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On the Progress of Industrial Revolutions: A Model to Account for the Spread of Artificial Intelligence Innovations across Industry

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Abstract

The present paper first provides a brief account of the causes and impacts of three previous industrial revolutions, with focus on the role of general-purpose technologies (GPTs) as sources of large numbers of complementary innovations that have driven the revolutions forward. Then, following an examination of the dynamics behind the emerging Fourth Industrial Revolution (see Schwab 2016), we propose a formal model to describe the spread of an innovation across an industry, using AI innovation as a test case. The differential equation models show that the rate of diffusion of a given AI technology among potential adopter companies is most rapid at early stages of adoption. Then, as saturation approaches, the growth rate decreases. When the diffusion of the technology is complete at time T, the growth rate drops exponentially as the particular innovation is regarded as obsolescent. At that time, some newer, more sophisticated AI innovation will replace the existing AI, causing an even more drastic change in the world.

Keywords: *Industrial Revolution, Innovation, Artificial Intelligence, General-Purpose Technology, Technology Diffusion*

1. INTRODUCTION

Following Schwab (2016), the present paper recognizes three industrial revolutions that have already occurred and a fourth industrial revolution that is still in its early stages. Each revolution can be associated with a General-Purpose Technology (GPT) that became an icon of that revolution and that led to many complementary inventions, which in turn had an impact across multiple industries. For example, the steam engine was a GPT for the First Industrial Revolution, and the steam pump, steam locomotive and steamship were complementary inventions that derived from it.

A GPT, as introduced by Bresnahan and Trajtenberg (1992 [1996]), has the following characteristics: pervasiveness (so that it comes to be applied across multiple industries), inherent potential for technical improvements, and innovational complementarities, so that innovation in the GPT leads to greater R&D productivity in downstream technologies. The diffusion of the GPT and its

Table 1: The First Three Industrial Revolutions

Dates	Industrial Revolution (IR)	Representative GPTs	Selected impact examples
c. 1760–1840	First IR: Mechanization	Steam engine	Increases in product quality, productivity, new types of jobs
c. 1870–1930	Second IR: Mass Manufacturing	Electric motor, assembly line, automobile	Urbanization, increase of specialist salaried jobs in manufacturing
c. 1960–present	Third IR: Digital ICT	Semiconductor, computer, Internet	Shift of retail activities to ecommerce

concomitant increases in productivity lead to decreases in the cost of the GDP and of its applications, a situation that leads to increases in demand. Often a GPT will lead to the creation of one or more new industries in order to satisfy the new demand. When such interrelated changes come to have a large impact on how people live and on how business is done, one can say that an industrial revolution has begun. For example, mass urbanization as well as a huge increase in the number of salaried jobs are associated with the Second Industrial Revolution.

It usually takes quite some time from the initial appearance of a GPT for the technology to evolve to the point that it has such major impact. Jovanovic and Rousseau (2005) use various empirical measurements, such as rapid increase in the share of a GPT item in comparison to the total capital stock of similar items, increase in the intensity of patenting activity, and better performance of young companies in comparison to incumbents, as indicators of the beginning dates for what they call the "GPT eras" of electricity and information technology (IT). They note that slowdowns in such measurements serve as indicators of the ends of those GPT eras. They did, however, find that the timing of each period reflected distinct, possibly unique, historical characteristics. For example, the spread of electric power was delayed by the high costs of installing the pre-requisite infrastructure for its adoption.

Several different individual technology items may serve as indicators of a GPT, and several GPTs may be associated with what is usually thought of as an industrial revolution. For example, the present paper takes the spread of digital information and communications technologies as a GPT of the Third Industrial Revolution. Jovanovic and Rousseau (2005) focus their discussion of this GPT on indicators such as computer systems and microprocessors, but other ICT technologies such as the Internet have had a similarly revolutionary impact during this era. An overview of the first three industrial revolutions appears in Table 1.

a. The First Industrial Revolution

The First Industrial Revolution began in Britain around 1760 as a consequence of inventions that had appeared some years earlier in that country. Among the early innovations that led to widespread mechanization were spinning and weaving machines for textile production and new technologies for purifying and working iron and other metals. Primitive steam engines had already been in limited use since the end of the 17th Century, but improvements in their efficiency by James Watt and others from around 1760 led to steam engines becoming the characteristic source of power for machines and transportation, and therefore a key GPT in the First Industrial Revolution. Accordingly, the beginning of the First Industrial Revolution is usually dated as beginning around 1760, when increases in industrial output in Great Britain began to correlate with an overall increase in the GDP of that country.

