DOI: 10.1111/joes.12422

JOURNAL OF ECONOMIC SURVEYS WILEY

ARTICLE

A review on the economics of artificial intelligence

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Abstract

The rapid development of artificial intelligence (AI) not only represents a scientific breakthrough but also has impacts on human society and economies, as well as on the development of economics. This paper focuses on the macroeconomic perspective, reviewing recent literature in order to answer three key questions. First, what approaches are being used to represent AI in economic models? Second, will AI technology have an impact on the economy different from that of previous new technologies? Third, in which aspects will AI have an impact, and what is the empirical evidence for these effects of AI?

On the first question, our review reveals that the incorporation of AI into economic models raises fundamental questions on economics and economic models. On the second question, while most empirical studies cannot deny the existence of the Solow Paradox for AI technology, some studies find that AI would have a different and broader impact than previous technologies. On the third question, studies on the labor market seem to suggest a stylized fact regarding the impact of AI on employment on different levels, and income inequality across skill levels and between developing and developed countries. The impacts of AI on international trade and education have been largely neglected and are worth further research in the future. It is also important for both theoretical and empirical studies to have a clear and accurate definition of AI so that the results are not misinterpreted.

KEYWORDS
artificial intelligence, development of economics, literature review

JEL CLASSIFICATION
A12, E1, E24, E65, F41, J21

1 INTRODUCTION

On October 19 2017, AlphaGo's team published an article in *Nature* introducing a new version of the artificial intelligence game AlphaGo Zero. This version of AlphaGo learned to be much better at the game of Go than all previous versions of AlphaGo at defeating human masters of the game. It did this in 40 days, without using input data from human games.[1] In other words, artificial intelligence (AI) could learn or train itself from nothing to defeat human experts. This was not only a breakthrough in the development of artificial intelligence, but also had important implications for human society.

Economists have become interested in AI, mainly because the labor share of income has been seen falling in recent decades. Figure 1 is from Karabarbounis and Neiman's (2014) study, showing

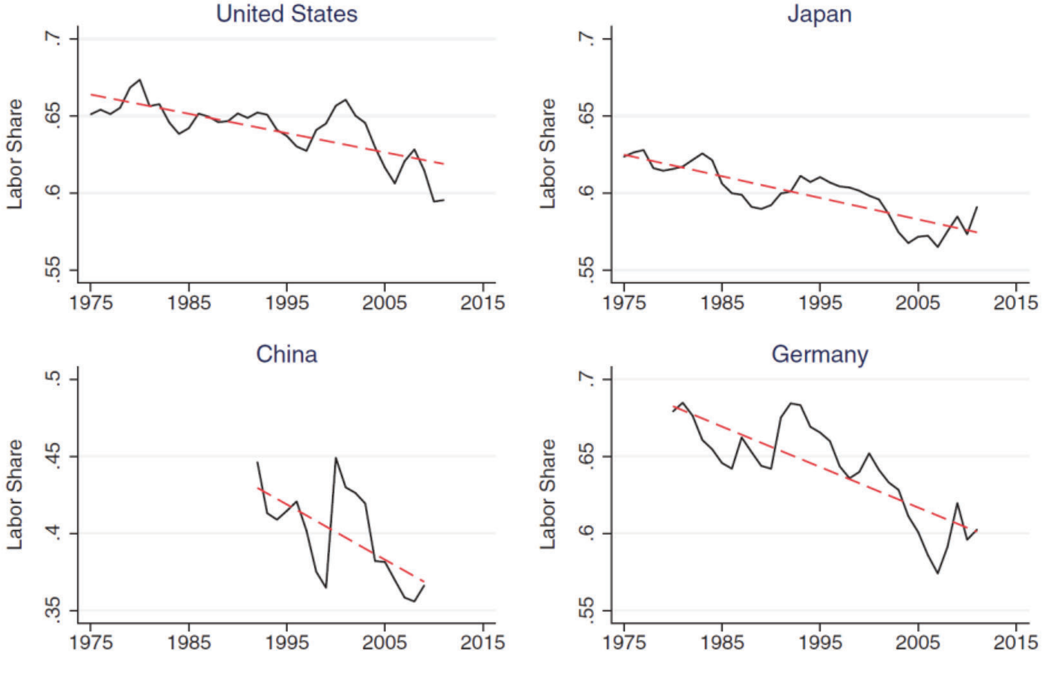


FIGURE 1 Labor share of the four largest economies
Note: The figure is from Figure II of Rob Karabarbounis and Neiman's (2014) paper
[Colour figure can be viewed at wileyonlinelibrary.com]

that labor shares in the largest economies have been declining since 1975. Technological progress has been "blamed" as a major culprit in this observation. In particular, as an upfront technology with rapid development, AI has become a focus of economic investigation. As a result, research on the economic impact of artificial intelligence has attracted much interest among economists in recent years. Due to the origin of the problem, it has been a hot topic in macroeconomic literature in particular.

To review these studies, it is important to first define what AI is in the literature of engineering and economics. It is clear in science terms, but vague in economic research. Economists use "automation," "robotics," "digitalization," or "computerization" variously to refer to the concept of artificial intelligence (i.e., AI) in a broader sense. In fact, there are differences between these terms. Agrawal et al. (2017) date AI's commercial birth to 2012. Cockburn et al. (2019) think that the domain of AI contains robotics, neural networks and machine learning, and symbolic systems. "Automation," "digitalization," and "computerization" may only reflect a part of artificial intelligence, and robotics can be, but is not necessarily, one form of AI. Automation and robots are not necessarily artificial intelligence, as they can simply be programmed to perform a given task, or set of tasks, and workers can supervise and maintain the robots. A key feature of AI is to process data to decide, for example, whether to offer people a mortgage or not, or to take in data from the physical environment and decide what to do, or else, use that data to learn. AI replaces labor, rather than functioning as a tool that increases the productivity of labor, which traditional technologies did. For convenience, we use the term "artificial intelligence (AI)" to refer to all the other terms used in various studies. However, the differences between these terms are discussed in detail in the following section and revisited from time to time throughout this paper.

Interestingly, at first glance, ideas around AI in economics can be grouped into three streams. From many consulting organizations' points of view, AI has great potential to enhance human life quality and economic growth, and the natural implication is that industries, investors, and consumers should embrace it as a blessing (BCG, 2015; MGI, 2017). However, policymakers are more concerned with its impact on employment, in that jobs might be destroyed and workers might be replaced by AI. Meanwhile, most economists seem to be on neither side, and tend to be more cautious about the future AI world. This cautiousness is due mainly to empirical studies using recent data. Crafts and Mills (2017) found that total factor productivity (TFP) growth has declined steadily from 1.5% to 1.0% per year over the past 50 years. Since the late 1990s, and after the Global Financial Crisis (GFC) in particular, almost all OECD countries have experienced a slowdown in labor productivity growth. This slowdown is also true in emerging and developing economies, whose productivity growth accelerated during the 2000s then peaked around the time of the GFC (Syverson, 2017). This creates a paradox between the potential of a highly automated world in the future and the sad reality of the current economic slowdown, which is referred to, by Gordon (2016), Brynjolfsson et al. (2019), and many others, as the Solow (1987) Paradox.

Although a discussion on AI economics has only recently opened up, and the research framework is still not clear, we suggest that it might be timely for a literature review, so that future directions can be seen. Varian (2018) published a literature review specifically on AI and industrial organization, which summarized some areas for future research. In this paper, we review macroeconomic studies relevant to AI, mostly from the past 5 years. We focus on providing a comprehensive understanding of AI's potential impact on various aspects of macroeconomy, and on the current development of AI economics, to help find gaps for future research and to provoke further thoughts on this topic.

This paper starts with a discussion of the definition of AI from both engineering and economic perspectives. Then, three questions are proposed and investigated: first, we ask how AI is represented in theoretical economic models by reviewing some important proposed models using different setups; then we address the question of whether AI technology might affect the economy differently from previous new technologies, using studies where historical trends and theoretical predictions are compared; third, by looking at the empirical evidence on the effects of the early stages of AI we ask, if AI were to prevail, what aspects of the economy would be affected and required to change. Finally, we conclude by identifying some gaps and possible directions for future research on this topic.

