Modern Economy, 2025, 16(9), 1607-1631
https://www.scirp.org/journal/me
ISSN Online: 2152-7261
ISSN Print: 2152-7245

Brynjolfsson versus Gordon on Artificial Intelligence and Productivity Growth: What the Science Says

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How to cite this paper: Beaudreau, B. C. (2025). Brynjolfsson versus Gordon on Artificial Intelligence and Productivity Growth: What the Science Says. *Modern Economy, 16,* 1607-1631.
https://doi.org/10.4236/me.2025.169074

Received: March 30, 2025
Accepted: September 20, 2025
Published: September 23, 2025

Abstract

Over the past decade, Erik Brynjolfsson and Robert Gordon have debated each other over the question of Artificial Intelligence (AI) and Productivity Growth, with the former predicting robust, sustained growth and the latter casting doubt over the ability of AI to replicate the growth rates of the 20th century. Until now, the debate has been largely anecdotal, with little scientific content. Brynjolfsson has focused on a number of promising forms of AI, while Gordon has raised a number of headwinds. This paper attempts to further the debate by invoking the principles of basic material processes. In other words, what does science have to say regarding the role of AI in productivity growth? To this end, it examines AI from the point of view of process engineering as well as various econophysics-based models of economic growth. The evidence presented provides support for Robert Gordon's position, but for entirely different reasons. Specifically, it is shown that because information is not physically productive, more and better information (obtained from machine learning and other algorithms) cannot and will not increase productivity and, as such, cannot increase growth. There are, however, exceptions. For example, more and better information can contribute to increasing second-law efficiency, triggering one-shot increases in output. In this regard, AI is seen as being analogous to the information and communications technology revolution in the 1980s and 1990s. Our results predict the AI equivalent of the information paradox, namely that in the future, you will see AI everywhere but in the growth statistics.

Keywords

Artificial Intelligence, Productivity Growth, Brynjolfsson versus Gordon, Science, Material Processes

1. Introduction

The productivity slowdown of the 1970s marked an important turning point in the study of economic growth. Until then, the profession devoted little time and/or effort to identifying the causes of growth. After all, growth had been robust for decades and, as such, there was no reason to doubt that it would continue. When it didn't, it was faced with an existential crisis, namely of being unable to not only explain past growth, but to predict future growth on the basis of technological change. Understandably, governments panicked, looking for ways in which to rekindle what had been a period of thirty years of robust growth. The time was nigh. Something, anything had to be done to steer the West—and indeed, the world as a whole—back on the path of prosperity. The hunt was on for the holy grail.

Fast forward to the present, where, despite multiple-pronged strategies and policies, growth has remained anemic (Gordon, 2014, 2015; Dieppe, 2020). Freer trade, fiscal reform, regulatory reform, and R&D subsidies have failed to restore post-WWII levels of productivity and hence output growth. Technologically speaking, a number of developments were touted as possibly being the answer. Among these was the information and communications technology (ICT) revolution. Computers would do what the steam engine and the electric motor had done in the 19th and 20th centuries, respectively. Happy days would be here again. Unfortunately, hope turned into despair. In the late 1980s, Nobel prize laureate, Robert Solow, pointed out that "we see computers everywhere, but not in the GDP data," a phenomenon he referred to as the information paradox. Some optimists like Stanford University economics professor Paul David attempted to calm the storm by pointing to lags between the introduction of a new technology and its effects on growth, using the dynamo in the early part of the 20th century as an example.

The past decade witnessed the emergence of another technological development that has since been touted as a game-changer in productivity and output growth, namely artificial intelligence (AI). Consisting of a combination of big data, machine learning and advanced robotics, it is seen by some, notably Stanford University economics professor Erik Brynjolfsson, as ushering in a new industrial revolution, complete with high, sustained growth rates. Others, however, are less sanguine, notably Northwestern University economics professor Robert Gordon who is skeptical, pointing to a number of so-called headwinds.

The resulting debate has been anything but reassuring. Based largely on anecdotal evidence, both sides have failed to mount a convincing argument. So much so that the two protagonists have resorted to wagering the outcome, betting $400.00 over whether "Private Nonfarm business productivity growth will average over 1.8 percent per year from the first quarter (Q1) of 2020 to the last quarter of 2029 (Q4)." Understandably, this is an unfortunate development. One would have hoped that after two and one-half centuries of studying growth, the profession would be in a better position to predict the outcome, which brings us to the purpose of the present paper, namely reaching out to other material scientists in the hope of understanding and thus predicting the effect of AI on productivity growth.

In other words, what does science (applied physics, process engineering) have to say about the effect of AI on wealth creation and growth?

The paper is organized as follows. To begin with, the shortcomings of the mainstream approach to understanding productivity growth, notably the residual approach, are examined critically. This then segues into a discussion of how the other material sciences analyze the growth of material processes. This then forms the basis of a re-examination of the role of AI in growth in each of these. The upshot is that in all of these, because AI is information-based and information per se is not physically productive, AI cannot and will not increase growth rates as argued by Brynjolfsson. It comes down on the side of Gordon, but for entirely different reasons.

2. Brynjolfsson versus Gordon: Respective Positions

In this section, we lay out each's position on the role of AI in productivity and thus in growth. Referring to Table 1, we see that according to Brynjolfsson, AI will result in important productivity growth, going as far as to describe it as the "Second Machine Age." Gordon, on the other hand, is less upbeat, arguing that it cannot be compared to the innovations of the post-Civil War period and will not, as such, restore the record growth levels of the post-WWII period. Despite being in its tenth year, the debate has not progressed to the point that neither side can claim victory. While Brynjolfsson has focused on the technical aspects of big data and machine learning, Gordon has focused on the scope of AI relative to the technological innovations that have come to define the modern world, including electricity, the internal combustion engine, sanitation, etc.

Table 1. Brynjolfsson and Gordon: Respective positions on AI and growth.

Erik Brynjolfsson	Robert Gordon
Position	**Position**
AI will, in time, result in important productivity growth, leading to overall economic growth. Refers to the current era as "The Second Machine Age."	AI cannot be compared to the productivity-increasing innovations of the past and will not restore growth to post-WWII levels.
Justification	**Justification**
AI and Machine Learning	Innovation has encountered diminishing returns
Progress is J-Shaped	New ideas are getting harder to find
High Wages Accelerate	Four headwinds: demography, education, debt and inequality
Digitalization	

Source: Bailey (2021): p. 1.

With no resolution in sight, the debate has morphed into a battle of wits, as the two banter back and forth. In many regards, it has become somewhat of a shouting match as neither is able to refute the other's allegations. Brynjolfsson is unable to show, conclusively, that AI is qualitatively and quantitatively speaking, in the same league as electricity and the internal combustion engine and Gordon is unable to refute Brynjolfsson's claims regarding the effects of AI on productivity. In fact, the debate has degenerated to the point that the two are now taking bets regarding AI and productivity growth.