The mechanization of the First Industrial Revolution greatly increased worker productivity but also led to some job losses, e.g. among handloom weavers. Accordingly, some handloom weavers and other laborers who feared losing their livelihoods instigated considerable social unrest through the original "Luddite movement" of the early 1800s. The movement was so named, because its proponents claimed to be following the orders of a mythical "General Ludd." The term "Luddite" remains in use today, referring more broadly to persons who resist the introduction of new technology. Ultimately, though, the First Industrial Revolution created more jobs than were lost, because cost reductions and productivity increases led to major increases in demand. In addition, new job categories and new industries evolved around many key inventions. For example, along with the steam locomotive came the railroad industry and large numbers of new positions required by that new industry. The effects of the First Industrial Revolution soon spread from Britain to other countries. Although the societal and economic developments from this era persist until the present day, the First Industrial Revolution is generally considered to have ended along with the occurrence of major economic slowdowns around 1840, when the rate of adoption of early innovations such as mechanized spinning and weaving slowed as their markets matured.

b. The Second Industrial Revolution

While inventions continued to be conceived during the 19th Century, the origin of the Second Industrial Revolution can be associated with the development of new ways to obtain value from the machines that had appeared in the First Industrial Revolution. Increasing precision in equipment and processes enabled a new approach to manufacturing, namely the use of interchangeable parts (often premanufactured). This new approach was stimulated by the need to scale up production rapidly to meet major increases in demand. Early attempts to use interchangeable parts can be found from around 1800, e.g. in musket manufacturing by the American inventor Eli Whitney, but it took about 50 years to achieve the necessary quality and systematic assembly techniques that allowed the use of interchangeable parts to become a feature common to almost all manufacturing. In addition, other innovations in manufacturing that served as precursors to the Second Industrial Revolution include the evolution of machine tools and the development of the Bessemer process for producing steel around 1850–1855. In the mid-19th Century, however, economic growth remained stagnated.

The Second Industrial Revolution, which is usually dated as beginning with a rapid increase in general economic growth from around 1870, is associated with the development of assembly line mass manufacturing and the rapid spread of major infrastructure systems for water, energy, telecommunications, and transportation. Major GPTs associated with the Second Industrial Revolution include electricity and the internal combustion engine, as well as others such as the radio. Electricity gradually replaced steam as the main source of fixed power for manufacturing, and the electric motor also led to complementary inventions such as the washing machine and vacuum cleaner. Complementary inventions from the internal combustion engine include the automobile and the airplane, to name but a few. Although the First Industrial Revolution originated in Britain, the Second IR centered on dramatic industrial growth in the U.S. and Germany.

One important impact of the Second Industrial Revolution was a drastic reorganization of the labor force, so that in advanced economies manufacturing became a major employer while the number of people engaged in agriculture shrank. Like the First, the Second Industrial Revolution led to problems, such as unsafe working conditions and urban poverty, which had negative implications for economic growth. Nevertheless, the overall impact of the Second Industrial Revolution was a continued increase in GDP per person worldwide as well as strong advances in national outputs. Many scholars mark the beginning of World War I (1914) as the ending date of the Second Industrial Revolution, but its dynamics continued to evolve until about the time of the Great Depression of 1929. Many of the patterns of work and life that evolved in the Second Industrial Revolution continue to be characteristic of society today.

c. The Third Industrial Revolution

The Third Industrial Revolution is characterized by the evolution and spread of digital technologies from around 1960, a trend that is continuing into the present time. Key GPTs include semiconductor technologies, the computer, and the Internet, among others. Many of the underlying technologies were invented earlier; for example, the use of punch-cards to save fabric designs for application to factory looms goes back to the 1800s. One of the first digital computers, the ENIAC, was developed at the University of Pennsylvania, U.S.A., in 1943–44. The impact of digital technologies on industry, however, really began to be felt after World War II, along with the spread of mainframe computers that