2 | DEFINITION OF AI IN THE ENGINEERING AND ECONOMICS LITERATURE

For economists, the definition of AI is both broad and narrow. The words most frequently used by economists referring to AI are "automation" and "robots," or even "machines" (Acemoglu & Restrepo, 2020; Sachs et al., 2015). For an engineer, "automation" and "robots" are well defined terms that can stand independently of the concept of AI. According to Groover (2014), automation is the technology by which a process or procedure is performed with minimal human assistance. However, AI means more than "automation" for engineers and scientists. Taddeo and Floridi (2018) point out that AI may be defined as a growing resource of interactive, autonomous, self-learning agency that enables computational artifacts to perform tasks that otherwise would require human intelligence to be executed successfully. Taddy (2019) explains that with recent improvements in Deep Neural Networks (DNNs) and related methods, application of high-performance machine learning (ML) algorithms has become more automatic and robust to different data scenarios. That has led to the rapid rise of an artificial intelligence (AI) that works by combining multiple ML algorithms—each targeting a straightforward prediction task—to solve complex problems. In contrast to earlier attempts at AI, the current instance of AI is ML-driven. ML algorithms are implanted in every aspect of AI and the evolution of ML is going toward status as a general purpose technology. This evolution is the main driver behind the current rise of AI. However, ML algorithms are the building blocks of AI within a larger context. McCarthy (2007) defines AI as the science and engineering of making intelligent machines, especially intelligent computer programs. It is related to the similar task of using computers to understand human intelligence, but AI does not have to confine itself to methods that are biologically observable.

However, the "narrow" definitions of AI in the economic literature are often unavoidable, especially in empirical studies, as data on machines or robots are at least available to a certain extent, compared to AI data in a broader sense (Acemoglu & Restrepo, 2020; Dauth et al., 2017; Graetz & Michaels, 2015). But if we look at the definitions of AI in theoretical models, they can be very broad. When one assumes that AI can substitute for low-skilled labor (Hémous & Olsen, 2016), it may mean "automation," but when one assumes that human capital or high-skilled labor can also be replaced by AI to generate innovation (Aghion et al., 2019), then AI can be a more inclusive conceptual term, far more meaningful than "robots." In this sense AI, in theoretical economic models, can cover a wider range of AI technology than what empirical studies can. Therefore, there exists a gap between empirical studies and theoretical ones.

In this literature review, since both theoretical and empirical studies are discussed, the difference in the definition of AI should be noted. The engineering definition of AI does not necessarily align with what AI means in economic research. In empirical studies, its definition tends to be narrow and specific, while in theoretical studies it tends to be wide and abstract. These differences will be revisited in our discussion below.

3 | HOW TO INCORPORATE AI INTO ECONOMIC MODELS?

Since AI is defined differently from other technologies, economists are interested in incorporating AI into theoretical economic models, to offer alternative theories for addressing topics such as economic growth, employment and welfare for the future (Acemoglu & Restrepo, 2020; Aghion et al., 2019; Hémous & Olsen, 2016; Sachs et al., 2015). To better facilitate the review of the theoretical models, we provide an analytical framework for the following discussion. We approach the problem from both the production side and the consumption side.

For the production side, we propose a highly abstract production structure to illustrate the possible treatment of AI in some important models:

$$Y(t) = G(N(t), y_i(t)), \tag{1}$$

$$y_i(t) = A(t) * F(\alpha(t) K_i(t), \beta(t) L_i(t)), \tag{2}$$

where t denotes time and can be constant if it is static model; and Y is the final good and is a function of a set of intermediate goods y_i and the quantity or the quality of innovations N. In Equation (2), intermediate good y_i is produced through a production function, which is determined by capital K_i and labor L_i. A is the total factor productivity, and α and β are the corresponding factor-augmenting productivity. Therefore, a direct question is: how can AI be represented in this production structure? The following studies offered different strategies and perspectives.

We start from Aghion et al.'s (2019) model that has a simpler structure. AI is defined as "automation" in their paper and it represents capital. The right-hand-side of our Equation (1) in their model is an integral of all the intermediate goods from 0 to 1. There are two types of intermediate goods: goods that have not been automated, and goods that have been automated. Therefore, a particular intermediate good i defined by our Equation (2) is simplified, to be produced with either capital alone, or labor alone. In this case, AI, or automation as called in the paper, is the only form of capital. The final good production (Equation (1)) then boils down to a constant elasticity of substitution (CES) nesting of labor and capital, which implies that AI (in this case the capital) can replace labor with constant elasticity of substitution. It is notable they find that, when the elasticity of substitution is less than one, automation is a labor-augmenting and capital-depleting technology, which is not what people generally expect. However, this result would be reversed if the elasticity of substitution were greater than one. In addition, this study later addresses the question of how AI affects the production of new ideas (innovation) with an idea production function. But since AI is taken as an exogenous input in the production of new ideas, they found that ongoing AI development can possibly generate exponential growth, when AI increasingly replaces the human being in generating ideas. In their singularities analysis, they even considered an extreme example that all tasks in idea production are automated and no human being is involved in idea production. In this case, if the growth rates of both capital and ideas rise sufficiently fast then it will deliver a singularity. In terms of the microeconomics of AI, the study does not provide a theoretical model but draws from recent relevant studies. It is predicted that more AI-intensive firms would hire more (or pay more to) high-skilled workers, outsource more low-occupation tasks to other firms, and pay a higher premium to low-occupation workers within the firm.

Hémous and Olsen (2016) adopted a framework in the vein of the "directed technical change" models to examine the impact of AI on horizontal innovation and income inequality. They also used the notion of "automation," but the automation in their paper expands the range of tasks that can be performed by machines. In their production setup, the final good production in

Equation (1) is a CES nesting of intermediate goods: $Y(t) = G(N(t),\ y_i(t)) = (\int_0^{N(t)} y(t,i)^{\frac{\sigma-1}{\sigma}} di)^{\frac{\sigma}{\sigma-1}}$, and when $N(t)$ increases, it means that there is technological progress, that is, horizontal innovations that expand the product variety. A different setting for intermediate production is that labor (L) is distinguished as low skill (-) or high skill (h), and AI (or automation) can be a perfect substitute for low-skilled workers. Our Equation (2), production of intermediate good, in their model is described as

$$y(i) = [l(i)^{\frac{\varepsilon-1}{\varepsilon}} + \alpha(i)(\tilde{\phi}x(i))^{\frac{\varepsilon-1}{\varepsilon}}]^{\frac{\varepsilon-1}{\varepsilon}} h(i)^{1-\beta},$$

where $x(i)$ is the type I machine that is enabled by the automation technology. There is also an indicator function $\alpha(i)$ to differentiate between firms with and without access to AI technology represented as types of machine, or capital (K) in our abstracted Equation (2). In addition, a part of the high-skilled worker group is hired as AI technology (or automation, in the paper) researchers, which are an investment from non-automated firms, as well as the source of innovation. Therefore, the real source of growth is the human capital that creates or controls the AI technology rather than the more general "capital" in Aghion et al.'s (2019) model. Following this setting, economic growth in this model goes through three phases. In the first phase, low-skilled wages are low, and there is little incentive for AI, and income inequality and labor's share of GDP are constant. The second is a transitional phase in which a rising low-skilled wage induces AI innovation, but reduces the labor's share and future low-skilled wages. Finally, a steady state is achieved in the third phase, where low-skilled wages grow, but at a lower rate than high-skilled wages. Based on the model, Hémous and Olsen point out that low-skilled wages actually grow in the long run, but not necessarily so, if there are middle-skilled workers present in the model.