3. The Strongest Headwind: The Non-Descript Nature of the Solow Residual

As mentioned, Robert Gordon points to a number of headwinds, factors that will militate against non-negligible increases in productivity and growth. In this section, we argue that the strongest headwind in the debate over the role of AI in productivity growth is the current state of growth theory in general and the non-descript nature of the Solow residual in particular. The latter is just what it says, a residual, being devoid of structure and direction. Most of post-WWII growth has been attributed to a residual variable. As such, it is not clear just what the innovations were and how they affected growth. In short, the residual has no structure, formally or informally making analysis all the more difficult, if not impossible.

Such is the case with AI. There is no theory of production that explicitly accounts for AI. Rather, what we have is a lot of arm waving in the form of anecdotes and impressions. Ideally, we would want a theory of production that allows us to evaluate scientifically the role of machine learning and big data in material processes. If they increase productivity and output, then how?

Table 2 presents the various anecdotes put forward by the two protagonists. What stands out is their speculative nature. Few are grounded in hard facts. For example, Brynjolfsson contends that "This era will be better for the simple reason that, thanks to digital technologies, we'll be able to produce more: more health care, more education, more entertainment, and more of all the other material goods and services we value." This is purely speculative in nature, devoid of any theory or statistics. It bears reminding that similar predictions were also made in the 1980s and 1990s regarding information and communications technology (ICT), all of which turned out to be false. Gordon's reference to the low-hanging fruits metaphor is reminiscent of Charles H. Duell, who, as the Commissioner of the U.S. Patent Office, was widely quoted as having stated in 1889 that the patent office would soon shrink in size and eventually close because everything that can be invented has been invented. This is not to say that it isn't true (low-hanging fruits), but rather that it is speculative given the non-descript nature of the Solow residual.

3.1. AI and the Modern Productivity Paradox

Brynjolfsson, Rock and Syverson (2017) raised the question of AI and what they referred to as the modern productivity paradox, namely that the expectations have not materialized as measured productivity (i.e. productivity statistics) has not increased—in fact, it has decreased (Dieppe, 2020). This is analogous to Robert

Solow's information paradox according to which the author commented: "we see computers everywhere but in the productivity data." And as was the case with the information paradox, Brynjolfsson, Rock, & Syverson (2017) point to lags. David (1991) attributed the failure of ICT to raise productivity to adoption lags. Ironically, three decades later, the effects of ICT have yet to be felt in the productivity data. In the next section, a detailed description of AI is presented, one that will provide background and structure to the analysis that follows.

Table 2. Anecdotes (non-scientific).

Brynjolfsson	Gordon
Digital technologies are doing for human brainpower what the steam engine and related technologies did for human muscle power during the Industrial Revolution. They're allowing us to overcome many limitations rapidly and to open up new frontiers with unprecedented speed. It's a very big deal (Bernstein & Raman, 2015).	Why has productivity growth slowed down by so much? A growing consensus has formed that the process of innovation has encountered diminishing returns. A group of Stanford economists showed that "New Ideas Are Getting Harder to Find," documenting the multifold increase in the number of research workers needed to achieve continued miniaturization of computer chips, or to discover new drugs. Other research shows that an explosion in the number of new patents has been more than offset by the diminishing importance of these patents. The number of robots in manufacturing doubled over the past decade, but productivity growth in manufacturing was actually zero between 2010 and 2019. Much-heralded innovations like autonomous cars are like "waiting for Godot" as the tallies of deaths from Tesla auto-driving software keep mounting up. These examples support the interpretation that the bigger the stock of existing inventions, the tougher it is to find new ones (Brynjolfsson & Gordon 2021).
This era will be better for the simple reason that, thanks to digital technologies, we'll be able to produce more: more health care, more education, more entertainment, and more of all the other material goods and services we value (Bernstein & Raman, 2015).	This productivity paradox is resolved when we recognize that advances since 1970 have tended to be channeled into a narrow sphere of human activity having to do with entertainment, communications, and the collection and processing of information. For the rest of what humans care about—food, clothing, shelter, transportation, health and working conditions—progress slowed down after 1970. Our best measure of the pace of innovation and technical progress is total factor productivity (TFP), which grew after 1970 at barely a third the rate achieved between 1920 and 1970 (Gordon, 2021).
Our one confident prediction is that digital technologies will bring the world into an era of more wealth and abundance and less drudgery and toil. But there's no guarantee that everyone will share in the bounty, and that leaves many people justifiably apprehensive (Bernstein & Raman, 2015).	Gordon predicts that the growth rate going forward will be a fraction of the 3.62 percent registered between 1929 and 1974, and will stay low "over the next decade or two." Some of the factors contributing to this slowdown, he argues, include a "decline in the growth rate of the working-age population," a fall in worker hours per capita "due primarily to the retirement of the baby boom generation" and "an ongoing slowdown in the growth rate of output per hour." (Edsall, 2016).

Continued

A wave of powerful technologies, particularly those involving AI and machine learning, that are just beginning to be implemented. Machines can now recognize images, whether faces of friends or pathologies in medical images. For the first time, we are beginning to talk to our machines, and they talk back, though admittedly not in the most scintillating conversation. Machines can now make better decisions than humans for placing ads, recommending products, granting loans, hiring employees, or even deciding who should get parole. And it's not just AI: mRNA vaccines have been developed at warp speed, the cost of solar power is dropping at rates that exceed all expectations, and we're even beginning to see the long-awaited flying cars (Brynjolfsson & Gordon, 2021).
Impressive as the above technologies are, we shouldn't expect them to instantly translate into productivity growth. The economics of powerful technologies typically follows a "J-curve", where productivity growth is initially unexpectedly slow or even negative while firms struggle to reinvent themselves, and then takes off as the benefits of the new processes and products are harvested. Instead, a period of painful restructuring is required, and that's what we've seen over the past decade (Brynjolfsson & Gordon, 2021).
That said, the pandemic accelerated 20 years' worth of digitization into 20 weeks, compressing the J-curve. Individuals, companies and industries are rapidly learning how to work digitally, whether that means teaching a class from home, as I have been doing, or shifting a whole company to remote work. Many of the needed technologies were already place when the pandemic hit, making the transition far less painful. Now that we know how to do these things, we're not going to go all the way back (Brynjolfsson & Gordon, 2021).
The aggressive fiscal and monetary policy that started with the last administration and continues with this one, driving down labor slack, boosting wages, and creating new incentives for productivity gains. For most of the past decade, the government ran the economy with a lot unused labor capacity and inflation often below the Fed's target level. Congress has begun pushing the accelerator with a series of large tax cuts and stimulus packages, while the Fed kept rates low. As the economy runs hotter, it becomes harder to find workers and more attractive to harvest some of the productivity potential of new technologies (Brynjolfsson & Gordon, 2021).