Table 2: Stages of the Third Industrial Revolution

Dates	Architecture	Notes
c. 1960–1980	Mainframe—terminal	Only limited processing done by the terminal, access to central computer is by time-share, applications are custom-made for each system
c. 1980–2005	Server—client	More processing done at "intelligent" clients (e.g. engineering workstations), Internet protocol gradually becomes dominant, standard computer operating systems (e.g. Windows) enable shrinkwrap applications
c. 2005–present	Cloud computing	Types of networked clients have proliferated (smart phones, smart appliances, as well as computers), much information processing done on "virtual machines" in data centers

could be accessed from multiple terminals. Accordingly, the present paper adopts 1960 as the beginning date for this revolution. An overview of the Third Industrial Revolution is shown in Table 2.

As shown in Table 2, the Third Industrial Revolution, which is sometimes known as the Digital Revolution, can be divided into three stages. The continual spread of digital technology is a unifying characteristic of all three. Throughout all stages of this period, digital data generation, transmission, storage, and analysis have driven rapidly accelerating economic growth. GDP per person in the U.S. in 1960 was $18,058 and in 2016 was $53,015 (in 2011 dollars); the comparable figures in Japan were $6,273 in 1960 and $37,465 in 2016. Like previous industrial revolutions, the Third has led to some problems, such as increasing inequality between rich and poor. Nevertheless, complementary inventions from semiconductors, computers, and the Internet have meant that digital technologies have become a ubiquitous aspect of everyday life and work for most people in advanced and developing countries.

During the Third Industrial Revolution, there has also been increasing diversity in the types of information that are being converted into digital data. Most early data analytic programs operated only on "structured" data, as is found in spreadsheets. Since about 2010, "unstructured" data as found in text messages, blogs, and computer logs have increasingly become the target of analysis along with structured data in more sophisticated big data analytics programs. Increasingly, video and audio signals are being digitized, so that such files now make up the majority of data traffic on the Internet. While most analysis of video and audio data is still based on text tags that describe the contents of a file, some analytics programs are starting to examine directly patterns in the nonverbal shapes that are digitally encoded. The next major data type that is becoming accessible for analysis can be called "Internet-of-things" data. IOT data include a wide range of sensor data, location data, and other readings from "smart" devices. Accordingly, the amount of digital data created annually has been predicted to rise from about 2 Zettabytes in 2010 to around 175 Zettabytes in 2025 (Statista 2018).

Because the spread of the collection of digital data to new types of information (from text to image to IOT data) is expected to continue to generate a huge expansion in the amount of data stored in the cloud, the present paper does not yet recognize an end to the Third Industrial Revolution. As with the previous Revolutions, the end of the Third Industrial Revolution will probably be calculated from economic factors, such as GDP growth or structural changes in the distribution of the labor force, rather than from the characteristics of its underlying GPTs.

2. THE FOURTH INDUSTRIAL REVOLUTION

Nevertheless, the present paper follows Schwab (2016) in recognizing that a Fourth Industrial Revolution is beginning to emerge around new tools for obtaining value from digital data. The authors see the emergence of this Fourth Industrial Revolution as paralleling the way in which the Second Industrial Revolution came about, when the spread of new transportation communication, and energy infrastructures enabled new manufacturing approaches that in turn led to the creation of huge new value from the mechanization of the First Industrial Revolution. Cloud computing infrastructure similarly enables new types of tools to

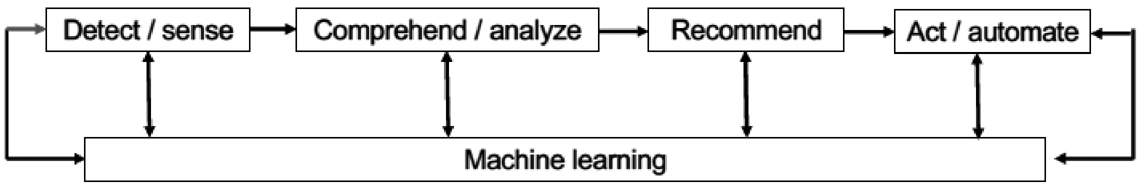

Figure 1: Model of how AI functions (adapted from Bataller and Harris 2016)

create value from the vast amount of online data that are now being created by many types of devices. New tools for creating new value in the Fourth Industrial Revolution include artificial intelligence, edge computing, blockchain, and quantum computing.