Acemoglu and Restrepo (2018) also provided a conceptual model to account for AI's role in economic growth, employment, and inequality. They also used the word "automation" in their paper, but they distinguished two types of technological changes: automation and the creation of new tasks. In this case, automation cannot create or introduce new tasks directly, but can induce new tasks to be created. Their basic model (the static version) is a task-based model. Different from Hémous and Olsen (2016), their technological innovation is "vertical" rather than "horizontal." The integral always runs between $N - 1$ and N, but an increase in N implies an upgrading of the quality of the unit measure of tasks. Therefore, as N or productivity increases, this model allows new tasks to be created in which labor has a comparative advantage. They assume that there are certain tasks that are automated by technologies in which labor and capital are perfect substitutes, but the extent of substitution is determined by the relative prices of labor and capital. The model shows a "directed-technical-change" feature, but uses a range of tasks to reflect factor augmentation. It develops from a static model to a dynamic endogenous growth model, where the generational issue is not addressed explicitly, yet is implied in the dynamics. In an extension of the model, the authors also consider heterogeneous skills, and address the inequality problem. In the full model, they find that in the long-run equilibrium, if the relative price of capital to labor is sufficiently low, an AI world will result. Under certain assumptions, there exists a stable balanced growth path in which traditional technology and AI technology can coexist. This stability is achieved by the fact that the changing relative price of factors (i.e., labor and capital) due to AI would lead to a self-correcting dynamic that would create new tasks. They also found that as AI adoption squeezes out low-skilled workers and creates new tasks that benefit high-skilled workers, inequality would increase in both cases, that is, in an AI world and a world with both traditional and AI technology.

Sachs et al. (2015) adopt an overlapping generation (OLG) framework, so that the impact of AI would have intergenerational effects. In their model, they used the term "robots" to distinguish it from traditional capital, and the goods are also produced by two different technologies: the traditional one that requires both labor and capital and the new one that only requires robots. Equation (1) cannot be represented explicitly in their model, but Equation (2) is still valid for summarizing the production of different types of firms, as defined in their one-sector and two-sector model. They defined the essential quality of robots (AI in general) as to "allow for output without labor." It is clear that in their model, AI is a substitute for labor. However, the substitution is not embodied in one production function directly, but is reflected in the total homogenous output from two types of firms, that is, firms with traditional technology and firms using robots. Therefore, substitutability depends on the mix of different production technologies, which is regulated by other model parameters. Finally, AI (or robotics in the model) is modeled on a more aggregate level, in the sense that there is no distinction between labor and human capital, or between low- and high-skilled workers. Therefore, AI or robots just replace "labor" in general terms. It is notable that this model treats "machines" and "robots" as different inputs in production, although they are both "capital" to households. In other words, there are two types of capital. Whether AI has positive or negative impacts on economic outcomes and welfare depends on the model parameters. Both one-sector and two-sector settings are analyzed, and the saving rate is a key parameter in both cases in this model. Sachs et al. (2015) found that, when the saving rate is sufficiently low, young workers and future generations will be worse off if the productivity of robots increases, and goods that are produced by traditional technology and AI technology are more substitutable. They also argued that redistribution policies should take generational effects into account, so that future generations could also benefit from the rise of AI technology.

The above models address AI from the production side, and the common assumption is that AI is usually called an automation technology, either as a simple programmed machine or as an advanced technology that can perform high-skill tasks, and it is one particular type of capital that can substitute for, or complement, labor or certain skill types of labor to different extents and on different production levels. In most models, AI is used to improve either labor or capital productivities. The innovation is ultimately generated by human capital that controls AI technology either in production or in research. In that sense, AI in these models is just another detailed representation of factor productivities. Therefore, the key element in such models is the relative price of labor and capital (including AI). However, Aghion et al.'s (2019) extreme case of idea production shows the possibility that AI can produce ideas without human beings. In such a scenario, the economy can have a mathematical singularity given that the growth of innovation generated by AI is sufficiently fast and ideas are nonrival. Another observation is that the assumption of multiple production layers facilitates the incorporation of AI into production systems. In addition, these models emphasize worries that AI would destroy jobs and deepen inequality.

While most models focus on the production side, it is worthwhile to think about the impact of AI from the consumption side. One valid question is how AI affects the labor supply or consumer's leisure time. This can be expressed in a utility function as follows:

$$u(t) = U(c(t), l[R(t)]), \tag{3}$$

where u is consumers' utility; c is the standard consumption goods; and l is leisure time. So consumers derive utility from consumption of goods and enjoyment of their leisure time. But AI, indicated by R, can impact leisure time or the way consumers enjoy the leisure time l.

Kavuri and McKibbin (2017) made such an attempt to incorporate AI from the consumer perspective. In their theoretical model, technology goods are distinguished from normal goods so that consumers form habits with purchased technology goods, enhancing their leisure activities, while normal goods do not have such a feature. The model then gives a persistent fall in the price of technology goods relative to normal goods. The increased consumption of technology goods would result in the real interest rate being lower than the rate of time preference, reducing the consumption growth of normal goods. They also used US data to confirm predictions from the theoretical model empirically. This study is inspirational, in the sense that AI can actually affect consumption, in addition to production, while the human being has a role in both. However, they assume that consumers or households do not supply labor, and do not derive any income from work. Therefore, this setting cannot address the impact of AI on the labor supply, which will then affect both the labor market and production.

It is notable that in Kavuri's thesis (2018, chapter 5), AI (robotics in the thesis) is introduced on both the production and consumption sides. There are four production sectors and two types of workers (and consumers). On the production side, there is a "robot production" sector and a sector that uses robots to replace humans. That is, robots (AI) will replace labor and become the sole input of production function as in Equation (2). On the consumption side, consumers also purchase robots to enhance their leisure activities. Therefore, both firms and consumers have a demand for robots. With this general equilibrium framework, they analyze the effect of the enhanced productivity of robots on economic wellbeing. It is found that the welfare of workers, measured by utility, can increase as a result of the rise of AI-enhanced leisure activities, and this is irrelevant to the productivity of robots (AI). Although the framework is comprehensive, the study does not provide an analysis of how AI and the rise of its productivity might affect the labor market.

All these models provide insights into the accommodation of AI into economic models. However, before incorporating AI into economic models, we need to take one step back and think two important questions: one is how different types of AI would impact on the economy; the other is how AI could influence the theory of economics fundamentally. For the first question, most of the current models assume AI as one type of automation technologies and the definition of such technology is very loose, but the development of AI actually has reached or will eventually reach a stage where AI can replace high-skilled labor to make decisions or even generate creative ideas rather than being programmed to perform low-skill tasks. Till now, very few economic models have captured such type of future scenario explicitly. This brings us to the second question regarding the fundamental issue in the theory of economics: what a human being is. In economics, the role of human beings has usually been narrowed down to "labor" and an optimization agent at the same time, but in endogenous growth models, "labor" is different from "human capital." The development of AI further challenges the role of the human being in the economic system. Does AI bring a new production technology or is it just another type of input to current production technology? Is AI a substitute for "labor," or "human capital," or even an independent decision-making agent? Parkes and Wellman (2015) even pointed out that a world of AIs may be more close to the economic theories than that of human agents, as AIs "better respect idealized assumptions of rationality than people, interacting through novel rules and incentive systems quite distinct from those tailored for people." More research into the attributes that distinguish between human beings and AI would help us to model and analyze the impact of AI in more depth.

Another aspect that is absent from the recent theoretical modeling work is the international dimension of the AI revolution: how AI may trigger a new round of technological and economic competition across nations through government investment strategies; how AI affects international trade structure; and how AI changes global value chains. These topics provide a wide area for future discussion and exploration by economists.

4 | HOW DIFFERENT IS AI TECHNOLOGY FROM PREVIOUS TECHNOLOGY INNOVATIONS?

There have been many important technological changes in history. The Industrial Revolution, so-called "Industry 1.0," was triggered by the invention of the steam engine. Machines began to develop to help human workers in production, leading to an increase in production capability and productivity. Later, at the beginning of the 20th century, the use of electricity allowed easier access to power so machines could be designed to be more portable, and mass production using assembly lines became common. This period can be called "Industry 2.0" and, during this time, machines were programmed and controlled by workers to increase efficiency, productivity, and quality. To some extent, machines started to replace certain functions of labor. Progressing to "Industry 3.0," the invention of computers followed by information and communication technology (ICT) changed the production function dramatically. The structure of labor and the skills required for jobs changed. Although many traditional jobs were destroyed, new jobs were also being created. Computer programs or software were increasingly automated and powerful, but they still needed to be programmed, controlled and applied. Until then, machines still served as tools used in human labor. These technologies affected productivity and the economy (Brynjolfsson et al., 2019). However, the revolution we are facing now, that is, the so-called "Industry 4.0," seems to be significantly different, in that it may change the roles of human beings and machines in production as well as in social life. AI technology could give machines "intelligence" and allow them to substitute for human labor in many aspects.

