Research Article

New Perspectives on Growth and Sustainability. Glimpses into the AI Industrial Revolution

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We study the concept of *Economic Productivity of Energy* (EPE), defined as the ratio of GDP produced and energy consumed at country or groups of countries level. We examine its behaviour over time using both historical data and recent, detailed databases. Our study compares the EPE for three different groups: underdeveloped, developing, and advanced countries. The underdeveloped countries exhibit the highest EPE, while an inversion occurs between developing and advanced countries around 2004, driven by a steady growth in EPE of the advanced economies from 1980 to 2018. Notably, during the onset of the first industrial revolution in England and Wales, the EPE decreased dramatically, with the trend reversing only decades later. We argue that, given AI's current status as an energy-intensive technology, the risk of a collapse in EPE is significant, in analogy with the first industrial revolution. However, AI is projected to generate GDP growth several times greater than the one seen in the first postwar (WW2) decade in Western societies. Additionally, AI's impact and adoption are expected to be more pronounced in advanced economies. We stress the need to investigate further these crucial questions: whether, when, and how the AI revolution will affect the currently positive global trend in EPE.

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1. Introduction

Climate change and the sustainability of our lifestyles occupy nowadays the news in most countries worldwide and, by consequence, their governments agendas. On one hand, modern economies need large amounts of energy, hundreds of times higher than in the pre-industrial era, to keep GDP growing or at

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least non-decreasing. On the other hand, the intensive use of fossil resources is causing the depletion of non-renewable sources and an increase in CO_2. While waiting for the discovery of new clean energy sources, like nuclear fusion, we face the challenge of decreasing energy consumption by making our global economies more efficient. From that perspective, several studies[1][2][3][4][5][6] have appeared about the relation between GDP and energy consumption. In particular, the works by Jancovici et al.[4][5][7] observe that, on average, GDP production, a crucial index—albeit not the only one—relating to the quality of life, grows approximately linearly with energy consumption. Several studies have further evidenced a strong positive correlation between energy consumption and GDP[2][4][6]. This correlation suggests that, generally, wealthier countries tend to consume more energy per capita than their less affluent counterparts. However, the direction of causality remains a subject of debate. While some analyses propose that increasing energy consumption facilitates GDP growth, others suggest that economic expansion drives higher energy use. Empirical investigations into this relationship have yielded inconclusive results, often depending on specific economic and regional contexts[2][4][8].

A country's or group of countries' GDP-energy ratio, which we call the *Economic Productivity of Energy* (EPE), measures the amount of GDP generated per unit of energy consumed in a specific year. EPE is thus a macro-index influenced by a country's economic and societal organization, domestic energy consumption, energy efficiency, industrial sector structure, and other factors. Notably, EPE is simply the reciprocal of the more commonly used *energy intensity* in economics literature[3][6]. Moreover, EPE has been considered a rough proxy for measuring the energy efficiency of a country's economic sector[9]. From an economic standpoint, *energy intensity* is a natural quantity, as it links production to energy consumption and facilitates the assessment of energy-related costs. However, we adopt a different perspective and focus on EPE, which we regard as a more natural measure of societal-level "efficiency", especially in light of its thermodynamic analogies. Taking the inverse is a shift from reasoning in terms of "how much energy do I require to make a definite profit?" to "with this limited energy, how much profit do I make?". Taking the inverse can reveal some relations that were hidden otherwise: for example, we find that (see Figure 2) EPE of advanced countries grows linearly over time, a behavior not observed when considering energy intensity.

Given the significance of EPE in assessing economic efficiency and energy consumption patterns which has impact on the environment, we aim to explore its historical evolution and recent trends. In this paper we address the following question: How has EPE evolved over time, and what are its recent trends across countries with different levels of economic development?