As in previous revolutions, these potential GPTs had their beginnings years ago. The present paper focuses on artificial intelligence (AI) as a technology that can already be considered to be an emerging GPT. AI has already begun to have major impact on business and society across a variety of application fields. Research that directly led to AI can be traced back as far as the work of English mathematician Alan Turing in the 1940s, and the term "artificial intelligence" appears to have been coined by John McCarthy, who in 1955 co-authored a proposal for a major research project into AI at Dartmouth College in 1956 (Moore 2006).

AI can be broadly defined as the use of computers to perform tasks that were earlier thought to require human levels of intelligence. The term includes a number of different approaches that are distinguished by different types of algorithms and problem-solving frameworks. Only some of the approaches to AI are modeled on processes of reasoning or knowledge representation used by humans, e.g. "expert systems." Most AI approaches replace simple Boolean logic (in which all values are either true or false) with complex statistical clustering or other approaches that are often termed "fuzzy logic." The present paper takes it as a definitional condition that artificial intelligence always includes an element of "machine learning," which refers to processes by which a computer program increases the accuracy of its solution by iteratively solving a problem with new data each time. A model of AI is shown in Figure 1.

In accordance with Figure 1, many AI programs only detect or sense patterns, e.g. anomaly detection for cybersecurity or voice-to-text conversion programs. Other AI programs perform more complex analysis on incoming data, e.g. natural language processing. Some AI programs contextualize analysis to the environment or conditions of the user so as to formulate recommendations, e.g. for stock trading or investment. The most complex AI programs automate the computer system's response to its analysis of incoming data, e.g. self-driving cars. No matter the complexity of the analysis, all AI programs incorporate machine learning for iterative problem solving.

The influence of AI in business accelerated dramatically with advances in a particular type of AI, namely "deep learning," around 2010. In 2009, Professor Fei Fei Li at Stanford published a collection of 14 million tagged visual images for use as training data in the "Large Scale Visual Recognition Challenge" (see <http://www.image-net.org/challenges/LSVRC/>). That same year, major advances were made in applying deep learning to speech and vocabulary recognition. Also in 2009, the company NVIDIA began to apply its graphics processing unit (GPU) computer chips to the training of deep learning neural networks. Accordingly, the present paper uses 2010 as an approximate date for the beginning of the Fourth Industrial Revolution.

Technical features of AI programs, such as their ability to handle problems with huge numbers of variables, their replacement of simple true-false logic with advanced statistical clustering, and their continuous improvement in accuracy through machine learning, mean that AI can solve problems that previously could were not solvable, such as the natural language interface of virtual assistants such as Amazon's Alexa. Accordingly, data owners are often motivated to adopt AI in order to obtain new value from their data, either in isolation or in conjunction with other datasets. AI adoption is also driven by the desire for increased productivity, e.g.

through much improved analytics (of customer behavior, factory performance, etc.) and through automation of many functions that previously required humans. The adoption of AI accordingly is already spreading across multiple industry sectors, and its growth reflects a number of different specific motivations.

Those businesses that are built around artificial intelligence solutions have already seen explosive growth over the last decade. Funding to AI-related startup companies worldwide has increased from \$670 million in 2011 to \$20.05 billion in 2018 (Statista 2019). Bughin et al. (2017) estimate that large corporations worldwide now spend about \$18–27 billion dollars each year on company-internal R&D into AI. New applications of AI are being launched on almost daily basis and include more advanced analytics and also automation, e.g. self-programming robots and self-driving vehicles.

Nevertheless, the impact of AI as a GPT for the Fourth Industrial Revolution is probably still in the early stages. New startups built on AI-based analysis are being launched on an almost daily basis, and complementary technologies, such as autonomous vehicles, drones, register-less retail stores, automated farming, and new financial services ("fintech") are under widespread development. At the same time, there is concern that AI may have negative impacts on society, including replacement of human workers by robots and intrusion by employers into worker privacy. Consequently, it is important to analyze systematically the likely impact of AI innovations.