Are previous experiences useful in predicting the consequent economic and social changes this time? In Brynjolfsson and McAfee's (2014) book *The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies*, they described the current point in time as "the early stages of a shift as profound as that brought on by the Industrial Revolution," that and said there is "no end of advancement in sight." They claimed, optimistically, that AI technology would transform global economics, although they noted that there were challenges and risks, which they thought were less about economics and more about moral aspects. Similarly, Saniee et al. (2017) also had an optimistic view. With their semiquantitative analysis (Saniee et al., 2017), they claimed that "there will indeed be a second productivity jump in the United States that will occur in the 2028–2033 timeframe…"

In terms of explaining the Solow Paradox, Brynjolfsson et al. (2019) attributed the current fall in productivity growth mainly to lags in diffusion of upfront AI technologies. They used portable power and information and communication technologies as examples to show that past productivity growth patterns were similar to the current situation and it usually took 25 years of slow growth before new technologies accelerated productivity growth continually over a decade-long period. They expected that AI technologies would also follow such a pattern; therefore, the current Solow Paradox is just a lag in technology take-off, as happened in history.

However, Acemoglu et al. (2014) found some unexpected results from IT-using manufacturing sectors in the United States: major productivity gains were concentrated in IT-producing sectors rather than IT-using sectors, and the so-called labor productivity gains in IT-using sectors were not associated with increasing output as a result of IT-induced cost reduction as expected, but were actually driven by declining output and more rapid decline of employment, rather than by technological progress. They claimed that the Solow Paradox has not been resolved with this recent technological progress. However, is this also true for advancements in technological change deeper than IT technology, such as the AI revolution?

Graetz and Michaels (2015) provided the first systemic evaluation of the economic impact of industrial robots. Their study was based on a new dataset, mainly from reports from 1993 to 2007 of the International Federation of Robotics, which is a panel of industries in 17 countries. They pointed out that AI technology or industrial robots can have different economic impacts from other new technologies, such as information and computer technology (ICT). They found that increased use of robots raised countries' average growth rates by about 0.37 percentage points and also increased both total factor productivity and wages. Although there was some evidence that low-skilled and middle-skilled workers may be affected, there was no significant effect from industrial robots on overall employment.

Acemoglu and Restrepo (2020) also used data on industrial robots from the International Federation of Robots to estimate the effect of industrial robots on employment and wages. Their estimation used a constructed measure of exposure to robots across industries in various commuting zones. This approach allowed them to estimate the equilibrium impact of industrial robots on local US labor markets. In contrast to Graetz and Michaels (2015), their results showed that, as the intensity of robots increases, employment and wages are reduced. In one of their robustness checks, they also showed that exposure to robots was unrelated to past trends in employment and wages from 1970 to 1990, when robotics technology had not attained rapid development.

While the above research shows that industrial robots have caused job and earnings losses in the United States, Dauth et al. (2017) explored the impact of robots on the German labor market. Despite the fact that there are many more robots around, Germany is still among the world's major manufacturing powerhouses with an exceptionally large employment share in manufacturing. It was around 25% in 2014 (compared to less than 9% in the United States) and has declined less dramatically over the last 25 years.

So is this time different? From the current literature, we can see that the Solow Paradox has not yet been satisfactorily resolved. But AI is regarded as a technology that differs from ICT in the sense that it would impact a broader range of sectors and, thus, would have different implications at the aggregate level and an unpredictable future development. However, the adoption of AI might follow a path similar to that of previous new technologies. It is also notable that ICT and robotics required high capital investment over a long period. However, AI will use data to develop computational models, and the availability of cloud services can enable the technology to be adopted with a much lower capital investment. This difference could potentially make AI's adoption pathway totally different from that of previous technologies.

Without answering this question, McKibbin and Triggs (2019) have gone one step further. They used a computable general equilibrium (CGE) model, *G-Cubed*, to investigate four alternative productivity growth scenarios. Several points are worth noting: even if a global productivity boom induced by AI technology were to happen, there would be certain short-term costs of such a boom, for example, a sharp rise in interest rates. In addition, first-mover benefits can flow to economies moving closer to the productivity frontier, which justifies AI competition across global economies.

5 | WHAT IS THE EMPIRICAL EVIDENCE ON THE EFFECTS OF THE EARLY STAGES OF AI?

Although Brynjolfsson and McAfee (2014) thought that the risks of AI technologies were not rooted in economics, economists do worry about many side-effects that AI technology would bring to the economy, including employment, inequality, education, trade, and policy responses to it. We provide a discussion for each topic below and a summary table of the major studies discussed in this section is provided in the Appendix.

5.1 | AI and unemployment

One of the most frequently asked questions is whether AI would displace employment. In recent years, quite a few research papers have addressed changing trends in the labor market and their relationship with AI technology. In Autor et al. (2020) and Autor and Salomons (2017), the falling labor share of GDP is explained using a "Superstar Firm" model, in which the dominant superstar firms benefited from globalization, and technological change increased the concentration of industries and decreased the labor share. A falling labor share is also observed in other relevant studies (e.g., Elsby et al., 2013; Karabarbounis & Neiman, 2014).

Then there is a big concern that AI is likely to replace existing jobs. Frey and Osborne (2017) devised an index to evaluate the susceptibility of occupations to automation. They found, surprisingly, that a substantial share of employment in service occupations is highly susceptible to automation in the United States. In the work of Ford (2009, 2015) and Brynjolfsson and McAfee (2014), the advancement of automation or AI technology was found to cause unemployment. However, Autor and Salomons (2017) found that as productivity rises employment at sectoral levels tends to shrink, although country-level employment generally grows with increased aggregate productivity. This finding is consistent with the stylized fact that the relationship between productivity gains and employment is negative within individual industries but probably positive for the overall economy.

One outstanding study is from Acemoglu and Restrepo (2020). Their study focused on the equilibrium impact of industrial robots on the local labor market. This equilibrium impact considers both the displacement effect and the productivity effect. In contrast to Autor and Salomons' (2017) results and the stylized facts, they identified large and robust negative effects from the use of robots on employment and wages across commuting zones. In particular, they found that "one more robot per thousand workers reduces the employment-to-population ratio by about 0.18–0.34 percentage points, and wages by 0.25%–0.5%." Their study calls for more research on the equilibrium effects of AI technologies on labor market outcomes.

Acemoglu and Restrepo (2019) present a framework for understanding the effects of automation and other types of technological change on labor demand, and use it to interpret changes in US employment over the recent past. Automation, which enables capital to replace labor in the tasks in which it was previously engaged, shifts the task content of production against labor, because of a displacement effect. As a result, automation always reduces the labor share in value added, and may reduce labor demand even as it raises productivity. The effects of automation are counterbalanced by the creation of new tasks in which labor has a comparative advantage. The introduction of new tasks changes the task content of production in favor of labor because of a reinstatement effect, and always raises the labor share and labor demand. Using industry-level data, the study infers the role of changes in the task content of production attributable to automation and new tasks. The empirical decomposition suggests that an acceleration in the displacement effect, especially in manufacturing, plus a weaker reinstatement effect and slower growth of productivity than in previous decades, accounts for the slower growth of employment over the last three decades.