3.2. AI Defined: Stanford University's Artificial Intelligence Report

In this section, artificial intelligence is defined in detail. The material is taken from the sixth edition of the Stanford University Artificial Intelligence Index Report, prepared by the HAI (Human-Centered Artificial Intelligence Group)[1]. Table 3 lists the dimensions of AI.

[1]The AI Index Report tracks, collates, distills, and visualizes data related to artificial intelligence. Our mission is to provide unbiased, rigorously vetted, broadly sourced data in order for policymakers, researchers, executives, journalists, and the general public to develop a more thorough and nuanced understanding of the complex field of AI. The report aims to be the world's most credible and authoritative source for data and insights about AI (Maslej et al., 2023).

Table 3. AI categories.

Category	Sub-Category
Computer Vision-Image	Image Classification
	Face Detection
	Deepfake Detection
	Human Pose Estimation
	Semantic Segmentation
	Medical Image Segmentation
	Object Detection
	Image Generation
	Visual Reasoning
Computer Image-Video	Activity Recognition
Language	English Language Understanding
	Sentiment Analysis
	Natural Language Inference
	Multitask Language Understanding
	Machine Translation
Speech	Speech Recognition
Reinforcement Learning	Reinforcement Learning Environments
Hardware	MLPerf Training Time
	MLPerf Inference
	Trends in GPU
Environment	Environmental Impact of Select Large Language Models
AI for Science	Accelerated Learning Through Learned Plasma Control
	Discover Novel Algorithms for Matrix Manipulation with Alpha Tensor
	Designing Arithmetic Circuits with Deep Reinforcement Learning
	Unlocking de Novo Antibody Design with Generative AI

Source: Maslej et al. (2023).

3.3. Why Has Modern Growth Theory Been Unable to Gauge the Effects of New Technologies on Productivity?

Despite decades of work and a series of Nobel prizes, the process of growth remains an enigma, both retrospectively and prospectively. On the one hand, it is unable to explain the past, from the industrial revolution to the present. On the other hand, it is incapable of understanding the present—the AI revolution being a case in point. Which raises the question, why? Why is it that in 2023, the leading growth theorists have to resort to anecdotes, arm-waving and wagering in what is a crucial debate for the future of the world economy?

In previous work (Beaudreau, 2020), I argued that the main reason lies in the very nature of growth theory (i.e., being divorced from the material sciences) and the amorphous nature of the Solow residual. In a nutshell, mainstream growth theory attributes growth to growth in capital and labor, and a residual, non-descript factor or variable referred to as the Solow residual (Aghion & Howitt, 1997). As neither capital nor labor is physically productive (Beaudreau, 1998, 2020), it therefore follows that from a purely physical point of view, modern growth theory explains virtually nothing, as it maintains that productivity growth results from non-descript innovations. But the clincher is that no one has been able to identify just what the key innovations are that are at play.

Because of this, the profession refers to innovation in general, without any distinctions. In short, broadly-defined innovation is seen as growth-inducing. As a result, there is a general consensus that R&D activities play a decisive role in fostering productivity growth. This relation was first formalized by Griliches (1973) and Terleckyj (1974) and has since been widely accepted.

Product versus Process Innovation

There are two fundamental types of innovation, namely product and process. Product innovation alters the nature of a product, altering or adding Lancasterian characteristics—that is, various product characteristics (e.g., durability, color, style). Process innovation, on the other hand, alters the material processes that create wealth. For example, better real-time information on the performance of a machine can improve outcomes—production efficiency. James Watt's external steam condenser is perhaps one of the most celebrated of process innovations as it increased the efficiency of fossil fuels. Unfortunately, there do not exist data on either product or process innovation per se—the data is, for the most part, consolidated and reported as such.

According to **Figure 1**, broadly-defied R&D expenditure in OECD countries has tripled over the course of the past two decades, a monumental feat if ever there was one. Today, the world does more research and development than anytime in history. And yet, growth remains stubbornly low, at rates well below those of the post-WWII period, oftentimes referred to as the glorious thirty years. In short, the Solow residual has all but disappeared, despite what many referred to as the third industrial revolution, namely the information and communication technology-based revolution.

This raises the question: Is the residual approach to the question of AI, based largely on R&D expenditure, all that we have? Is this all that the scientific community can come up with to answer this question? This paper argues that it is not and that the material sciences can shed light on the question. Specifically, it is argued that theoretical and applied physics/engineering can provide important clues regarding the role of AI and ICT in productivity growth. However, to do so, production activity (i.e., wealth creation) has to, first, be redefined in terms of the material sciences, and then the laws of physics have to be invoked in order to address the question of whether AI (**Table 3**) will or will not increase wealth?

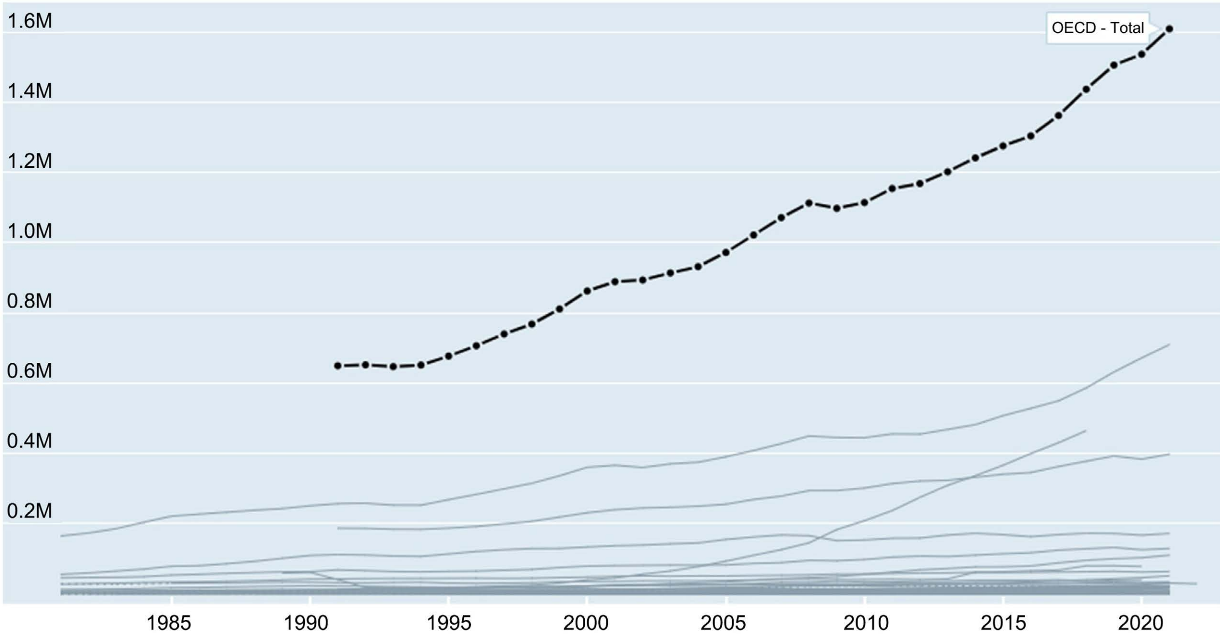


Figure 1. OECD R&D expenditure 2000-2020. Source: OECD (2023), gross domestic spending on R&D (indicator). https://doi.org/10.1787/d8b068b4-en (Accessed on 22 June 2023).