3. MODEL

The present paper provides a formal account of the spread of an AI innovation across companies. In this model, suppose that an AI innovation is introduced into a community of N companies at time $t=0$. Let $x(t)$ define the number of companies who have adopted the AI innovation at time t. It is clear that $x(t)$ has integer values, but we can approximate that $x(t)$ has a continuous function of time. Assuming that, in the general process of spread, a company that is an early adopter of the AI innovation will be regarded by other companies as having a positive reputation, the number of companies, δ_x, which adopt the AI innovation in a very small time interval, δ_t is proportional to both the number of companies $x(t)$ which have already adopted and the number of companies $N-x(t)$ which have not adopted. Thus, $\delta_x = \alpha x(N-x)\delta_t$, where α is a positive constant. We obtain the following differential equation by divided δ_t and letting $\delta_t \to 0$. $\frac{dx}{dt} = \alpha x(N-x)$……….1)

Equation 1) is a logistic equation and we can rewrite the solution as

$$x = \frac{Ne^{\alpha Nt}}{N-1+e^{\alpha Nt}}\text{, assuming } x(0)=1\text{……….2)}$$

This function gives us a sigmoid shape. Now, we can surmise that a company can easily acknowledge the spread of AI innovation through advertising of SNS, etc. This fact will play an important role in the early stages of the adoption process. Suppose that in the small time δ_t, the number of companies being influenced through the mass media is proportional to the number of companies which have not adopted the AI innovation, namely, $\beta(N-x)\delta_t$ where β is a positive constant. The new equation is now

$\delta x = \alpha x(N-x)\delta t + \beta(N-x)\delta t$, giving the differential equation

$$\frac{dx}{dt} = (\alpha x + \beta)(N-x)\text{……….3)}$$

We can easily solve the variables separable equation as

$$\int \frac{dx}{(x+\gamma)(N-x)} = \int \alpha\, dt\text{, where } \gamma = \frac{\beta}{\alpha}.$$

$$\text{Thus, } \frac{1}{(N+\gamma)} \int \left[\frac{1}{(x+\gamma)} + \frac{1}{(N-x)}\right] dx = \alpha t + \mathrm{A} \text{……….4)}$$

i.e. $\ln\left(\frac{x+\gamma}{N-x}\right) = (N+\gamma)(\alpha t + \mathrm{A})$ and we write the arbitrary constant as $\ln \mathrm{B} = (N+\gamma)\mathrm{A}$, we have $\frac{x+\gamma}{N-x} = \mathrm{B}e^{(N+\gamma)\alpha t}$. If we will solve for x, and with the initial condition $x(0)=1$, it gives us

$$x = \frac{(\alpha+\beta)Ne^{(\alpha N+\beta)t} - \beta(N-1)}{\left[(N-1)\alpha + (\alpha+\beta)e^{(\alpha N+\beta)t}\right]}\text{……….5)}$$

Here, we have a sigmoid type growth again. The spread of AI innovations can be expressed theoretically by equation 5) through the number of companies adopted.

However, we must also consider the impact of the adoption of AI on the growth and profitability of a company. Suppose that company growth will decrease without the help of AI. The decrease is assumed to have approximately linear function. Namely, $\log G = -\lambda t + \mu$, where G is the growth rate, t time and λ and μ constants.

Thus, $\frac{dG}{dt} = -\lambda G$ ....6) when there is no AI adoption. We now formulate the model mathematically. If $A = A(t)$ is the diffusion rate of AI, then from 6), if $A \equiv 0$, $\frac{dG}{dt} = -\lambda G$. Now, if $A \not\equiv 0$, we assume that the increase of growth rate is proportional to the diffusion rate of AI, A, and also to the degree to which the market for the innovation is still unsaturated. Namely, $(M - G)/M$, where M is the saturation level of the growth. Thus, M is the practical limit of growth that can be generated and $(M - G)/M$ is the degree of the market share which has still not adopted the AI. Combining these assumptions leads to the differential equation $\frac{dG}{dt} = rA\frac{(M-G)}{M} - \lambda G$ where r is a constant, and rearranging the formula gives $\frac{dG}{dt} + \left(\frac{rA}{M} + \lambda\right) G = rA$ ....7)

This is a linear first order differential equation, and its solution will depend on the form of the growth function $A = A(t)$ For example, suppose A is constant over a specified time interval and zero thereafter, $A(t) = \begin{cases} \bar{A} & 0 < t < T \\ 0 & t > T \end{cases}$ ....8)

And that initially (i.e. at $t = 0$), $G = G_0$ Then for $0 < t < T$

$\frac{dG}{dt} + \left(\frac{r\bar{A}}{M} + \lambda\right) G = r\bar{A}$ and writing $b = r\bar{A}/M + \lambda$, we have integrating factor $e^{\int bdt} = e^{bt}$.