What the above studies have in common is that they all use the terms "automation," "robots," or "robotics" and focus on potential gross job destruction and cannot provide an answer to actual job destruction, net job displacements or labor market turnover, all of which would be necessary to assess the challenge of AI from a policy perspective. Earnst et al. (2018) aims at addressing this knowledge gap, to gain a better understanding of the economic and social implications of artificial intelligence. In order to do so, the study starts from a granular analysis of how previous waves of automation have changed occupations and employment opportunities in the past. Specifically, the study looks at experiences of advanced and emerging economies with the automation of physical tasks through the rise in robotization. This approach can shed some light on the likely impact that the development and widespread diffusion of artificial intelligence might have on employment, incomes, and inequality through the automation of mental tasks—as per the distinction between AI and robots/mechanization above. The study finds moderately optimistic results that new, AI-based digital technologies may allow larger segments of the labor market to improve their productivity and to access better paying occupations and, thereby, may help promote (inclusive) growth. This requires, however, that a certain number of policies are put in place that support the necessary shift in occupational demand, maintain a strong competitive environment to guarantee diffusion of innovation and to keep up aggregate demand, in order to support structural transformation.

Seamans and Raj (2019) summarize existing empirical findings on the adoption of robotics and AI and their effects on aggregated labor and productivity, and argue for more systematic collection of data on the use of these technologies at the firm level. Existing empirical work uses statistics aggregated by industry or country primarily, which precludes in-depth studies regarding the conditions under which robotics and AI complement, or substitute for, labor. They argue that firm-level data would also allow for studies of effects on firms of different sizes, the role of market structure in technology adoption, the impact on entrepreneurs and innovators, and the effect on regional economies, among others.

5.2 | AI and inequality

Inequality induced by AI has been another frequently discussed topic so far. Inequality can be international and national. It is argued that the AI revolution will have an impact on both dimensions. Empirical results (e.g., Chandy & Seidel, 2017; UNCTAD, 2017; World Bank, 2016, 2017) found that within-country inequality has been rising sharply since the 1990s (with a slight decline since 2008) while global inequality has experienced a small decline. Rapid technological change accompanied by globalization during that period benefited developing countries and narrowed the income gap between developed and developing countries. However, in terms of wealth, global inequality did not necessarily decline.

Thomas Piketty (2014) points out that when the return on capital is higher than aggregate growth in an economy, inequality will rise. This might be an argument to support the view that the AI revolution will deepen inequality at the national level, although this general law has been criticized by Acemoglu and Robinson (2015) for neglecting institutional and policy factors contributing to the inequality. At the global level, the industrialization and globalization that once benefited developing countries have reached their peak, and the pace of developing countries' growth has already slowed (Baldwin, 2016). Norton (2017a) points out that automation (or AI technology) may further hinder developing countries' catch-up with developed countries, as it will shift the balance of "advantage of locating light manufacturing close to consumers rather than close to cheap labor," that is, offshoring versus reshoring.

On the positive side, there is the possibility of technological leapfrog by developing economies with a limited manufacturing base, according to the World Bank (2017). If countries can leapfrog into using new technologies, there may be no cost to them for not having developed a manufacturing sector at this point. However, if countries need to have developed a manufacturing sector using traditional (Industry 2.0) methods to build the capabilities needed to support more sophisticated processes in the future, the dynamic cost of not industrializing now could be that manufacturing opportunities are closed off in the future (World Bank, 2017).

In terms of within-country inequality, Norton (2017b) summarized several mechanisms through which AI technology may enlarge national inequality gaps: (1) boosting the advantage of capital over labor; (2) relative declines in medium- and low-skilled employment shares; (3) weakening of labor institutions; and (4) reduction of tax bases, thus, weakening governments' capacity for redistribution. Although most empirical studies find that AI technology will not destroy aggregate employment (see Section 3.1), it does create intersector inequality and will change the labor structure so that the relative share of low-skilled labor is reduced and, therefore, inequality is deepened. A very important implication here is that how AI technology is adopted in the economy will determine how society is restructured, and who are the losers and winners. In this sense, the welfare effect of AI technology is uncertain. Two recent papers (Tyers & Zhou, 2017; Zhou & Tyers, 2019) have attempted to address this issue.

Based on an elemental three-household general equilibrium model, Zhou and Tyers (2019) quantified the links between real income inequality, on the one hand, and changes in factor abundance, total factor productivity, factor bias, the relative cost of capital goods, labor force participation rates, the fiscal deficit, and the unemployment rate, on the other hand, in China. Relative expansions in stocks of skill and physical capital have, by themselves, mitigated inequality. Yet their effects have been dominated by the combination of structural change and biased technical change, with the latter having a dominant effect. Zhou and Tyers (2019) expect the future to bring continued structural change and a further technical twist away from low-skilled labor, this time toward physical capital owing to automation. They found that if the new technology delivers only a shift in technical bias, then aggregate performance would be impaired by worker displacement that could cause the unemployment rate to rise to anywhere between 20% and 55%, and drive low-skilled wages downward. If the government protects the welfare of low-skilled households via tax-funded transfers, the transfer burden, either to maintain the welfare of low-skilled households or to constrain income inequality, makes capital owners significant losers in this case. The worker displacement and the capital income tax rate required to contain the rise of income inequality are lessened, the more the new technology also delivers increments to TFP. But the rates of TFP growth needed are high relative to what has been achieved by China in recent decades, and the potential for continuing this pattern, constrained as it is by the shrinkage of opportunities for "catch-up" productivity advances, will rely on the productivity effects of AI and robotic advances.

Tyers and Zhou (2017) examined the issue of robotics and income inequality in the US economy using a similar elemental three-household general equilibrium model, as in Zhou and Tyers (2019). In this application to the United States, changes in factor bias are shown to have been the primary cause of the observed increase in inequality between 1990 and 2016. The widely anticipated future twist away from low-skilled labor toward capital is then examined, in combination with expected changes in population and its skill composition. With downward rigidity of low-skilled wages, the potential is identified for unemployment to rise to extraordinarily high levels, with possible exacerbation from intensive population growth among low-skilled workers, and productivity growth that is no greater than that achieved since 1990. Indeed, the results suggest that productivity growth at twice the pace since 1990 would be needed to constrain unemployment, though even this would not slow the concentration of income. The superior policy response is shown to be a generalization of the US "earned income tax credit" system, with financing from taxes on consumption, rather than capital income.

Earnst et al. (2018) argues that AI applications raise the potential for productivity growth for the interpersonal, less technical occupations and tasks, leading to a higher demand for such work, which is likely to dampen the inequality trends observed over recent decades. However, a particular challenge arises for developing countries when they are part of a value chain that forces them to adopt capital-intensive technologies, despite an abundance of underutilized labor. Here, AI-driven automation might further drive up informality unless governments ensure a widespread adoption and diffusion of digital technological change beyond the supply chain sectors. In other words, the productivity-enhancing potential of AI is real, but the specific characteristics of this new technology require policy responses that differ from those given during previous waves of technological change in order to generate shared benefits for the world of work.

