelerating middlestage growth. However, as constraints like cognitive load and system maturity lead to diminishing returns in the late stage, generative AI cannot infinitely enhance learning.

3.2 Skill acquisition dynamics

$$\frac{dS}{dt}=\lambda\rho \cdot E(t) \cdot S(t) \tag{4}$$

$$S(t)=\frac{S_{max}}{1+\left(\frac{S_{max}}{S_0}-1\right)\cdot e^{\lambda\rho\int E(t)dt}} \tag{5}$$

In the model, $S(t)$ represents skill acquisition, and both $S(t)$ and $E(t)$ are normalized between 0 and 1, which ensures that the variables do not exceed realistic levels for skill acquisition or education level, reflecting the finite capacity for learning. Equation 4 suggests that the rate of change in skills depends on both the current level of skills $S(t)$ and education level $E(t)$. It also implies that the rate of skill acquisition is proportional to the remaining potential for growth. Equation 5 can be simplified as the following:

$$S(t)=\frac{1}{1+e^{-\lambda\rho\cdot E(t)}} \tag{6}$$

We assume λ as the learning rate which controls the steepness of the curve.

Although these two equations are not mathematic equivalent, they have the same characteristics as sigmoid models and effectively capture the dynamics of skill acquisition with diminishing returns. Both of them have an S-shape that shows a characteristic S-shape curve over time, with a slow start, rapid growth in the middle, and slow levelling off as it approaches its maximum. The functions are bounded, indicating that they cannot exceed the maximum skill level, making it ideal for modelling growth that eventually saturates. Moreover, the growth rate transitions gradually from rapid to slow. In our case, in either form, the model starts with rapid growth, driven by the initial education level and learning rate. As $S(t)$ increases, the growth slows due to the self-limiting term $\left(1-\frac{S(t)}{S_{max}}\right)$, reflecting diminishing returns. Eventually, $S(t)$ approaches the upper bound, S_{max}, which represents the maximum capacity of skills.

Therefore, for low values of $E(t)$, the term $e^{-\lambda\rho E(t)}$ becomes large, making $S(t)$ close to 0. It reflects low skill acquisition when education is low. As $E(t)$ increases, the term $e^{-\lambda\rho E(t)}$ decreases, and $S(t)$ approaches 1, reflecting the diminishing returns in skill acquisition as education improves.

We adopt the Total Factor Productivity (TFP) function and make a connection with the equation for skill acquisition $S(t)$, taking into account how skill, as human capital, influences the productivity of labor in the production function. Skills can be regarded as an enhancement of labor input in the production process, which contributes to both output growth and total factor productivity.

Let us start with the TFP equation. The basic TFP growth decomposition is given by:

$$\frac{\dot{A}}{A}=\frac{\dot{Y}}{Y}-\alpha\frac{\dot{L}}{L}-\beta\frac{\dot{K}}{K} \tag{7}$$

Where: $\frac{\dot{A}}{A}$ is the growth rate of TFP, $\frac{\dot{Y}}{Y}$ is the output growth rate, $\frac{\dot{L}}{L}$ is the labor growth rate, $\frac{\dot{K}}{K}$ is the capital growth rate, α and β are the elasticities of labor and capital, respectively.

Then we modified the Cobb-Douglas Production Function to combine skills with TFP. The original production function becomes:

$$Y = A \cdot K^{\beta} \cdot (L \cdot S(t))^{\alpha} \tag{8}$$

This means that the effective labor input is now adjusted by the level of skills $S(t)$. It shows that higher skills result in more productive labor, even if the total number of workers remains constant. Continuously, we modify the TFP growth equation to account for the skill-adjusted labor input. The growth rate of labor $\frac{\dot{L}}{L}$ is replaced with the growth rate of the effective labor $L(t) \cdot S(t)$. The new TFP equation becomes:

$$\frac{\dot{A}}{A} = \frac{\dot{Y}}{Y} - \alpha\left(\frac{\dot{L}}{L} - \frac{\dot{S(t)}}{S(t)}\right) + \beta\frac{\dot{K}}{K} \tag{9}$$

The new equation indicates that the growth of effective labor comes from two resources: growth in the quantity of labor $\frac{\dot{L}}{L}$ and in the quality of labor $\frac{\dot{S(t)}}{S(t)}$