Thus, $e^{bt}\frac{dG}{dt} + e^{bt}bG = e^{bt}r\bar{A}$ i.e.

$\frac{d}{dt}(e^{bt}G) = e^{bt}r\bar{A}$

$e^{bt}G = \int e^{bt}r\bar{A}dt = r\bar{A}\int e^{bt}dt = \frac{r\bar{A}e^{bt}}{b} + c$, where c is the constant of integration.

Hence $G = \frac{r\bar{A}}{b} + ce^{-bt}$

for $0 < t < T$. Now at $t = 0$, $G = G_0$ giving

$G_0 = \frac{r\bar{A}}{b} + c$;

Thus, $c = G_0 - r\bar{A}/b$ and for $0 < t < T$,

$G(t) = \frac{r\bar{A}}{b} + \left(G_0 - \frac{r\bar{A}}{b}\right)e^{-bt}$ ....9)

Now for $t > T$, $A = 0$, and from 7) we have $\frac{dG}{dt} - \lambda G = 0$, which has solution $G = ke^{-\lambda t}$, where k is a constant. At $t = T$, $G = G_t$, so that $G_T = ke^{-\lambda T}$.

Hence for $t > T$, $G(t) = G_T e^{-\lambda(t-T)}$ ....10) and from 9), G_t has the value

$G_T = \frac{r\bar{A}}{b} + \left(G_0 - \frac{r\bar{A}}{b}\right)e^{-bT}$.

Thus, combining 9) and 10) substituting for b, we finally obtain the predicted growth as

$$G(t) = \begin{cases} G_0 e^{-(\lambda + r\bar{A}/M)t} + \dfrac{r\bar{A}}{(\lambda + r\bar{A}/M)}\left(1 - e^{-(\lambda + r\bar{A}/M)t}\right) \\ G_t e^{-\lambda(t-T)} \end{cases}$$

A typical solution is shown in Figure 2. It can be seen that the rate of increase of growth is most rapid at an early stage. But as saturation approaches, the rate decreases. So, when the diffusion of AI finishes at time T, the growth rate drops off exponentially along with general recognition of its obsolescence. Judging from this analysis, we can notice that the adoption of AI will initially accelerate the growth rate of companies as having good reputations, but as the diffusion of AI saturates, say, the growth rate decreases along with the emergence of a bad reputation for obsolescence (of the existing AI).

We can show two ideas of AI innovations to explain this phenomenon (=the spread of AI and decrease of growth rate due to saturation) of Figure 2. According to Inoue (2017), there are two conflicting effects. The details that we quoted from Inoue (2017) are as follows. One is "Shoulder Effect." This Shoulder Effect means that we can easily find out the new invention of technology by referring to the accumulation of the existing technologies. The other is "Elimination Effect." This Elimination Effect means that the invention of new idea will be difficult with the progress of innovation, because simple invention is easily achieved. If only the Shoulder Effect is at work, new technology will be born according to the accumulation of technology.