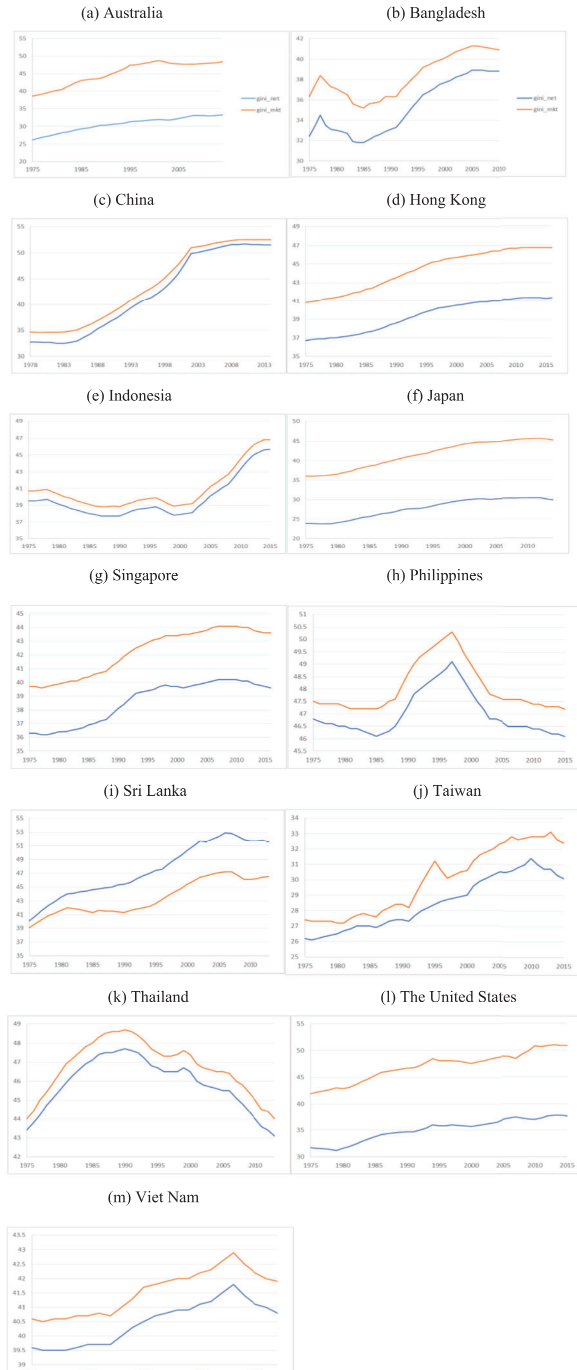
Therefore, we arrive at another stylized fact that AI-induced productivity growth would cause employment redistribution and trade restructuring that would tend to increase inequality within and across countries. Some studies seem to suggest that automation replaces low-skilled labor and increases demand for workers with higher skill levels. Automation may exert upward pressure on income inequality, at least in the short run. Therefore, access to high-quality education becomes more important. Households that are relatively well-off will be able to provide good education to their children, who will then gain skills and capacity to compete in the labor market in the future. If there is strong inequality of opportunity, income inequality could worsen over generations (Golley et al., 2019; UN ESCAP, 2017). Policies that aim at reducing inequality of opportunity will help alleviate income inequality (Figure 2) and its negative impact when societies are increasingly faced with the rise of robotics and artificial intelligence. Policies such as universal basic income or earned income credit could be adopted to help support the welfare of individuals experiencing job loss due to technical change and to help constrain income inequality, but this is hotly debated (Jessen et al., 2017; Stiglitz, 2017). Agrawal et al. (2019) also pointed out that labor and antitrust policies will influence the consequences of AI in terms of employment, inequality, and competition.

5.3 | AI and education

AI and education interact in both directions. On the one hand, AI has changed the way the content and the places education is delivered; on the other hand, education is the source of technological innovation and, therefore, impacts the development of AI.

With the rise of automation and artificial intelligence, how could individuals adapt to these rapid technological changes? On the one hand, automation and artificial intelligence may demand more workers who have skills in programming and mathematics. On the other hand, the new technologies may reach a stage of maturity whereby people no longer need advanced maths or programming skills to utilize the technology, that is, the "singularity" in which machines surpass humans and machines produce more machines (Korinek & Stiglitz, 2019; Nordhaus, 2021). At that stage, skills in liberal arts would become more important and the most important skills are likely to be emotional and communication skills (Baldwin, 2019; Huang & Rust, 2018). Before the

FIGURE 2 (a)–(m) Gini coefficient pretax and pretransfer and Gini coefficient posttax and posttransfer in selected economies in the Asia-Pacific region
Source: SWIID database.
Note: The orange line is the Gini index of inequality in equivalized household disposable (posttax and posttransfer) income. The blue line is the Gini index of income inequality in equivalized household (pretax and pretransfer) income.
[Colour figure can be viewed at wileyonlinelibrary.com]



"singularity" is reached; however, problem-solving and analytical skills, and mathematics and programming skills are likely to be increasingly in demand in the future.

Forbes published an article "How AI Impacts Education" on December 27, 2017,[2] describing the potential for AI to replace human labor in grading, the admission process, tutoring outside classrooms, personalized online courses, interactive teaching resources, and immersive technology used in classrooms. The author stated that students, teachers, and administrators all benefit from a smarter, more personalized approach to education, with AI being more integrated into the education system. Zawacki-Richter et al. (2019) point out that artificial intelligence in education (AIEd) is one of the currently emerging fields in educational technology. The study provides an overview of research on AI applications in higher education through a systematic review. Their results show that most of the disciplines involved in AIEd papers come from computer science and STEM, and that quantitative methods were the most frequently used in empirical studies. The synthesis of results presents four areas of AIEd applications in academic support services, and institutional and administrative services: (1) profiling and prediction, (2) assessment and evaluation, (3) adaptive systems and personalization, and (4) intelligent tutoring systems. The conclusions reflect a nearly entire lack of critical reflection of challenges and risks of AIEd, the weak connection to theoretical pedagogical perspectives, and the need for further exploration of ethical and educational approaches in the application of AIEd in higher education.

AI technology would also modify what education contains. Riccardo Campa (2017) argued that AI not only impacts low- and medium-skilled workers but also affects highly educated workers; therefore, more maths, science, and engineering in education would not be sufficient to prevent future massive unemployment due to thriving AI technology. He emphasized that different types of ability such as critical thinking, artistic creativity, philosophical understanding, and social sensitivity would be most important in future education. This is somewhat similar to the point that Jeffrey Sachs made at the NBER conference on the economics of AI (Toronto, 2017): what humans can do in the AI era is just to be human beings, because this is what robots or AI cannot do. This leads to a philosophical question: what is a human being? As mentioned before, in economics, it is also a valid question to ask and rethink over time. For a long time, the functionality of human beings has been explored and emphasized in economics. However, AI economics challenges economists to include other values and dimensions of humanity in their economic models, and to rebuild the concept of "economic agents." Another valid question to think about is preferences for human or AI-provided services. If people have strong preferences for human-provided services, then substitutability between human and AI-provided services will be low.

5.4 | AI and trade

There are very limited studies on how AI technology impacts international trade explicitly. But there are some potential effects of AI technology on trade activities and, consequently, on employment. Although the shrinking labor cost differential is favorable for reshoring, counterforces exist. First, the advantages of producing in close proximity to the customer do not favor reshoring if the customer is not located in the home country or region of the company. Offshoring is motivated not only by seeking lower cost, but also by the need to enter new markets and to be closer to customers in foreign countries. So, for some firms, closeness to customers works in favor of staying offshore and was already an essential motive for previous offshoring decisions. According to Sebastian Duchamp, a GE spokesman: "The global environment for manufacturing is changing in a way where we must innovate differently…innovation has to be in the markets you play in, close to your customers; and close to access [to] the best talent wherever it exists in the world." GE, like other companies, is responding to the trend in what's called "mass customization" or making products to meet an individual customer's preferences. As a result, companies are finding it more suitable to have plants closer to their markets and to their research and development units. Industry 4.0 enhances production for customized products and, hence, may better serve local customers and help prevent offshoring.

Second, there are steps in production in certain industries that are hard to automate, as yet. For example, in the sportswear industry, the chief executive of Adidas said “Asian plants will become more automated, but there were some processes of the roughly 120 steps in creating an Adidas shoe that remain stubbornly resistant to automation…The biggest challenge the shoe industry has is how do you create a robot that puts the lace into the shoe…I’m not kidding. That’s a completely manual process today. There is no technology for that.”[3] Bottlenecks in automation technologies will slow down reshoring activities.

Third, being a supplier reduces the likelihood of reshoring in all specifications of the regression. This can be explained by the fact that many suppliers have offshore production to follow their clients. These customer relations seem to provide an effective “glue” to keep manufacturing activities at foreign locations, even if external factors such as wages or costs of materials change (Dachs et al., 2012). If Industry 4.0 strengthens supply linkages between firms, it could act as a force preventing reshoring. For systematic reviews of manufacturing reshoring, please refer to Brennan et al. (2015), Stentolft et al. (2016), Dachs et al. (2012), and Delis et al. (2019). How new technologies will affect reshoring is still under debate.