As the growth rate of $S(t)$ is:

$$\frac{\dot{S(t)}}{S(t)} = \beta\rho \cdot E(t) \cdot (1 - S(t)) \cdot \frac{dE(t)}{dt} \tag{10}$$

The final combined TFP growth equation is given by:

$$\frac{\dot{A}}{A} = \frac{\dot{Y}}{Y} - \alpha\left(\frac{\dot{L}}{L} + \lambda\rho \cdot E(t) \cdot (1 - S(t))\right) - \beta\frac{\dot{K}}{K} \tag{11}$$

This equation now incorporates both the growth in labor input and the growth in skills $S(t)$ as a function of education level $E(t)$. The new labor term now reflects both the quantity and quality of labor. In spite of the number of workers, an increase in skills due to education will lead to more effective labor input, enhancing output. And the sigmoid function for skills $S(t)$ introduces diminishing returns to education. As workers become more skilled, the growth in skills slows down, reflecting that there is a limit to how much education can improve productivity. Especially, for the term $1 - S(t)$, it reflects the idea that productivity improvement (or skill acquisition) is easy and rapid in the early stages but becomes progressively harder as workers approach their maximum potential. In the real world, early gains in education or training lead to large improvements in skills and productivity but later stages require much more effort for marginal improvements because there is less left to learn or fewer gains to be made. This kind of approach highlights the importance of human capital (skills and education) in economic growth, making it an integral part of the productivity analysis.

By substituting $S(t)$ into this equation and making an arrangement, we can get:

$$\frac{\dot{A}}{A} = \frac{\dot{Y}}{Y} - \alpha\left(\frac{\dot{L}}{L} + \lambda(1 - S(t)) \cdot (1 - E(t)) \cdot \left(1 + \frac{\rho}{1 + e^{-\gamma(t - t_0)}}\right)^2\right) - \beta\frac{\dot{K}}{K} \tag{12}$$

The term $\lambda(1-S(t))$ captures the normal contribution of skill acquisition to labor productivity. When the skill gap $(1-S(t))$ is high, the normal impact of skill development on productivity is also high, indicating that more potential remains for skill improvement to contribute to productivity. As $S(t)$ increases, this impact diminishes, reflecting diminishing returns to skill acquisition in the absence of generative AI. The interaction term $(1-E(t))$ extends the normal impact of skill by incorporating the education gap. It suggests that the combined impact of skill and education on labor productivity is more significant when both skill levels and education levels are low. As workers become more skilled $(S(t)\to 1)$ and educated $(E(t)\to 1)$, the joint impact of skill and education diminishes under normal conditions (without generative AI).

Moreover, the term $\left(1+\frac{\rho}{1+e^{-\gamma(t-t_0)}}\right)^2$ represents the amplification effect of generative AI on productivity, particularly through its influence on skill and education levels. During the early stages of generative AI adoption $(t \approx t_0)$, the logistic term $1+\frac{\rho}{1+e^{-\gamma(t-t_0)}}$ starts low, implying that generative AI's amplification effects are limited. As time progresses $(t > t_0)$ and generative AI adoption accelerates, the logistic term increases rapidly, indicating a boost in the impact of skill and education on productivity. The squared term further magnifies this effect, suggesting that generative AI significantly enhances productivity when skill and education levels are still developing. Then, as generative AI adoption matures $(t \gg t_0)$, the logistic term stabilizes near ρ, presenting the maximum potential impact of generative AI on skill and education integration. The amplification effect remains strong, but it does not contribute to increases.

The overall term $\lambda(1-S(t))\cdot(1-E(t))\cdot\left(1+\frac{\rho}{1+e^{-\gamma(t-t_0)}}\right)^2$ captures the synergistic effects of skill, education, and generative AI on labor productivity. Specifically,

(1) Synergy between skills and generative AI: As workers acquire more skills, generative AI further amplifies their productivity by automating complex tasks, enhancing decision-making, and facilitating advanced learning.

(2) Synergy between education and generative AI: Generative AI facilitates individuals to be more likely to obtain higher education effectively. Higher education levels in return allow workers to leverage generative AI more effectively, leading to better integration of AI tools and higher productivity gains.

(3) Interaction effect of skill, education, and generative AI: The term reflects that the joint effects of skill and education on productivity are non-linear and highly dependent on generative AI's presence. When generative AI is more developed (as represented by ρ), the combined impact of skills and education on TFP growth is much greater than in the absence of generative AI.