4. Material Processes as Seen in the Physical Sciences

Material processes lie at the core of virtually all sciences, including economics. They are typically defined in terms of outputs and inputs. Examples include the basis of all life on earth, namely photosynthesis where the outputs are the various sugars (carbohydrates) and the inputs include carbon dioxide, water and solar radiation. In this section, we examine the various analytical constructs used across the fields to describe these processes.

4.1. Work as Defined in Classical Mechanics and Thermodynamics

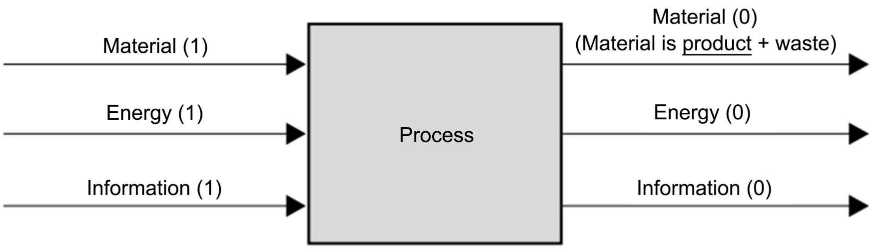
We begin by asserting that wealth creation is a material process, one governed by the laws of physics. And the first law is simple, namely that work is achieved by the application of force/energy[2]. Moreover, force and force alone is physically capable of doing work. Put differently, it is the only physically productive. Neither tools nor information can take its place.

4.2. Material Process Engineering Approach

Consider, first, the following description of production processes taken from Alting's (1994) *Manufacturing Engineering Processes*: "the term process can in general be defined as a change in the properties of an object, including geometry, hardness, state, information content (form data), and so on." To produce any change in property (value added (VA)), according to Alting, three essential agents

[2]Something can only work if it has energy. Hence, no energy, no work. Not being a source of energy, tools cannot perform work alone.

must be available: material, energy and information (Figure 2).



Source: Alting (1994, p.32)

Figure 2. Material processes as modeled in engineering.

Put simply, materials are transformed by energy (i.e., the source of work) in the presence of information. The latter, however, is not physically productive in keeping with the laws of classical mechanics. Specifically, energy and energy alone can perform work—that is, be physically productive.

4.3. Biology: Photosynthesis

As pointed out, one of the key—if not the key—material processes in life on earth is photosynthesis, described in Figure 3.

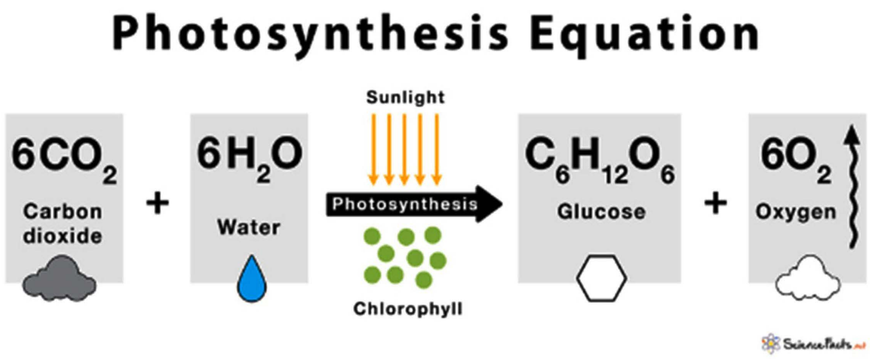


Figure 3. Photosynthesis as a material process.

Hence, sunlight (solar radiation) is applied to carbon dioxide and water in the presence of chlorophyll to produce glucose (sugars) and oxygen. Again, only the sunlight is productive. All other elements are either organizational in nature or material inputs.

There exists a number of approaches to understanding material processes in general (Hoke et al., 2021). Some focus on energy and information, others on energy and organization. Some include matter, while others focus exclusively on kinetics (i.e., the value added). In this paper, the energy-organization approach developed in Beaudreau (1998) is used. As its title suggests, it reduces material processes to a generalized energy component and a generalized organization component. The former is, according to classical mechanics, thermodynamics and kinetics, physically productive, while the latter provides the organizational framework in which the former performs work. Putting it in equation form yields Equation

(1), where W is output, E is the energy input and $\eta[T,S,I]$ is the organization input, defined as second-law efficiency—that is, the efficiency with which energy performs work. It is affected by *T,* tools, *S*, supervision and *I*, information and its values lie between 0 and 1.[3]

$$W = \eta[T,S,I]E \tag{1}$$

Growth can be described as the first derivative of the log of Equation 1 with respect to time which yields Equation (2).

$$\frac{\dot{W}}{W} = \frac{\dot{\eta}}{\eta} + \frac{\dot{E}}{E} \tag{2}$$

According to Equation (2), the rate of growth of work is equal to the sum of the rate of growth of second-law efficiency. Put differently, output growth depends on the combination of energy growth and increases in second-law efficiency. A good example of the latter is James Watt's external condenser which increased the efficiency of the Newcomen steam engine by 300 percent. Put differently, tasks that required 100 tons of coal now only require 25. In this case, better tools (i.e. the external condenser) improved second-law efficiency by reducing energy loss (i.e. required to cool the cylinder), making it economically viable.

The EO framework attributes changes in $\eta[T,S,I]$, second-law efficiency to three factors, namely *S*, the quality of the overseeing or supervision of the process, *T*, the quality of the tools that together define the process and *I*, the information available to the supervisory input. It is worth noting that second-law efficiency is never 100 percent, and in most cases, is considerably less. For example, the internal combustion engine is 33 percent efficient. Moreover, it is highly stable and resistant to large-fluctuations (Beaudreau & Lightfoot, 2015).

4.4. The EO Framework in the Historical Record

Recognizing that energy is the only physically-productive input in wealth-related material processes, while conventionally-defined capital and labor are organizational inputs, has a rather checkered history in science in general and economics in particular. This owes to, among other factors, the fact that early political economists were and modern-day economists are moral philosophers, not natural philosophers[4]. Their training, both in the past and present, is devoid of natural philosophy. Newtonian (i.e. classical) physics is clear: all work is the result of the application of force. There can be no exceptions[5].