In such a scenario, our life will become

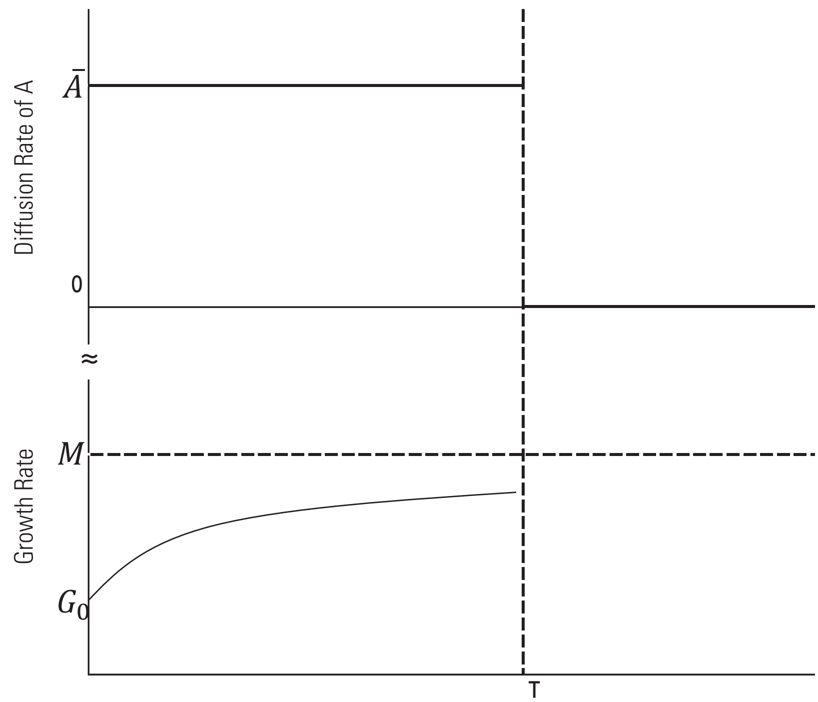

Figure 2: Estimated Growth Response for Diffusion of AI

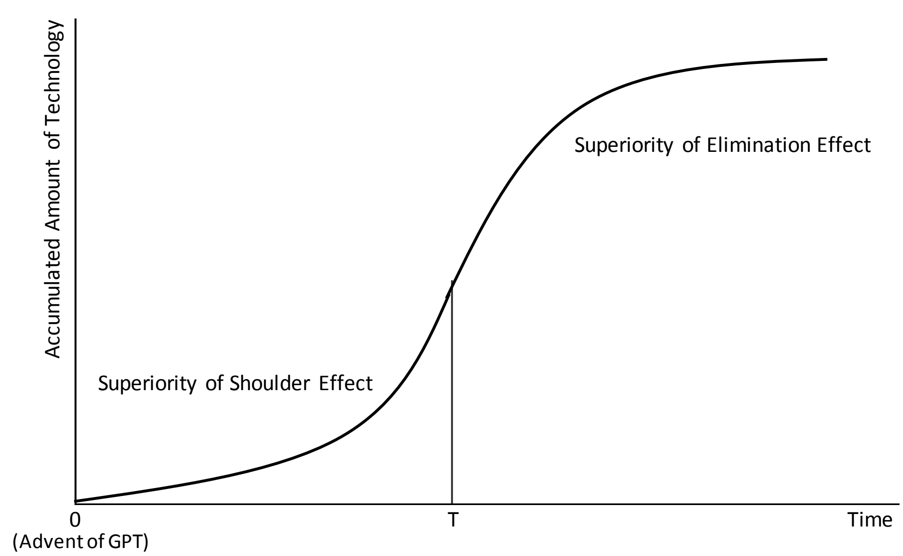

Figure 3: Transition of Accumulated Amount of Technology

Source: Future of AI and Economy written by Inoue Tomohiro

prosperous year by year. However, real life isn't like that. Instead, the Elimination Effect cancels the action of Shoulder Effect. We can confirm this fact by referring to Figure 3.

Namely, after emergence of GPT at time 0, Shoulder Effect is predominant at initial stage and accelerate the accumulation of technology. But Elimination Effect surpasses Shoulder Effect after passing at time T and the accumulation of technology decelerate until the emergence of next GPT.