This model also indicates that the negative term (adaptation costs) remains significant during the initial phase of generative AI adoption, particularly when skill and education levels are low. However, as $S(t)$ and $E(t)$ improve over time, the diminishing skill and education gaps reduce the size of negative effects. The amplification effects of AI driven by ρ ensure that the positive contributions to TFP growth from skill and education improvements become dominant over time, leading to a net increase in TFP. As a conclusion, generative AI not only offsets initial adaptation costs but also increases a multiplicative effect on productivity growth as skill and education levels increase, leading to a sustained rise in TFP over time.

3.3 Effects on labor demand

We start the analysis with a modified version of the Cobb-Douglas production function, considering generative AI acts as a substitute for low-skilled workers;

$$Y = A \cdot (L_L \cdot \rho_{(t)}{}^{-\gamma})^{\alpha_L} \cdot L_H^{\alpha_H} \cdot K^{\beta} \tag{13}$$

where: L_L: Low-skilled labor

γ: we use the rate of generative AI adoption γ to represent its substitution effect on low-skilled labor to simply the model for the reason that the more generative AI adoption, the greater impact on the replacement of low-skilled labor. Thus, $\gamma > 0$ captures the degree to which generative AI substitutes for low-skilled labor.

- if $\gamma = 0$. there is no substitution effect.
- as γ increases, generative AI has a stronger substitutive impact on low-skilled labor.
- α_L, α_H, β: Elasticities on low-skilled labor, high-skilled labor, and capital, respectively.

$$L_L^d = \left(\frac{\alpha_L \cdot A \cdot L_H^{\alpha_H} \cdot K^{\beta}}{w_L / P} \right)^{\frac{1}{1-\alpha_L}} \cdot \rho_{(t)}{}^{\frac{-\gamma\alpha_L}{1-\alpha_L}} \tag{14}$$

When γ is high, generative AI adoption not only occurs faster but also more strongly reduces the demand for low-skilled labor as it can perform tasks that low-skilled labor would traditionally handle, making the marginal product of low-skilled labor lower and, thus, reducing its demand. When γ is low, generative AI adoption is slower, leading to a more gradual decline in low-skilled labor demand, reflecting slower substitution.

We assume;

$$A = A_0 \cdot (1 - \alpha_L) \cdot \rho(t) \tag{15}$$

This assumption simplifies total factor productivity to depend on the baseline productivity A_0, the potential for non-low-skilled labor productivity growth $a - \alpha_L$, and the time-varying factor $\rho(t)$ that captures the dynamics of productivity growth to generative AI adoption. The term $\rho(t)$ refelcts the overall impact of generative AI adoption, which directly accounts for the dynamic contribution of skill and education development.

Using the assumption $A = A_0 \cdot (1 - \alpha_L) \cdot \rho(t)$, the analysis becomes more straightforward. It combines multiple factors into a single variable $\rho(t)$, simplifying the dynamics without losing the essence of how skill, education, and technology affect productivity growth. It also retains the core logic, as the time-varying impact of $\rho(t)$ still reflects the S-shaped diffusion of generative AI, skill improvement, and education gaps over time.

The low-skilled labor demand function becomes:

$$L_L^d=\left(\frac{\alpha_L\cdot A_0\cdot(1-\alpha_L)\cdot L_H^{\alpha_H}\cdot K^{\beta}}{w_L/P}\right)^{\frac{1}{1-\alpha_L}}\cdot\rho_{(t)}{}^{\frac{1-\gamma\alpha_L}{1-\alpha_L}} \tag{16}$$

The power of ρ in the equation is:

$$\frac{1-\gamma\alpha_L}{1-\alpha_L} \tag{17}$$

The parameter γ here captures the degree of substitution between generative AI and low-skilled labor. Its influence is evident from this power term.

a. When $\gamma<\frac{1}{\alpha_L}$:

if $\gamma<\frac{1}{\alpha_L}$, then exponent $\frac{1-\gamma}{1-\alpha_L}$ is positvie, meaning that increasing $\rho(t)$ will increase low-skiled labor demand L_L^d.