Perhaps one of the first to acknowledge this was Charles Babbage in *The*

[3]Second-law efficiency varies across energy-based material processes. For example, the internal combustion engine is roughly 35 percent efficient. That is, it converts 33 percent of its potential energy into useful work, the other 65 percent being lost in the form of heat. In general, second-law efficiencies in industry vary considerably, but are relatively constant. In other words, once maximum efficiency has been reached, it is awfully difficult to increase it.

[4]Moral philosophy is defined by its constituent fields (i.e. logic, rhetoric, law, history, morality). Natural philosophy consists of physics and its applied fields (chemistry, biology, astronomy).

[5]Unfortunately, neoclassical economics violates basic physics by assuming that both labor and capital are productive.

> *Economy of Machinery and Manufactures* who pointed out: Of the class of mechanical agents by which motion is transmitted—the lever, the pulley, the wedge, and many others—it has been demonstrated, that no power is gained by their use, however combined. Whatever force is applied at one point can only be exerted at some other, diminished by friction and other incidental causes […]. Of those machines by which we 10 produce power, it may be observed that although they are to us immense acquisitions, yet in regard to two of the sources of this power—the force of wind and of water—we merely make use of bodies in a state of motion by nature; we change the directions of their movement in order to render them subservient to our purposes, but we neither add to nor diminish the quantity of motion in existence […]. The force of vapour is another fertile source of moving power; but even in this case, it cannot be maintained that power is created. Water is converted into elastic vapor by the combustion of fuel. The chemical changes which thus take place are constantly increasing the atmosphere by large quantities of carbonic acid and other gases noxious to animal life (Babbage, 1832: p. 11).

This brings us to conventionally-defined labor which, surprisingly, is ignored in process engineering and descriptions of thermodynamic systems (production processes). Put differently, workers are absent from the analysis, raising the obvious question of why? Why is the labor input ignored in engineering? The reason, we posit, has to do with the very role of labor in modern production processes, namely as machine operatives, a point made by 19^{th}-century neoclassical economist Alfred Marshall over a century ago. Labor simply oversees machinery (thermodynamic system):

> We may now pass to the effects which machinery has in relieving that excessive muscular strain which a few generations ago was the common lot of more than half the working men even in such a country as England […] in other trades, machinery has lightened man's labours. The house carpenters, for instance, make things of the same kind as those used by our forefathers, with much less toil for themselves […]. Nothing could be more narrow or monotonous than the occupation of a weaver of plain stuffs in the old time. But now, one woman will manage four or more looms, each of which does many times as much work in the course of a day as the old hand loom did; and her work is much less monotonous and calls for much more judgment than his did. (Marshall, 1890: p. 218)

Broken down by tasks, machine operatives, like modern-day, computer-based manufacturing control devices, collect information on material processes and respond to such information in predetermined algorithms. Put differently, workers are "overseers" in the sense of overseeing material processes (Ludema et al., 1987; Lutters et al., 1998). This is also known as the human-machine interface defined as operator interface terminals with which users (in this case, labor) interact in order to control other devices. The point here is that the modern-day labor input is no longer a source of energy/force but rather a human benig-based control device, collecting and processing material process-related information. This, we argue, provides new avenues for formalizing the role of computers and control devices in manufacturing processes, namely as a low-cost substitute for human control devices. Ludema et al. (1987: p. 71), in *Manufacturing Engineering: Economics and Processes*, describes automation and control similarly:

> machines that control their own motions within prescribed limits are said to be automatic; or by virtue of having control devices connected to them, tools or machines are automated […]. In many instances, a tool or machine is automated to maintain product quality, A hamburger grill may become too hot to produce quality hamburgers, unless controlled. Likewise, the chemistry of an uncontrolled electroplating bath may vary from the acceptable range, necessitation the stopping of production while adjustments are made […]. Automatic machines can often produce parts with greater accuracy, uniformity, and speed than can manually-operated machines; they also relieve humans of some tedious, dangerous, and hard jobs. (Ludema, 1987: p. 71)

As such, replacing a worker by a control device (computer, etc.) will, in most instances, be profit-increasing; however, it will not increase physical productivity the latter being measured as the ratio of output of VA (work) per unit of energy (second-law efficiency). Firms will simply reduce their demand for labor, or put differently, human-based control devices. *Ceteris paribus*, conventionally defined labor productivity (ratio of output to labor input) will increase as a result owing to a smaller denominator (i.e., labor input)[6].

To summarize, labor and capital, the bread and butter of standard neoclassical economics, can be deconstructed in terms of each's information content. The modern-day labor input is, for the most part, a supervisory input, collecting and processing information on specific material processes[7]. Capital, on the other hand, embodies the information that defines the material process in question. What is important to note, however, is the fact that neither is physically productive, not being sources of force/energy.

4.5. Kinetics and Historical Productivity Growth

Beaudreau (2017, 2020) argued that historically-speaking, machine speed, governed by the laws of kinetics, was the key factor in productivity growth, with the steam engine and the electric motor being the key enabling technologies. More to the point, the first and second industrial revolutions were about speed, specifically greater speed based on greater and greater energy use (kinetic energy). Equation 3 describes the resulting growth process, specifically output growth is the sum of a technological scaler, the rate of growth of energy per unit of capital and the rate

[6]Clearly, the conventional definition of labor productivity is obsolete and in dire need of revision.
[7]Marshall (1890) referred to labor/workers as "machine operatives» as did the London-based Board of Trade in its production data in the early 1900s.

of growth of capital[8]. The second term is referred to as energy deepening which captures increases in machine speed. For example, a five percent increase in energy per unit of capital will result in a two and one-half percent increase in machine speed/productivity per machine unit. The first term (technology scaler) is defined as second-law efficiency which depends on information, material process design and supervision.

$$\frac{\dot{y}}{y} = \frac{\dot{\alpha}}{\alpha} + 0.5\left[\frac{\dot{e}}{e} - \frac{\dot{k}}{k}\right] + \frac{\dot{k}}{k} \tag{3}$$

The productivity slowdown of the 1970s and 1980s, he argued, owed to the physical limits of speed-ups having been reached. In other words, by the late 1960s/early 1970s, most material processes had reached their maximum speed, making further speed-based increases in productivity impossible/uneconomical.[9] Perhaps the most telling metaphor was airplane speed which plateaued in the 1960s and even decreased in the 1970s and 1980s.

Table 4. Output and input growth rates, manufacturing.