We are currently in the era of artificial intelligence (AI), which is revolutionizing and already changing our economic and social paradigms. The modern machines that learn from huge databases with deep learning techniques by synthesizing raw information into knowledge play a similar role to that of heat engines had in the old industrial revolution, where they produced work by extracting it from an energy source[10]. It might seem, in retrospect, that during the early days of the first industrial revolution, the only relevant technological advance was the "engine." Yet, a closer look reveals a rich landscape of diverse technologies at play: various types of steam engines, more efficient mechanical devices, and a range of innovative applications. The first industrial revolution, beginning in Britain around the 1760s, ushered in an era of factories, mass production, and a fundamental shift from agrarian to industrial societies. In a comparable way, AI is reshaping our world by automating tasks, altering labor markets, and transforming entire sectors. AI stands at the core of the fourth industrial revolution, alongside the Internet of Things, robotics, and other emerging technologies. Together, they promise to drive radical change through automation, advanced data analysis, and increased efficiency[11]. Historically, industrial revolutions have led to a decrease in EPE during the early stages of the transition[12]. This can be caused by different reasons: technological devices are not scientifically well-developed, economic pressure to make profit prioritizes GDP generation while disregarding energy consumption and its environmental impact and, most importantly, society is not yet sufficiently organized to efficiently use the new technology. The analogy with today's developments is grounded in a key commonality: technological adoption depends on profitability. This principle holds true both for the 18th century and for our present time.

In this work, we analyze the historical and recent evolution of EPE for various clusters of countries. This analysis sets the foundation for a future research program aimed at answering key questions about the impact of AI on EPE trends: having established that traditionally, technological revolutions come with non-optimal performances, what future do we face with the AI revolution? In other words, will AI technology improve global EPE, and if so, on what time scale? The few data points that we know as of today indicate that AI, as in 18th-century machines, is extremely eager for energy[13]. Nevertheless, since the forecasts of AI's impact largely agree on GDP growth of the same order as that in the postwar years for Western countries, it seems unthinkable to stop or slow down the race toward its adoption. Therefore, the risk of going down the same path as in the past, following only GDP maximization without considering how the new technology impacts the correlation between GDP and energy, is very high.

On the other hand, it is also true that the AI revolution is the only industrial revolution, so far, accompanied by a global concern about the danger of climate change due to the intensive use of non-renewable energy sources and massive water consumption[14]. Furthermore, AI has the advantage of potentially solving a complex problem like the optimization of EPE, even without the advent of new energy sources. This could be done with improvements at a technological and societal level, devoting large efforts and investments to fundamental research in AI[15]. In the near future, once robust data become available, we plan to repeat the analysis presented in this paper to determine which of the potential effects of AI discussed here has played the predominant role in influencing the EPE trend.

The paper is organized as follows: In Section 2, we introduce the main quantity of interest, the EPE and discusses its trends from historical to recent data; AI and its associated economic growth and energetic impact are discussed respectively in Sections 3 and 4; Section 5 gives a general conclusion and perspective on the topic.

2. EPE Trends

In this section we introduce the mathematical formula for EPE and apply it to data by considering the EPE index for an entity, which can be, e.g., a country or a set of countries, fixing a time interval. The EPE measure is given by the total GDP produced, measured in US$, over the total energy consumed, measured in kWh (kilowatt-hour) yearly

$$EPE := \frac{GDP}{Energy}. \tag{1}$$

Thus, EPE indicates how well a society converts energy into monetary output. An entity has higher EPE if a smaller amount of energy is used to generate more goods and services. On the other hand, an entity has lower EPE if it needs to use more energy to generate income.

Drawing an analogy with the thermal efficiency of a heat engine (work or heat) in thermodynamics seems reasonable, and similar ideas have already been explored by studies aiming to transfer thermodynamic concepts into economics[16][17][18]. Yet, it is essential to note that the EPE is not a pure, dimensionless, number; rather, it is an empirical measure of dollars per kilowatt-hour ($\mathrm{US\$/kWh}$).

It is worth highlighting that EPE plays a crucial role in considerations of global warming and enters the well-known Kaya identity[5][19], which measures the global CO_2 emissions from human sources.

2.1. Historical trends

Studies conducted on European aggregate data report that historically (16th-21th century) energy consumption per capita experiences an almost permanent growth over time[20][21]. Such growth is particularly consistent in the period after the outbreak of a technological revolution, with some latency time: the different revolutions coincide with the introduction and diffusion of respectively coal-steam, electricity-oil, and information and communication technologies (ICT).