For advanced economies, the risk to employment is still likely to prevail, even if reshoring does occur. This is because new manufacturing plants in advanced economies may translate into more jobs for robots than for humans. Lower costs of automation technologies could mean that firms are simply completing the transition that would have taken place earlier without offshoring. Therefore, reshoring may not necessarily boost employment. Chances are that if there were any positive effect on employment, automated factories would require highly skilled workers, often with training in technology and computers. For developing economies, the concern is, first, that the increased use of robots in developed countries risks eroding the traditional labor-cost advantage of developing countries; second, that robot use is working to the advantage of countries with established industrial capacity; and, third, that the share of occupations that could experience significant automation is actually higher in developing countries than in more advanced ones, where many of these jobs have already disappeared. This could further damage growth prospects in developing countries, where manufacturing has stalled or where “premature deindustrialization” is already being experienced (UNCTAD, 2016; World Bank, 2017). Furthermore, if future international competition hinges on the intensification of the use of robots, the observed effects of automation on employment and wages in advanced economies may also take place in developing economies as these robots are increasingly adopted.

So far the academic research has focused on the AI impact at the national level but overlooked its international dimension, especially the strategic implications between countries triggered by AI technology development. The structure of global value chains could be potentially changed by prevailing AI technology adoption, and the supply of AI technology could be a new dimension of “comparative advantage.” Goldfarb and Trefler (2019) pointed out that trade policy should take into account the characteristics of AI technology, including economies of scale, creative knowledge, and the geography of knowledge diffusion. They also suggested that policies such as data localization rules, limited access to government data, and industry regulation may be used to protect domestic firms. Clearly, there is much more research space to be explored regarding the impact of AI on international trade.

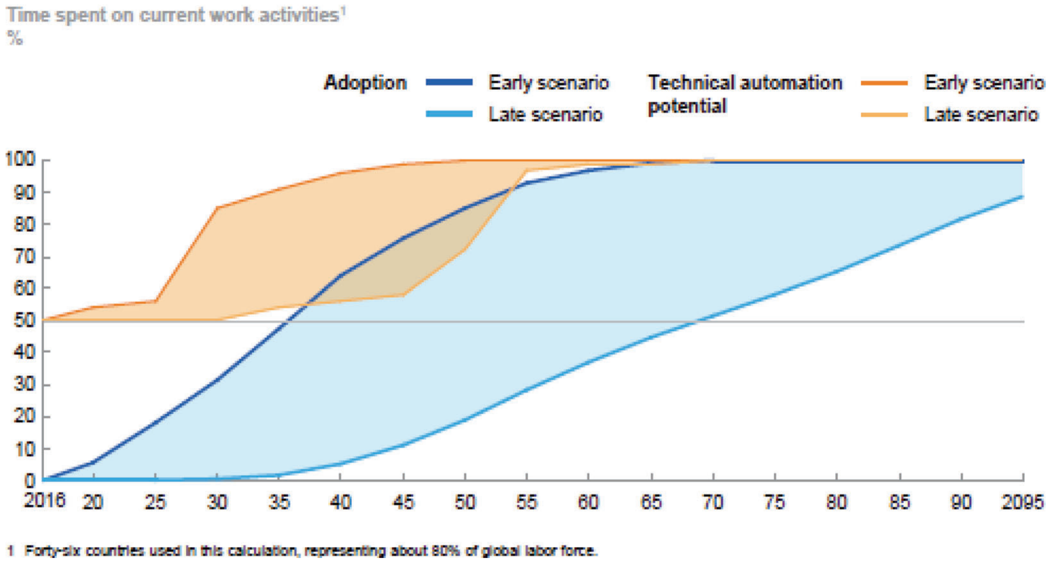


FIGURE 3 Early and late scenarios of adopting automation technology
Note: This figure is from the McKinsey report (McKinsey, 2017), Exhibit 15 on page 70
[Colour figure can be viewed at wileyonlinelibrary.com]

5.5 | The timeframe and the scale of the AI revolution

The timing of the adoption of AI technology on a large scale is unpredictable, but many studies agree that it could take decades. As mentioned before, Brynjolfsson et al. (2019) argued that the time lag to technology diffusion might explain the Solow Paradox. They used two examples to show the long time span of introducing innovative technologies. On example is portable power (1890–1940) and the other example is information technology (1970–2016). They observe some similarity in pattern for both eras: (1) it took 50 years for each new innovative technology to be placed into production after it had been invented; (2) in both eras there was initially slow productivity growth over about 25 years; and (3) then there was a decade-long acceleration in productivity growth. Müller and Bostrom (2016) conducted a survey of expert opinion on the future progress of AI and the result they got is that there is 50% chance for high-level machine intelligence to be developed around 2040–2050, but that chance will rise to 90% by 2075 according to their median estimates of respondents. Experts expect that systems will move on to superintelligence in less than 30 years thereafter.

There is no rigorous academically economic research providing projections or predictions regarding the timeframe and the scale of the AI revolution, but many consulting institutions do give some information on it. For example, the BCG report (BCG, 2015) claimed that Germany's Industry 4.0, which is based on AI technology, will stimulate employment increases of 6% over the next 10 years (i.e., 2015–2025). According to Accenture (2016),[4] AI has the potential to boost labor productivity by up to 40% by 2035 in the 12 developed economies studied. McKinsey's report (MGI, 2017) presents two extreme scenarios: one is the "earliest" scenario of faster automation; the other is the "latest" scenario where adoption of automation technology is slow (see Figure 3).

In general terms, all of these consulting institutions have high estimates of future productivity growth. They are all optimistic toward AI technology and indicate potential positive impacts, not only on productivity, economic growth, and business opportunities but also on employment. Although these predictions are not necessarily convincing, they do shed some light on the future picture of a world with AI technologies.

6 | CONCLUSION

The development of AI technology poses new challenges, not only for the economy, but also for economics research. In this paper, we reviewed recent literature on AI economics from a macroeconomic perspective by posing three questions. First, how is AI introduced and dealt with in economic models? Second, is the impact of AI technology different from that of previous technological changes? Finally, what are the major empirical impacts of AI that have attracted economic research in this area?

The first question opens up an exciting area to explore; it is also the most challenging, though. Almost all of the current economic models addressing AI assume AI is a substitute for the human being to some extent and on different levels. Although they have different assumptions and setups, these models predict that the economy could have different growth paths under certain parameters and conditions, among which the evolving relative price of capital to labor is a key twist. All these models confirm concerns that AI would destroy jobs, at least to a certain extent, and that AI would increase inequality. To provoke further thoughts on modeling, we point out that some fundamental issues should be resolved before incorporating AI into the model, one of which is the essential attributes distinguishing human beings from AI, that is, the role of AI and human beings in the economic system, from both the production and the consumption side. To address this issue, it involves two key questions: one is what AI is and will be and the other is what human being is and will be? Of course, this is not just an economic issue; it is also a moral, and even philosophical, question that has been discussed for a long time. But we need to make a clear definition and establish this "value" judgment before heading to modeling. Another aspect worth noting is the international impact of AI, which relates to global AI competition, global value chains, and international trade policies.

For the second question, we found that, so far, empirical studies cannot deny that the Solow Paradox remains unresolved, which implies that AI would also fall into this paradox as does other technological progress. But that may be a limitation of empirical studies when we are actually looking into the unpredictable future. The empirical results that drew their conclusion from the past and current data may not provide good estimations about the future state. Some studies believe that AI would have a larger and broader economic impact, but its adoption may follow a path similar to that of previous new technologies, which have had adaptation lags.

To answer the third question, we consider several aspects. Some have been addressed more thoroughly, while some have been insufficiently discussed. Employment and inequality are the current focus of economists. When we look at empirical studies of historical trends (e.g., Autor & Salomons, 2017; Brynjolfsson et al., 2019; Graetz & Michaels, 2015), some stylized facts have been generally, but not necessarily universally, agreed on: (1) the growth rate of labor productivity has slowed down in recent decades, especially after the GFC; (2) the relationship between productivity gains and employment is negative within individual industries, but probably positive for the overall economy; and (3) productivity growth would cause employment redistribution and tend to increase inequality. However, in terms of topics like education and international trade, the research is insufficient. In particular, the empirical relationship between AI and economic growth is not sufficiently addressed and tested against the various hypotheses from theoretical models.

These underaddressed aspects are important in the sense that policy implications from these areas would be valuable in offsetting the negative effects on employment and inequality, as well as in preparing people for future AI development. Last but not least, a clear definition of AI is absent in many empirical studies: more often these studies use "automation" and "robots" to represent AI; however, this may lead to misleading conclusions as "automation" and "robots" are not even anything close to AI in the prospect. This actually echoes the first question we questioned about the theoretical models.