USA	1950-1984	1950-1973	1974-1984
USVA	2.684	3.469	0.121
USE	4.052	5.371	0.246
USN	0.662	0.900	0.091
USK	3.694	3.614	3.4008
Germany	**1963-1988**	**1962-1973**	**1974-1988**
GERVA	2.462	6.522	1.486
GERE	2.894	5.883	1.366
GERN	0.785	0.592	0.938
GERK	2.945	5.620	1.406
Japan	**1965-1988**	**1965-1973**	**1974-1988**
JAPVA	3.826	8.844	3.099
JAPE	3.559	11.320	0.965
JAPN	0.082	2.297	0.367
JAPK	7.520	13.536	5.182

Source: Beaudreau (1998: p. 138).

[8]Equation (3) is based on a specific functional form for Equation (2) above, namely $\frac{y}{k} = \alpha\left[\frac{e}{k}\right]^{0.5}$ where y is aggregate output, k the aggregate capital stock (tools), e aggregate energy consumption, and α, aggregate second-law efficiency-based ultimately on the fundamental law of kinetics KE = 1/2 mv^2, were KE = kinetic energy, m = mass, and v = velocity.

[9]This manifested itself in a rate of growth of energy consumption that tracked the rate of growth of the capital stock.

The productivity slowdown, he argued, witnessed a significant decrease in the rate of growth of energy use in the late 1960s/early 1970s. Referring to **Table 4**, we see that the rate of growth of energy per unit capital decreased substantially in the 1974 to 1988 period, bringing with it, the rate of growth of output.

Output is measured in terms of real VA, while inputs include electric power consumption, broadly defined labor (N), and capital (K). We see that in all three cases, broadly defined labor has actually decreased from 1974 to 1988. Broadly defined capital, on the other hand, has increased at rates equal to or greater than the rate of growth of VA. For example, in US manufacturing, VA increased at an average annual rate of 0.121 percent from 1974 to 1984. Broadly defined labor decreased at an average annual rate of 0.091 percent, while broadly defined capital increased at an average annual rate of 3.4008 percent. This stands in marked contrast with 1950-1973 when capital and labor were increasing in VA.

5. Implications for the Byrnjolfsson versus Gordon Debate over AI and Productivity Growth

This brings us to the crux of the matter, namely can artificial intelligence contribute to raising the productivity and growth rates in Western industrialized economies, hopefully restoring them to post-WWII levels? Can it kick-start growth and make for higher, long-term rates? Brynjolfsson believes it can, comparing it to the first industrial revolution. Gordon is skeptical, to the point of being downright bearish. The science is clear: AI can only increase productivity and growth by increasing second-law efficiency. This follows from the fact that information and intelligence are not energy forms and thus cannot perform work. This, however, comes at a cost, namely of training the various AI algorithms. It therefore follows that for AI to increase productivity and growth, it must be the case that the second-law efficiency-based gains in productivity and growth outweigh its cost.

5.1. AI: The Costs

AI distinguishes itself from conventional intelligence (i.e. human) in that it is highly energy intensive. Whereas conventional scientists and engineers use what their food/energy/calorie intake is to generate knowledge/innovations, AI uses *kwhs*, lots of them. In other words, AI and its spoils are not free, but rather impose a cost on society—much like Bitcoins.

This implies that the more a sector of the economy invests in AI, the more energy will be required, and thus, the less energy will be available for the actual production of the good/service. Accordingly, society will have to choose between devoting energy to AI-based process and product innovation versus the actual production of goods and services. Ideally, the increase in second-law efficiency that results from process innovations would need to be such so as to offset the loss of energy available for production. Set in terms of Equation (3), $\frac{\dot{\alpha}}{\alpha}$ would need to be greater than $0.5\left[\frac{\dot{e}}{e}-\frac{\dot{k}}{k}\right]$ which would be negative, given that the AI will be cannibalizing energy from the real economy.

5.2. AI: Potential Benefits

As pointed out, according to the science of material processes, AI can only increase productivity if it increases the growth of energy use and/or second-law efficiency, not being a source of energy itself. In what follows, an attempt is made to classify the growth potential of the various components of AI as identified by the Stanford University AI Index 2023 Report. The discussion will focus on the two universal components of growth, namely AI's effect on energy use growth and its effect on second-law efficiency (see Equation (3)). AI product-based innovation will be viewed as being growth-neutral as it affects the set of product characteristics, not the relevant underlying material process. However, as pointed out, this ignores the energy cost of such innovation that will, in general, be growth decreasing.

In Table 5, we consider the various components of AI as described by the Stanford University HAI program listed in Table 2.

Table 5. Benefits of AI technology.

Category	Sub-Category	Product or Process	$\frac{\dot{E}}{E}$ or $\frac{\dot{\eta}}{\eta}$
Computer Vision-Image	Image Classification	Product	n/a
	Face Detection	Product	n/a
	Deepfake Detection	Product	n/a
	Human Pose Estimation	Product	n/a
	Semantic Segmentation		
	Medical Image Segmentation		
	Object Detection	Product	n/a
	Image Generation	Product	n/a
	Visual Reasoning	Product	n/a
Computer Image-Video	Activity Recognition	Product	n/a
Language	English Language Understanding	Product	n/a
	Sentiment Analysis	Product	n/a
	Natural Language Inference	Product	n/a
	Multitask Language Understanding	Product	n/a
	Machine Translation	Product	n/a
Speech	Speech Recognition	Product	n/a

Continued

Reinforcement Learning	Reinforcement Learning Environments	Product	n/a
Hardware	MLPerf Training Time	Product	n/a
	MLPerf Inference	Product	n/a
	Trends in GPU	Product	n/a
Environment	Environmental Impact of Select Large Language Models	Product	n/a
AI for Science	Accelerated Learning Through Learned Plasma Control	Product	n/a
	Discover Novel Algorithms for Matrix Manipulation with Alpha Tensor	Product	n/a
	Designing Arithmetic Circuits with Deep Reinforcement Learning	Product	n/a
	Unlocking de Novo Antibody Design with Generative AI	Product	n/a

Source: Maslej et al. (2023).

What stands out immediately is that none of these components are speed- or acceleration-related (i.e. increasing the e/k ratio). That is, no components of artificial intelligence appear to be involved in increasing the rate of growth of energy use in material processes, whether for the economy as a whole or for specific sectors. And, it is not at all clear whether any of the new products will contribute to increasing the second element in Equation (3), namely α, second-law efficiency. An example of the latter would be reducing energy losses in thermal-based material processes (e.g. reducing heat generation in high-speed computing).

Rather, the analysis suggests that AI should be seen as a new sector of industrial economies that compete with existing sectors for factor inputs (energy, labor, capital, management, etc.). Its products will be either altogether novel or improvements of existing products. A good example is the use of AI in Hollywood where AI-created actors will compete with actual human actors, *kwhs* replacing human calories as the source of energy[10]. Given its colossal energy requirements, there is every reason to believe that it will adversely affect non-AI sectors. As will be discussed later, this is and no doubt will continue to be a going concern for the AI sector.