This implies that generative AI adoption acts as a complement to low-skilled labor, enhancing their productivity and increasing demand.

b. When $\gamma>\frac{1}{\alpha_L}$:

if $\gamma>\frac{1}{\alpha_L}$, the exponent $\frac{1-\gamma}{1-\alpha_L}$ is negatie, indicating that increasing $\rho(t)$ will decrease low-skiled labor demand L_L^d.

This scenario represents the substitutive effect of generative AI, where higher generative AI adoption reduces the need for low-skilled labor by replacing their tasks.

c. When $\gamma=\frac{1}{\alpha_L}$:

if $\gamma=\frac{1}{\alpha_L}$, the exponent becomes zero, reflecting that $\rho(t)$ has no effect on low-skilled labor demand. In this case, the level of generative AI adoption doesn't affect the demand for low-skilled workers.

In conclusion, as γ increases, the power of $\rho(t)$ becomes more negative (or less positive), implying a stronger substitution effect. In other words, a higher γ means that generative AI more effectively replaces low-skilled tasks, leading to a greater reduction in low-skilled labor demand as generative AI adoption rises. As γ decreases, the power of $\rho(t)$ becomes more positive (or less negative), indicating a weaker substitution effect. Lower values of γ suggest that generative AI acts more as a complement to low-skilled labor, enhancing their productivity rather than replacing them.

Similarly,

$$L_H^d=\left(\frac{\alpha_L\cdot A_0\cdot(1-\alpha_L)\cdot L_H^{\alpha_H}\cdot K^\beta}{w_H/P}\right)^{\frac{1}{1-\alpha_L}}\cdot\rho_{(t)}{}^{\frac{1-\gamma\alpha_L}{1-\alpha_H}} \tag{18}$$

The power of ρ in the equation is:

$$\frac{1-\gamma\alpha_L}{1-\alpha_H} \tag{19}$$

Basically speaking, if $\rho(t)$ increases (representing an increase in generative AI capabilities), and $\gamma>0$, it effectively reduces the need for low-skilled labor. It makes low-skilled labor less critical in production, potentially reducing the marginal benefit of high-skilled labor where high-skilled workers oversee or coordinate with low-skilled labor. As a result, demand for high-skilled labor also declines if it relies on coordination with low-skilled tasks.

if $\rho(t)$ decreases, low-skilled labor productivity decreases, which can lead to a greater reliance on high-skilled labor for overall productivity. In this case, demand for high-skilled labor may increase to offset the reduced productivity of low-skilled labor, as more complex or decision-intensive tasks become relatively more important.

In essence, the role of $\rho(t)$ and γ have impacts on low-skilled labor L_L. Higher $\rho(t)$ with high γ means that low-skilled labor's productivity is greatly reduced by generative AI, implying that generative AI acts as a close substitute for low-skilled labor. Lower $\rho(t)$ or low γ means that generative AI does not strongly substitute for low-skilled labor, allowing low-skilled labor to retain its productivity. Although high-skilled labor L_H is not directly modified by $\rho(t)$, its demand is influenced through changes in low-skilled labor productivity caused by $\rho(t)$ and the degree of substitutability γ.

3.4 Indirect Impact on High-Skilled Labor Demand

The parameter $\rho(t)$ affects high-skilled labor demand indirectly through its impact on low-skilled labor. The relationship unfolds as follows:

3.4.1 Marginal Productivity of High-Skilled Labor (MPL_H)

The demand for high-skilled labor L_H depends on its marginal productivity, which is influenced by the productivity of other inputs in the production function, including L_L. The marginal product of high-skilled labor MPL_H is:

$$MPL_H=\alpha_H\cdot A\cdot(L_L\cdot\rho(t)^{-\gamma})^{\alpha_L}\cdot L_H^{\alpha_H-1}\cdot K^\beta \tag{20}$$

In this formula, even though $\rho(t)$ does not directly modify L_H, it affects MPL_H through the term $(L_L\cdot\rho(t)^{-\gamma})^{\alpha_L}$, which adjusts the effective productivity of low-skilled labor.

3.4.2 How $\rho(t)$ and γ Affect High-Skilled Labor Demand

Case 1: High $\rho(t)$ and High γ (Strong AI Substitution for Low-Skilled Labor)

With high $\rho(t)$ and large γ, generative AI significantly reduces the productivity of low-skilled labor, as the term $L_L \cdot \rho(t)^{-\gamma}$ becomes very small. This reduced productivity of low-skilled labor means that less output is produced by low-skilled labor, and more reliance maybe placed on high-skilled labor to maintain production. However, this effect can also mean that as low-skilled labor becomes less productive and potentially less necessary, high-skilled labor may also experience reduced demand if high-skilled tasks are linked to supervising or coordinating low-skilled tasks.