The work in[12] focuses on per capita energy and per capita GDP trends in the time period 1560-1900 in Central and Northern Italy and in England and Wales. By analyzing the data in the study, we observed that EPE values were substantially lower (around $0.1 - 0.3$ $/kWh) than the current ones in both areas. Moreover, EPE consistently decreased in England and Wales at the time of the first industrial revolution: it nearly halved, passing from a pre-industrial EPE of around 0.21 $/kWh to 0.11 $/kWh during the early stages of the revolution and 0.13 in the successive period. On the other hand, in Italy, where the industrial revolution arrived much later, EPE stayed steady. This suggests that EPE significantly decreases at the start of a technological revolution, when the adoption of the innovative technology is profitable regardless of its energetic impact. At the beginning, indeed, the new technology is still unregulated and its use is lead by the private sector which is naturally driven by profit maximization. On the other hand, EPE starts to grow when the revolution is more mature and the energy consumption of the new technology plays a more important role.

In the second half of the 20th century, in general, both total energy use and EPE have increased over time, globally[1][3][6]. In these years, citing[6], "although efficiency has increased, per capita energy use has increased over time, and when we also take population growth into account total energy use has risen strongly, though at a slower pace than total world economic output".

The consistent variation of the quantities in the game, both energy consumption and economic growth, during every technological revolution in the past justifies our spotlight on EPE trends during the current technological revolution, driven by AI machines.

2.2. Recent trends

The data used for this study is obtained from the following databases: the U.S. Energy Information Administration (2023)[22]; Energy Institute - Statistical Review of World Energy (2024)[23]; Bolt and van Zanden - Maddison Project Database 2023[24] – with major processing by Our World in Data[25]. There, GDP measures are adjusted for inflation and differences in the cost of living between countries (*Purchasing Power Parity*). Energy use refers to the use of primary energy before transformation to other end-use fuels, which is equal to indigenous production plus imports and stock changes, minus exports and fuels supplied to ships and aircraft engaged in international transport. The data used in this study was analysed using the Julia Programming software version 1.9.3. Figure 1 displays the log-log relationship between total energy consumption in kWh and total GDP in USD from 1965 to 2018. An almost linear relation between GDP and energy consumption is found on the log-log scale. Furthermore, a very high Spearman correlation[26] indicates that the two variables are strongly monotonically related.