5.2.1. Diagnostic AI and Productivity: The Underlying Physics

Perhaps one of the most salient applications of AI is in the field of diagnostics (medical, architectural, engineering). It has been argued that in many instances,

[10]As I write these lines, the Al-Jazeera news network is reporting that the Screen Actors Guild will strike in order to protect its members from AI.

AI performs better than professional (e.g. doctors, architects). How are we to understand this within the context of the model developed in Section 2—that is, in terms of productivity and thus of growth. First, it bears reminding that professionals are trained in diagnostic techniques. Physically, this implies training their kilocalorie-fueled brains to diagnose problems (e.g. illness). The cost per diagnosis is the physical cost of maintaining the professional's brain in operational health. This contrasts with AI, where the cost of per diagnosis, once the algorithm has been developed, is much lower, and in actual fact, close to zero. In other words, an AI-based diagnosis costs infinitely less than a professional's diagnosis. In this regard, AI algorithms increase second-law efficiency by essentially eliminating the professional's energy cost (i.e. 2000 kilocalories per day). Moreover, the latter can, in the presence of AI algorithms, perform multiple diagnoses per unit of energy compared to that of the professional.

In this regard, AI will increase second-law efficiency of the energy devoted to diagnoses, leading to an increase in the output of the industry/sector in question. However, the demand for diagnoses is not infinite, the implication being that the gains in overall output will be bounded from above, from the number of patients exhibiting symptoms.

5.2.2. The Stanford HAI Report: Effects on the Economy

In its most recent report, the Stanford HAI report on the effects of AI on the economy pointed to a number of recent tendencies, presented in **Table 6**. What stands out is the fact that the demand for AI, as expressed in terms of the demand for AI-related workers, has increased, albeit marginally. However, globally, AI-related private investment in 2022 had decreased relative to 2021.

It is worthwhile noting that previous paradigm-changing innovations (the steam engine, the electric motor) had decades-long effects on growth (David, 1991). For example, the steam engine (Watt) affected growth in England from the 1760s to the late 19th century. Electric unit drive impacted growth in the United States from the turn of the century to the 1960s. In each case, the demand for the new technology was robust throughout the period in question. This, however, does not appear to be the case with AI.

Interestingly, AI investment appears to be concentrated in a number of sectors, which again stands in contrast with past process innovations (i.e. the steam engine, the electric motor). Specifically, in 2022, the AI focus area with the most investment was medical and healthcare (\$6.1 billion); followed by data management, processing and cloud (\$5.9 billion); and Fintech (\$5.5 billion). Clearly, the bulk of AI-investment is product-related. Surprisingly, the number of companies adopting AI has, according to the survey, plateaued, which would suggest a limited role for AI in increasing η, second-law efficiency—if at all. In other words, whatever gains in terms of second-law efficiency from AI would be punctual in nature and not on-going in time—in short, one-shot occurrences[11]. Hence, while

[11]Second-law efficiency-based productivity gains are bounded by the value of one, and thus cannot be a source of on-going productivity growth.

AI may improve second-law efficiency (i.e. η), the effects will be short lived, and will not affect the growth rate over time.

Table 6. Stanford AI index report 2023: Effects on the economy.

Effect	Description
The demand for AI-related professional skills is increasing across virtually every American industrial sector.	Across every sector in the United States for which there is data (with the exception of agriculture, forestry, fishing, and hunting), the number of AI-related job postings has increased on average from 1.7% in 2021 to 1.9% in 2022. Employers in the United States are increasingly looking for workers with AI-related skills.
For the first time in the last decade, year-over-year private investment in AI decreased.	Global AI private investment was $91.9 billion in 2022, which represented a 26.7% decrease since 2021. The total number of AI-related funding events as well as the number of newly funded AI companies likewise decreased. Still, during the last decade as a whole, AI investment has significantly increased. In 2022 the amount of private investment in AI was 18 times greater than it was in 2013.
Once again, the United States leads in investment in AI.	The U.S. led the world in terms of total amount of AI private investment. In 2022, the $47.4 billion invested in the U.S. was roughly 3.5 times the amount invested in the next highest country, China ($13.4 billion). The U.S. also continues to lead in terms of total number of newly funded AI companies, seeing 1.9 times more than the European Union and the United Kingdom combined, and 3.4 times more than China.
In 2022, the AI focus area with the most investment was medical and healthcare ($6.1 billion); followed by data management, processing, and cloud ($5.9 billion); and Fintech ($5.5 billion).	However, mirroring the broader trend in AI private investment, most AI focus areas saw less investment in 2022 than in 2021. In the last year, the three largest AI private investment events were: 1) a $2.5 billion funding event for GAC Aion New Energy Automobile, a Chinese manufacturer of electric vehicles; 2) a $1.5 billion Series E funding round for Anduril Industries, a U.S. defense products company that builds technology for military agencies and border surveillance; and 3) a $1.2 billion investment in Celonis, a business-data consulting company based in Germany.
While the proportion of companies adopting AI has plateaued, the companies that have adopted AI continue to pull ahead.	The proportion of companies adopting AI in 2022 has more than doubled since 2017, though it has plateaued in recent years between 50% and 60%, according to the results of McKinsey's annual research survey. Organizations that have adopted AI report realizing meaningful cost decreases and revenue increases.
AI is being deployed by businesses in multifaceted ways.	The AI capabilities most likely to have been embedded in businesses include robotic process automation (39%), computer vision (34%), NL text understanding (33%), and virtual agents (33%). Moreover, the most commonly adopted AI use case in 2022 was service operations optimization (24%), followed by the creation of new AI-based products (20%), customer segmentation (19%), customer service analytics (19%), and new AI-based enhancement of products (19%).
AI tools like Copilot are tangibly helping workers.	Results of a GitHub survey on the use of Copilot, a text-to-code AI system, find that 88% of surveyed respondents feel more productive when using the system, 74% feel they are able to focus on more satisfying work, and 88% feel they are able to complete tasks more quickly.
China dominates industrial robot installations.	In 2013, China overtook Japan as the nation installing the most industrial robots. Since then, the gap between the total number of industrial robots installed by China and the next-nearest nation has widened. In 2021, China installed more industrial robots than the rest of the world combined.

Source: Maslej et al. (2023).

5.2.3. Future Energy Requirements of Increased AI

The elephant in the room in so far as AI is concerned is its colossal energy consumption, something that is typically overlooked by its pundits. Machine learning and training, it turns out, are extremely high energy intensive activities, consuming more energy than whole cities. This poses a number of problems. For example, given that energy is not a free good, it stands to reason that the AI sector is already or will soon be in direct competition with the non-AI sectors for the available supply of energy, thus increasing its price/cost, which may be detrimental to growth in general, not unlike the OPEC-induced energy crises of the 1970s.