In summary, high $\rho(t)$ or low γ can lead to reduced demand for both low- and high- skilled labor if generative AI significantly displaces low-skilled roles, diminishing the need for high-skilled roles that are complementary to low-skilled work. For instance, generative AI reduces the need for basic programming, and fewer elementary programmers means that senior developers may be needed less to oversee or improve programming processes and might shift more towards overseeing systems design instead.

Case 2: Moderate $\rho(t)$ or Low γ (Weak Substitution for Low-Skilled labor)

With moderate $\rho(t)$ or low γ, generative AI has a less impact on low-skilled labor productivity, meaning low-skilled labor retains more of its productivity. In this case, low-skilled labor remains an important part of the production, and high-skilled labor that complements or coordinates with low-skilled tasks remains valuable.

As a result, demand for high-skilled labor could increase as high-skilled workers remain necessary to oversee or enhance low-skilled labor productivity.

The case is different for high-skilled labor. Since high-skilled labor (L_H) is not directly modified by the generative AI term in the production function, we'll examine how the indirect effects of generative AI adoption on total productivity.

In summary, moderate $\rho(t)$ or low γ supports continued demand for both low- and high-skilled labor, as generative AI does not fully displace low-skilled worker, preserving the roles of high-skilled workers who work alongside them.

In some sector, generative AI does not replace low-skilled labor entirely but will augmented its productivity, which aligns with the model's case of moderate $\rho(t)$ or low γ. In these cases, generative AI can support high-skilled labor by keeping low-skilled tasks relevant while making both types of labor more productive. For instance, generative AI assist doctors (high-skilled) with diagnostics, and low- skilled medical staff (nurses, technicians) are still needed to provide care. Here, generative acts as an augmentation tool, supporting high-skilled roles without displacing low-skilled roles entirely. Another example can be easily found in the finance area, generative AI supports analysts and data scientists by processing data effectively, but the demand for high-skilled finance professionals remains as the interpret and apply generative AI-driven insights.

Additionally, $\rho(t)$ represents generative AI and its impact on low-skilled labor productivity in the production function, the term $(L_L \cdot \rho(t)^{-\gamma})$ reflects how generative AI affects the effective productivity of low-skilled labor:

$$(L_L \cdot \rho(t)^{-\gamma})^{\alpha_L} = (L_L)^{\alpha_L} \cdot \rho(t)^{-\gamma\alpha_L} \tag{21}$$

This breakdown means that $L_L^{\alpha_L}$ captures the direct contribution of low-skilled labor L_L to production and $\rho(t)^{-\gamma\alpha_L}$ reflects the adjustment to low-skilled labor productivity due to generative AI. A higher ρ (more generative AI adoption) with a positive γ reduces the effective input of low-skilled labor, indirectly impacting the demand for high-skilled labor L_H.

In the complementary effects scenario (moderate ρ and low γ, the term $\rho(t)^{-\gamma\alpha_L}$ could be excluded justifiably if the indirect effect of generative AI on high-skilled labor demand is minimal. Because if generative AI adoption is very low, then $\rho \approx 1$, making $\rho(t)^{-\gamma\alpha_L} \approx 1$. The impact of generative Ai on low-skilled labor productivity is negligible, and the term $\rho(t)^{-\gamma\alpha_L}$ can be excluded without significantly affecting the high-skilled labor demand equation. And if γ is close to zero, generative AI has minimal substitutive power over low-skilled labor. This implies that generative AI adoption does not greatly impact low-skilled labor productivity, so $\rho(t)^{-\gamma\alpha_L} \approx 1$. Under these circumstances, excluding the term might reasonable because generative AI's effect on high-skilled labor demand through low-skilled productivity is weak.