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ENDNOTES

[1] "AlphaGo Zero: Learning from scratch," available at https://deepmind.com/blog/alphago-zero-learning-scratch/

[2] https://www.forbes.com/sites/theyec/2017/12/27/how-ai-impacts-education/#1e58484d792e

[3] https://qz.com/966882/robots-cant-lace-shoes-so-sneaker-production-cant-be-fully-automated-just-yet/

[4] https://newsroom.accenture.com/news/accenture-report-artificial-intelligence-has-potential-to-increase-corporate-profitability-in-16-industries-by-an-average-of-38-percent-by-2035.htm

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How to cite this article: Lu Y, Zhou Y. A review on the economics of artificial intelligence. *J Econ Surv*. 2021;*35*:1045–1072. https://doi.org/10.1111/joes.12422

APPENDIX
SUMMARY OF EMPIRICAL STUDIES IN SECTION 5

Major empirical studies	Topic	AI definition used	Main findings
Autor et al. (2020); Autor and Salomons (2017)	Unemployment	No explicit definition of AI, but a general productivity growth	• Industry-level employment robustly falls as industry productivity rises while country-level employment generally grows as aggregate productivity rises. • The "Superstar" firms in each industry benefited from globalization, and technological change increased the concentration of industries and decreased the labor share.
Frey and Osborne (2017)	Unemployment	Automation	• An index to evaluate the susceptibility of occupations to automation is devised. • A substantial share of employment in service occupations is highly susceptible to automation in the US by using this index.
Ford (2009, 2015); Brynjolfs-son and McAfee (2014)	Unemployment	Automation, robots, automation that can substitute human with software-driven machines.	• The advancement of automation technology was found to cause unemployment.

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Major empirical studies	Topic	AI definition used	Main findings
Acemoglu and Restrepo (2020)	Unemployment	Industrial robots	• Large and robust negative effects are identified from the use of robots on employment and wages across commuting zones. • In particular, they found that "one more robot per thousand workers reduces the employment-to-population ratio by about 0.18—0.34 percentage points, and wages by 0.25%—0.5%."
Acemoglu and Restrepo (2019)	Unemployment	Automation	• The study infers the role of changes in the task content of production attributable to automation and new tasks. • The recent stagnation of labor demand is explained by an acceleration of automation, particularly in manufacturing, and a deceleration in the creation of new tasks and plus a slower productivity growth.
Earnst et al. (2018)	Inequality, unemploy-ment	Automation, robots, digital transformation	• The study finds moderately optimistic results that new, AI-based digital technologies may allow larger segments of the labor market to improve their productivity and to access better paying occupations and, thereby, may help promote (inclusive) growth. • The productivity-enhancing potential of AI is real, but the specific characteristics of this new technology require policy responses that differ from those given during previous waves of technological change in order to generate shared benefits for the world of work.
Seamans and Raj (2019)	Unemployment	Robotics*	• A review of existing empirical studies on the adoption of robotics and AI and their effects on aggregated labor and productivity. • Existing empirical work uses statistics aggregated by industry or country primarily, which precludes in-depth studies regarding the conditions under which robotics and AI are complement, or substitute for, labor. • Firm-level data studies are necessary.

(Continues)

Major empirical studies	Topic	AI definition used	Main findings
Norton (2017a)	Inequality on the world level	Automation	• Automation (or AI technology) may further hinder developing countries' catch-up with developed countries, as it will shift the balance of "advantage of locating light manufacturing close to consumers rather than close to cheap labor."
Norton (2017b)	Inequality on the national level	Automation	• The study summarized several mechanisms through which AI technology may enlarge national inequality gaps
Tyers and Zhou (2017)	Income inequality in the US	Automation, robotics	• This study used general equilibrium model to simulate the potential impact of future changes of automation on income inequality in the US. • Changes in factor bias are shown to have been the primary cause of the observed increase in inequality between 1990 and 2016 in the US. • Productivity growth at twice the pace since 1990 would be needed to constrain unemployment, though even this would not slow the concentration of income.
Zhou and Tyers (2019)	Income inequality in China	Automation, robotics	• This study used general equilibrium model to simulate the potential impact of future changes of automation on income inequality in China. • More new technology delivers increments to TFP. • But the rates of TFP growth needed are high relative to what has been achieved by China in recent decades, and the potential for continuing this pattern, constrained as it is by the shrinkage of opportunities for "catch-up" productivity advances, will rely on the productivity effects of robotic advances.
Korinek and Stiglitz (2019)	Declining labor share and AI	AI in general or worker-replacing technological progress	• The study shows that the advances in information technology and the computer age contributed to decreases in the relative price of investment goods, and induced firms to shift away from labor toward capital.

(Continues)

Major empirical studies	Topic	AI definition used	Main findings
Nordhaus (2020)	Economic growth and AI	AI in general, but it seems to include the more advanced computation and information technology	• The paper tests the issue of "Singularity," which refers to the idea that the rapid growth in computation and artificial intelligence (AI) will cross some boundary after which economic growth will accelerate sharply. • The tests show that "Singularity" is not near given the available economic data.
Baldwin (2019)	Education	Robotics or AI in general	• The book proposes a four-step progression of how AI will change the global economy: transformation, upheaval, backlash, and resolution. • The author depicts how the future work will be transformed: skills in liberal arts would become more important and the most important skills are likely to be emotional and communication skills.
Huang and Rust (2018)	Education	AI adopted in service sectors	• The paper identified four intelligences in service sectors: mechanical, analytical, intuitive, and empathetic. • The study implies that analytical skills will become less important, as AI takes over more analytical tasks, giving the "softer" intuitive and empathetic skills even more importance for service employees.
Zawacki-Richter et al. (2019)	Education	Various AI definitions are reviewed	• The study provides an overview of research on AI applications in higher education through a systematic review. • The synthesis of results presents four areas of AIEd applications in academic support services, and institutional and administrative services: (1) profiling and prediction, (2) assessment and evaluation, (3) adaptive systems and personalization, and (4) intelligent tutoring systems. • There is the need for further exploration of ethical and educational approaches in the application of AIEd in higher education.

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Major empirical studies	Topic	AI definition used	Main findings
Riccardo Campa (2017)	Education	Technological progress that leads to unemployment	• AI not only impacts low- and medium-skilled workers, but also affects highly educated workers; therefore, more maths, science, and engineering in education would not be sufficient to prevent future massive unemployment due to thriving AI technology. • Different types of ability, such as critical thinking, artistic creativity, philosophical understanding, and social sensitivity, would be most important in future education.
Goldfarb and Trefler (2019)	Trade	AI in general	• Trade policy should take into account the characteristics of AI technology, including economies of scale, creative knowledge, and the geography of knowledge diffusion. • Policies such as data localization rules, limited access to government data, and industry regulation may be used to protect domestic firms.
Brynjolfsson et al. (2019)	Timeframe and scale of AI development	AI in general	• The study argued that time lag to technology diffusion might explain the Solow Paradox. • There is some similarity in pattern for previous large technological progress that AI may also follow: (1) it took 50 years for each new innovative technology to be placed into production after it had been invented; (2) in both eras there was initially slow productivity growth over about 25 years; and (3) then there was a decade-long acceleration in productivity growth.
BCG (2015)	Timeframe and scale of AI development	AI in general	• Germany's Industry 4.0, which is based on AI technology, will stimulate employment increases of 6% over the next 10 years (i.e., 2015–2025).
Accenture (2016)	Timeframe and scale of AI development	AI in general	• AI has the potential to boost labor productivity by up to 40% by 2035 in the 12 developed economies studied.

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Major empirical studies	Topic	AI definition used	Main findings
MGI (2017)	Timeframe and scale of AI development	AI in general	• The report presents two extreme scenarios: one is the "earliest" scenario of faster automation in which AI will take up more than 50% of current work time by 2035; the other is the "latest" scenario where adoption of automation technology is slow in which AI will take up more than 50% of current work time by 2070.