According to Gregoreite (2022), AI now consumes roughly one-half of a percent of the world's supply of electricity, estimated to be 35,000 Twh, which is more than half the countries in the world production and consumption of electricity. It is estimated that this will double in the next few years. At the firm level, it is estimated that ChatGPT consumes between 1.5 - 23 Gwhs per month (Gregoreite, 2022).

The second problem consists of the environmental fallout from AI activity, powered in large measure by fossil fuel-based energy, which generate greenhouse gases. Furthermore, data centers consume massive amounts of groundwater in order to cool the supercomputers, which adds to the toll.

In fact, if anything, AI and conventional ICT, not to mention cryptocurrencies, being energy intensive, will lower energy availability for other sectors of the economy, which will hinder growth perspectives, raising the specter of lower real growth as non-ICT, non AI sectors of the economy are energy (electric power) constrained.

6. Comparisons with the ICT Revolution

Our analysis raises the question of ICT and how it compares with AI. It is worthwhile noting that the ICT revolution failed to increase long-term growth rates—something referred to in the literature as the information or Solow paradox. Will AI succeed where ICT failed? According to most analysts, AI is an extension of sorts of the ICT, one that involves a range of technological advances such as machine learning, deep learning and natural language processing. Whereas ICT was about increasing the amount of information (stored and transmitted), AI is about replicating learning in a highly data-intense environment. An example is learning using principal components analysis in a big-data environment. However, the fact remains that like ICT, it consists of information, not energy. Hence, there is every reason to believe that it will not increase productivity and overall growth.

7. Summary and Conclusion

This paper has sought to shed light on the current debate over AI and productivity growth pitting Brynjolfsson against Gordon by invoking the underlying science. The latter consisted of the various approaches to modeling material processes found in the literature. In short, material processes were shown to be energy-based and defined by the relevant organizational inputs. The latter are not physically productive. Rather, energy is seen as performing work within the context of an organizationally defined framework. Greater output can result from more energy or more efficient use of energy. Information and tools are, as such, not physically productive.

This simple framework was then used to examine the question of AI and productivity growth, more specifically, the debate between the two AI protagonists, Erik Brynjolfsson and Robert Gordon. It was shown that of the two, Gordon's pessimistic view of the role of AI in productivity growth appears to be supported by science; however, not for the reasons Gordon invoked. Not low-hanging fruit, not fiscal policy, not fertility, but rather the laws of classical mechanics, kinetics and thermodynamics militate against the possibility of any AI-based sustained and prolonged increase in productivity and hence, economic growth. Rather, if anything, the growth of the AI sector over the coming years will be achieved at the expense of growth in non-AI sectors.

While the science is clearly bearish on the growth potential of AI, the one area that has benefited from the AI revolution is the prognosticator industry, where predictions regarding the future abound, and crystal-ball gazing has become a sport of sorts. For example, in a response to Robert Gordon's article, Kevin Kelly, Founding Executive Editor of *Wired* magazine, predicted that when students in 2095 are asked to write about why Gordon was wrong in 2012, they will say things like, "He missed the impact of the real inventions of this revolution: big data, ubiquitous mobile, quantified self, cheap AI, and personal work robots—he was looking backward instead of forward" (Kelly, 2012). Kelly's response implies that humanity is not running out of ideas; on the contrary, he sees it beginning another industrial revolution.

Such statements and their rejoinders reflect poorly on the state of economics, the science of wealth, and its ability to understand the past and predict the future. While the profession continues to struggle to understand the past (e.g., the causes of post-WWII growth), it brashly feels confident that it can say something about the future.

This paper is an example of how science can be used to settle—or attempt to settle—what is a key debate in the field, as well as one of the overriding questions in the last half-century. Unlike the Brynjolfsson-Gordon debate, which is infused with hearsay, with anecdotes, with pleasant bantering on the part of the two protagonists, science provides unequivocal insights and predictions, namely that AI cannot and will not increase output and productivity growth the way the massive energy deepening of the past two centuries did, for the simple reason that information is not physically productive.

In such an era, when students in 2095 are asked to write about why Gordon was right and Brynjolfsson was wrong, they will point to the laws of physics, specifically that information, unlike energy, is not physically productive. If in the intervening years, energy consumption per worker/machine did not increase (predicted here), then the same students will be able to confirm the obvious, namely that productivity and thus wealth per capita have not increased.

AI will have introduced a number of new processes, but not increased the overall level of available energy, nor will it have had a significant impact on second-law efficiency. If anything, its energy consumption will have actually compromised the growth of other sectors of the economy.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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Appendices

These appendices re-examine the positions of both Brynjolfsson and Gordon on AI and growth through the prism of science.

1) Brynjolfsson and McAfee (2014) *The Second Machine Age* as Seen through the E-O Framework

Their analysis suffers from the same problems that characterize neoclassical growth theory, namely focusing on capital and ignoring the underlying physics of material processes. The first machine age wasn't about machines, but rather about what machines allowed Westerners to do, namely increase energy consumption, machine speed and thus productivity. Machines themselves (simple and complex tools paired with a power-drive technology) were not physically productive. Rather, they allowed for the use, over two centuries, of increasing amounts of energy use, speed and thus of output.

Because AI is not a form of energy/force, it cannot and will not increase productivity, except in the case where it improves second-law efficiency—that is, the productivity of energy. As pointed out above, in most existing material processes, second-law efficiency has been relatively constant over the course of the past half-century. Moreover, it is in general extremely difficult to increase. A good example is the energy efficiency of the internal combustion engine which has remained relatively constant over the course of the last half-century despite billions of dollars of R&D.

The authors argue that AI and ubiquitous connectivity will "substitute for and augment our cognitive power." The problem is that our cognitive power has not, does not and will not drive the material processes that together comprise a modern-day industrial economy. Again, the gains (i.e. increases in second-law efficiency) will be miniscule to non-existent.

2) Gordon (2000) *Great Innovations of the Past* as Seen through the E-O Framework

Seen through the prism of the E-O framework, all of Robert Gordon's "Great Innovations of the Past" were energy- and speed-based. The two key innovations were abundant, inexpensive electricity and the internal combustion engine, both of which contributed to accelerating existing material processes. In factories, electric unit drive accelerated throughput rates, thus increasing conventionally-measured productivity. In some case, it allowed for the mechanization of material processes that relied on muscles and brawn, the best example being power tools, winches and lifts (i.e. elevators).

The internal combustion engine did likewise for beast-of-burden powered material processes such as plowing and harrowing, not to mention horse and buggy transportation. Improved sanitation and plumbing were also made possible by electric motors, resulting in unprecedented increases in life expectancy.

Without realizing it, Gordon is *de facto* making the same argument as we are. In short, innovations in energy transmission were largely responsible for what he refers to as the great innovations of the past. Without the force of steam and electricity, none of these innovations would have materialized. It therefore follows that AI, not being a form of energy, cannot and will not have the same effect on productivity and growth.