Therefore, the high-skilled labor demand equation can be simplified in this way:

$$L_H^d = \left(\frac{\alpha_H \cdot A_0 \cdot (1-\alpha_L) \cdot \rho(t) \cdot L_L^{\alpha_L} \cdot K^{\beta}}{w_H / P} \right)^{\frac{1}{1-\alpha_H}} \tag{22}$$

3.5 Influence of Generative Ai ($\rho(t)$) and the Substitution Paramenter (γ)

a. High Rate of Generative AI adoption (High $\rho(t)$)

In this scenario, it can be found that a high rate of generative AI adoption rapidly enhances productivity. This productivity growth increases the marginal product of high-skilled labor, as high-skilled workers are needed to utilise, oversee, and interpret generative AI improvements. High-skilled workers also become more essential as they take on roles that involve collaborating with generative AI or managing generative AI-integrated workflows. This leads to an increase in high-skilled labor demand, as these workers are critical for maximizing the effectiveness of the generative AI-driven productivity gains.

b. High Substitution Parameter for Low-Skilled Labor (γ)

As mentioned before, when γ is high, generative AI substitutes strongly for low-skilled labor, displacing these workers. High-skilled labor demand rises as companies look for employees capable of performing non-routine, complex tasks that generative AI cannot handle autonomously. Moreover, high-skilled workers may be required to oversee or supervise AI systems. ensuring quality control, ethical compliance, and troubleshooting tasks that require expertise beyond what low-skilled labor can provide.

c. Low Rate of Generative AI Adoption (Low $\rho(t)$)

If generative AI adoption is slow, the complementary effect on high-skilled labor is less immediate, as the productivity gains are smaller and more gradual. Demand for high-skilled labor may increase slowly, as companies gradually integrate generative AI into workflows. However, slower adoption means that high-skilled workers have more time to adapt and find complementary roles with generative AI, potentially increasing demand at a more measured pace.

4 conclusion

This paper analyses the relationship between education, skill acquisition and generative AI. AS a branch of AI, generative AI has the potential to reform the mode of production in domains and industries that rely on creativity, innovation, and knowledge processes. It can help both low-skilled and high-skilled workers improve their abilities to adapt to the new requirements put forward by updated industries and create new demands as the era of AI advances. In particular, this technology unlocks new possibilities for applications that were previously considered impossible or impractical to automate. These include realistic virtual assistants, personalized education and services, as well as the creation of digital art (Feuerriegel, Hartmann, Janiesch, & Zschech, 2024).

It is represented as a transformative technology that influences both labor demand and supply, creating shifts in occupational structures. While low-skilled, routine jobs face displacement due to automation, generative AI creates opportunities in high-skill, cognitive, and innovative roles. This duality fosters economic restructuring and necessitates skill acquisition for displaced wokers by facilitating personalized learning. We assume learning patterns and generative AI adoption follow an S-curve, with a slow start, rapid middle-stage growth, and eventual plateau as knowledge reaches cognitive upper limits and generative AI becomes integrated into workflows. This characteristic reflects their impacts on productivity, with early gains being the most significant. Education and skill development are shown to be mutually reinforcing, with generative AI accelerating middle-stage growth and narrowing the gap between low- and high-skilled workers. We emphasis that generative AI acts as a substitute for low-skilled labor while complementing high-skilled labor. This substitution effect depends on the degree of adoption (ρ) and the substitution parameter (γ). Higher value of γ signify stronger displacement of low-skilled labor, whereas moderate values promote complementarity, enhancing the productivity of both labor type. In addition, our model includes a synergy between generative AI, skills, and education, amplifying productivity when both education and skill levels are low. The inegration of genreative AI into production models shows a significant boost to TFP by improving both the quality and quantity of labor input.

Our analysis suggests that while generative AI introduces adaption costs intiially, its long-term benefits outweigh these cost by driving sustained TFP growth. The potential for generative AI to narrow skill gaps and enable continuous learning makes it a critical tool for addressing labor market inequalities. The main limitation of this paper is assumption that we assume λ (learning rate) and ρ (impact of generative AI) are constant and straightforwardly parameterized. In reality, these parameters likely vary significantly across individuals, industrials, and over time, influenced by factors such as adaptability, access to technology, and sector-specific requirements. Furtur research could address this limitation by exploring and comparing how λ and ρ differ across industries and demographics, provding a more nuanced understing of generative AI's impact on skill acquistion and productivity.

Appendix A Skill acquisition dynamics

The logistic model can be derived from a differential equation that includes a self-limiting

$$\frac{dS}{dt}=\lambda\cdot E(t)\cdot S(t)\cdot\left(1-\frac{S(t)}{S_{max}}\right) \tag{A1}$$

Here, we assume S_{max} is the maximum skill level that makes sense because each worker faces a natural limitation for their skills, and the term $\left(1-\frac{S(t)}{S_{max}}\right)$ indicates the remaining capacity for growth. It decreases as $S(t)$ approaches S_{max}.