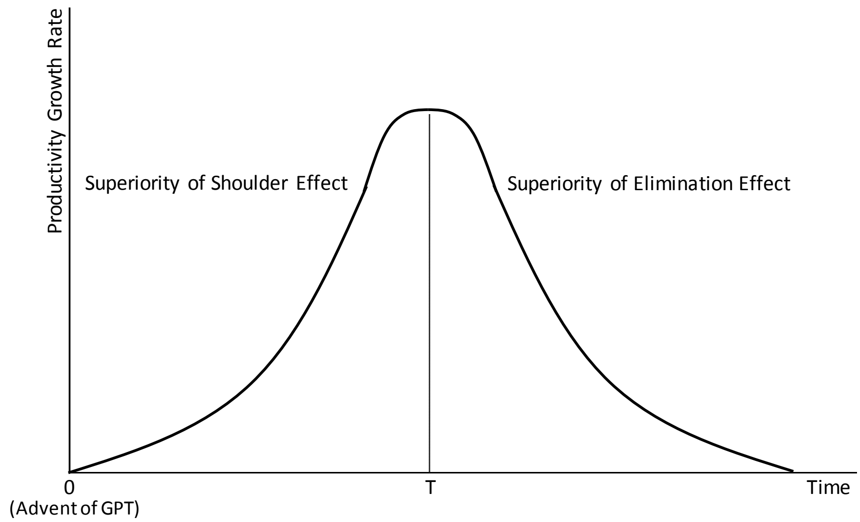

Figure 4: Transition of Productivity Growth Rate

Source: Future of AI and Economy written by Inoue Tomohiro

This curve is called "Logistic Curve." Generally speaking, the productivity of macro economy will increase in accordance with the accumulation volume of technology. If we replace perpendicular axis from accumulated amount of technology to productivity growth rate, the transition of productivity growth rate can be shown in Figure 4.

The following data are based on the database of Ministry of Internal Affairs and Communications, Japan in 2017. If we consider the population (=2,592 in total) of Japanese companies, the percentage of Japanese companies that adopted AI is 14.1 percent and IoT is 14.6 percent respectively. There is a tendency that relatively small companies (=capital asset is less than 100 million Yen) adopt AI in Japan and the adoption rate of financial institutions and insurances are 19.1 percent, transportations and postages are 18.7 percent and services are 16.2 percent respectively. In addition, if we compare the situations of AI adoption with U.S., U.K., and Germany, we notice that Japanese companies are far less behind other three countries. Namely, Japanese companies adopt only 16.8 percent in the data analysis by AI. And the companies in U.S., U.K. and Germany adopt almost close to 40 to 50 percent. Furthermore, we can exemplify state space model that have constraint conditions in state variables, in other words, estimation of Cobb-Douglas production function by using Kalman filter technique. As a next step, this model will become competing model of the population in AI diffusion.

Thus, as the innovation approaches obsolescence, newer sophisticated AI will appear and replace the existing AI, causing even more drastic change to the world.

4. DIRECTION OF AI BUSINESS

As a GPT, artificial intelligence can be expected to continue to spawn new innovations and complementary technologies for some time. In the diffusion of AI, labor-intensive business activities gradually will be automated by AI technology. For example, AI can already automate harvest timing in agriculture, precision measurement in construction, sorting and visual inspection in food processing, and visual inspection of assembly processing. This trend can also expand further in fields such as manufacturing, logistics and nursing.

Our model would account for the current rapid spread of specific innovations in AI, e.g. "deep learning," which is already being adopted widely in medical imaging and facial recognition. In medical imaging, deep learning technology is being applied to early detection of cancers and other diseases in advanced countries. Meanwhile, deep-learning based facial recognition is widely used to enable business functions such as payment authorization and, especially in China, for more controversial government functions of security and social monitoring. We can expect the use of deep learning to continue to expand to new functions for the time being, but eventually it will become regarded as relatively obsolescent in comparison to some newer approach. At that point, its growth will drop as the market comes to preference the newer approach.

5. CONCLUSION

The present paper began by describing the basic dynamics of the three Industrial Revolutions so far. While the spread of digital technology that characterizes the Third Industrial Revolution is still continuing, the world is already beginning to experience the impact of a Fourth Industrial Revolution in which new tools and systems are being developed to capture new value from digital technologies. One of the major new tools of the Fourth Industrial Revolution is AI. As a GPT, AI is generating various new waves of innovations and complementary technologies that are beginning to change our life drastically. Consequently, the present paper has proposed a model to account for the pattern by which an AI innovation spreads. Through the use of this model, we can observe that the adoption of an AI innovation initially accelerates the growth rate of a company as having a good reputation early in the wave of diffusion. But, as the diffusion of the particular AI innovation saturates the market, its impact on the growth rate of the company decreases as it becomes associated with a bad reputation for obsolescence in comparison to some newer technology. At that point, the new, more sophisticated approach to AI will supplant the earlier AI innovation, causing the world to change even more drastically.

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