Then we separate the variables $S(t)$ and t in the differential equation:

$$\frac{1}{S(t)}\cdot\left(1-\frac{S(t)}{S_{max}}\right)dS=\lambda\cdot E(t)dt \tag{A2}$$

Thus, the differential equation becomes:

$$\left(\frac{1}{S(t)}+\frac{1}{S_{max}-S(t)}\right)dS=\lambda\cdot E(t)dt \tag{A3}$$

We integrate both sides:

Left Side Integration:

$$\int\left(\frac{1}{S(t)}+\frac{1}{S_{max}-S(t)}\right)dS \tag{A4}$$

$$\ln|S(t)-\ln|S_{max}-S(t) \tag{A5}$$

Right Side Integration:

$$\int\lambda\cdot E(t)dt \tag{A6}$$

And, combining both sides, we get:

$$\ln\left(\frac{S(t)}{S_{max}-S(t)}\right)=\lambda\int E(t)dt+C \tag{A7}$$

Where C is the constant of integration.

Then, we exponentiate both sides to eliminate the logarithm.

$$\frac{S(t)}{S_{max}-S(t)}=e^{\lambda\int E(t)dt+C} \tag{A8}$$

and let $e^{C}=C_0$, where C_0 is a constant.

$$\frac{S(t)}{S_{max}-S(t)}=C_0\cdot e^{\lambda}\int E(t)dt \tag{A9}$$

Thus:

$$S(t)=\frac{C_0\cdot S_{max}\cdot e^{\lambda\int E(t)dt}}{1+C_0\cdot e^{\lambda\int E(t)dt}} \tag{A10}$$

and let's redefine C_0 in terms of initial conditions. Assume the initial skill level is $S(0)=S_0$, so when $t=0$:

$$C_0=\frac{S_0}{S_{max}-S_0} \tag{A11}$$

Plug C_0 back in to the expression for $S(t)$:

$$S(t)=\frac{S_{max}\cdot S_0\cdot e^{\lambda\int E(t)dt}}{(S_{max}-S_0)+S_0\cdot e^{\lambda\int E(t)dt}}=\frac{S_{max}}{1+\left(\frac{S_{max}}{S_0}-1\right)\cdot e^{\lambda\int E(t)dt}} \tag{A12}$$

In this equation, S_{max} is the upper limit of the skill lever. The term $\left(\frac{S_{max}}{S_0}-1\right)$ determines the initial deviation from the maximum skill level, and $\lambda\cdot\int E(t)$ represents the cumulative effect of education, scaled by the learning rate. The form of this expression is indeed a sigmoid model. We do not focus on analysing the process of accumulating education but just the education level once achieved (the instantaneous education level at time t). Therefore, the model can be simplified as:

$$S(t)=\frac{1}{1+e^{\lambda E(t)}} \tag{A13}$$

Continuously, differentiate this sigmoid function to find the rate of change of $S(t)$ with respect to time, i.e., $\frac{dS(t)}{dt}$.

$$\frac{dS(t)}{dt}=-\frac{d}{dt}(1+e^{-\lambda E(t)})\cdot\left(\frac{1}{(1+e^{-\lambda E(t)})^2}\right) \tag{A14}$$

And, $1-S(t)$ is:

$$1-S(t)=\frac{e^{-\lambda E(t)}}{1+e^{\lambda E(t)}} \tag{A15}$$

Substitute this into the derivative expression and get the final result:

$$\frac{dS(t)}{dt} = \lambda \cdot S(t) \cdot (1 - S(t)) \cdot \frac{dE(t)}{dt} \tag{A16}$$

There are three factors affecting the rate of change in skills. The first one is the current value of $S(t)$, which denotes how much skill has already been acquired. The second one is the remaining capacity for growth, represented by $1-S(t)$. As $S(t)$ approaches 1 (the maximum level), $1-S(t)$ approaches 0, meaning there is less room for further growth, which introduces diminishing returns. The last one is the rate of change of the driving factor $E(t)$ and the parameter λ. $\lambda \cdot \frac{dE(t)}{d(t)}$ suggests that the rate at which education level $E(t)$ influences skill acquisition, moderated by the parameter λ. Furthermore, in the case of skill acquisition, the term $\frac{dE(t)}{dt}$ indicates that the rate at which skills change depends not only on the current skill level and the remaining growth potential but also on the rate of change of education. In other words, skill acquisition is directly influenced by how quickly education or learning progressing.

According to the product rule, the derivative of the product of the original function $\frac{(L \cdot \dot{S(t)})}{L \cdot S(t)}$ is:

$$L \cdot \dot{S(t)} = \frac{d}{dt}(L \cdot S(t)) - \dot{L} \cdot S(t) \tag{A17}$$

Thus:

$$\frac{L \cdot \dot{S(t)}}{L \cdot S(t)} = \frac{\frac{d}{dt}(L \cdot S(t)) - \dot{L} \cdot S(t)}{L \cdot S(t)} \tag{A18}$$

Then:

$$\frac{L \cdot \dot{S(t)}}{L \cdot S(t)} = \frac{\dot{L}}{L} + \frac{\dot{S(t)}}{S(t)} \tag{A19}$$

Here, $\frac{dotL}{L}$ represents the growth rate of labor over time and $\frac{\dot{S(t)}}{S(t)}$ represents the growth rate of skills over time

References

Acemoglu, D., & Autor, D. (2012). What does human capital do? a review of goldin and katz's the race between education and technology. *Journal of Economic Literature*, *50*(2), 426-463.

Acemoglu, D., & Restrepo, P. (2018). The race between man and machine: Implications of technology for growth, factor shares, and employment. *American economic review*, *108*(6), 1488-1542.

Aparicio, J.T., Aparicio, M., Aparicio, S., Costa, C.J. (2024). Predicting the impact of generative ai using an agent-based model. *arXiv preprint arXiv: 2408. 17268.*

Autor, D.H., Dorn, D., Hanson, G.H. (2015). Untangling trade and technology: Evidence from local labour markets. *The Economic Journal*, *125*(584), 621-646.

Bai, C., & Lei, X. (2020). New trends in population aging and challenges for china's sustainable development. *China Economic Journal*, *13*(1), 3-23.

Brynjolfsson, E., Li, D., Raymond, L.R. (2023). *Generative ai at work* (Tech. Rep.). National Bureau of Economic Research.

Caselli, F. (1999). Technological revolutions. *American economic review*, *89*(1), 78-102.

Chui, M., Hazan, E., Roberts, R., Singla, A., Smaje, K. (2023). The economic potential of generative ai.

Dedrick, J., Gurbaxani, V., Kraemer, K.L. (2003). Information technology and economic performance: A critical review of the empirical evidence. *ACM Computing Surveys (CSUR)*, *35*(1), 1-28.

Feuerriegel, S., Hartmann, J., Janiesch, C., Zschech, P. (2024). Generative ai. *Business & Information Systems Engineering*, *66*(1), 111-126.

Frey, C.B. (2019). The technology trap: Capital, labor, and power in the age of automation. *The technology trap*. Princeton University Press.

Jorgenson, D.W. (2001). Information technology and the us economy. *American Economic Review*, *91*(1), 1-32.

Luo, Y., Su, B., Zheng, X. (2021). Trends and challenges for population and health during population aging – china, 2015-2050. *China CDC weekly*, *3*(28), 593.

Mokyr, J., Vickers, C., Ziebarth, N.L. (2015). The history of technological anxiety and the future of economic growth: Is this time different? *Journal of economic perspectives*, *29*(3), 31-50.

Nelson, R.R., & Phelps, E.S. (1966). Investment in humans, technological diffusion, and economic growth. *The American economic review*, *56*(1/2), 69-75.

Noy, S., & Zhang, W. (2023). Experimental evidence on the productivity effects of generative artificial intelligence. *Science*, *381*(6654), 187-192.

Romer, P.M. (1990). Capital, labor, and productivity. *Brookings papers on economic activity. Microeconomics*, *1990*, 337-367.

Webb, M. (2019). The impact of artificial intelligence on the labor market. *Available at SSRN 3482150*.

Zarifhonarvar, A. (2024). Economics of chatgpt: A labor market view on the occupational impact of artificial intelligence. *Journal of Electronic Business & Digital Economics*, *3*(2), 100-116.