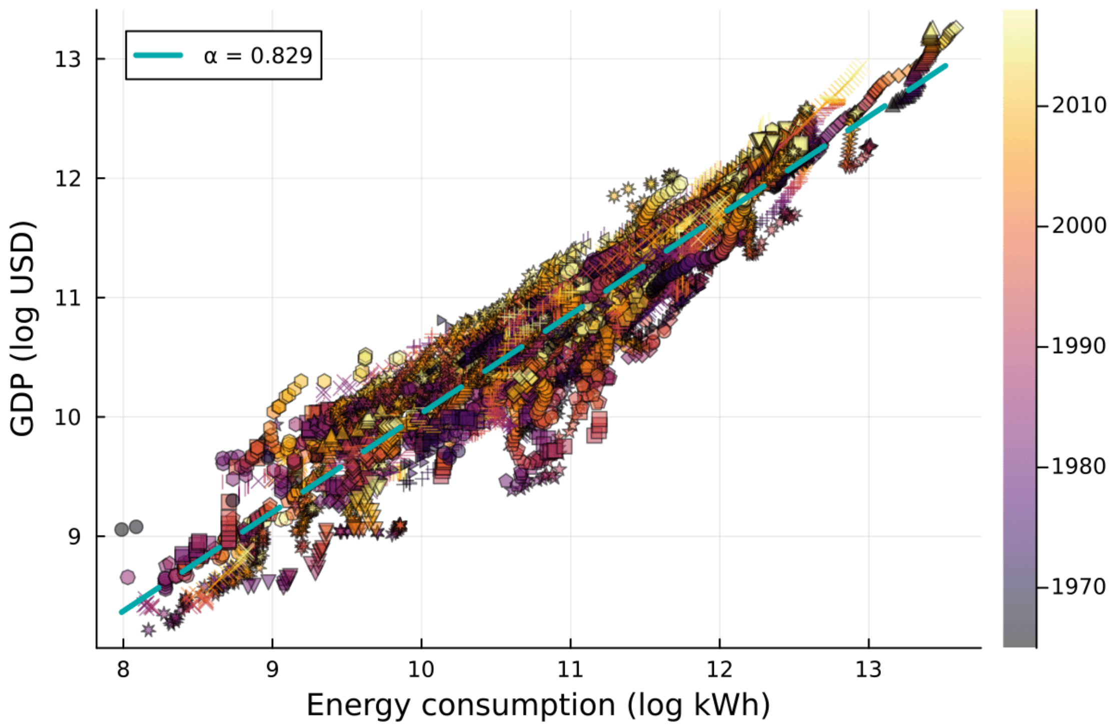

Figure 1. Countries' GDP vs Energy consumption, over time. Different years are represented by different colors as shown by the colorbar. Different countries have different markers. The measured Spearman coefficient value is 0.94.

We analyze EPE trends based on a country's classification into one of three macro groups: advanced, developing, or underdeveloped economies. To do so, we consider representative economies from each category. The division into these three clusters is performed following[27][28][29]. The ISO alpha-3 codes for the countries used in our analysis are as follows:

- Advanced Economies: AUS, AUT, BEL, CAN, CYP, CZE, DNK, FIN, FRA, DEU, GRC, HKG, ISL, IRL, ISR, ITA, JPN, LUX, MLT, NLD, NZL, NOR, PRT, PRI, SGP, KOR, ESP, SWE, CHE, TWN, GBR, USA.
- Developing Economies: ALB, DZA, ARG, BHR, BRB, BOL, BWA, BRA, BGR, CMR, CPV, CHL, CHN, COL, COG, CRI, CIV, DMA, DOM, ECU, EGY, SLV, GNQ, SWZ, GAB, GHA, GTM, HND, HUN, IND, IDN, IRN, IRQ, JAM, JOR, KEN, KWT, LBN, LBY, MYS, MUS, MEX, MNG, MAR, NIC, NGA, OMN, PAK, PAN, PRY, PER, PHL, POL, QAT, ROU, LCA, SAU, SYC, ZAF, LKA, SYR, THA, TTO, TUN, TUR, URY, VEN, VNM, ZWE.
- Underdeveloped Economies: AFG, AGO, BGD, BEN, BFA, BDI, KHM, CAF, TCD, COM, COD, DJI, ETH, GMB, GIN, GNB, HTI, LAO, LSO, LBR, MDG, MWI, MLI, MRT, MOZ, MMR, NPL, NER, RWA, STP, SEN, SLE, TZA, TGO, UGA, YEM, ZMB.

These countries were selected based on the availability of data. Here, we are interested in two aggregate measures of EPE: one considers the total GDP of the countries in the cluster over the total energy,

$$EPE_C = \frac{\sum_{i\in C} GDP_i}{\sum_{i\in C} E_i} \tag{2}$$

while the other considers the weighted average by country's population:

$$EPE_C^{(Pop)} = \frac{\sum_{i\in C} \frac{GDP_i}{E_i} Pop_i}{\sum_{i\in C} Pop_i}. \tag{3}$$

Here GDP_i, Pop_i, and E_i are respectively the gross domestic product, the population, and the energy consumption of country i, belonging to cluster C. The two measures [eff_country] and [eff_Pop] can generally be different. Equation [eff_country] is the ratio of the total GDP of all countries in cluster C to the total energy consumption of all countries in C. It represents the average GDP generated per unit of energy used by the entire cluster C, giving more importance to countries that consume more energy. This gives an idea of how efficiently an entire cluster is converting energy into GDP, with a focus on total energy use. The second measure, equation [eff_Pop], is the weighted mean of GDP per energy, where the weighting factor is the population of each country. Here, countries with larger populations have more influence on the overall average. For instance, highly populated countries with relatively low values of GDP and energy are more influential in $EPE_C^{(Pop)}$ than in EPE_C. If their EPE is high with respect to the other countries in the cluster, then $EPE_C^{(Pop)} > EPE_C$.

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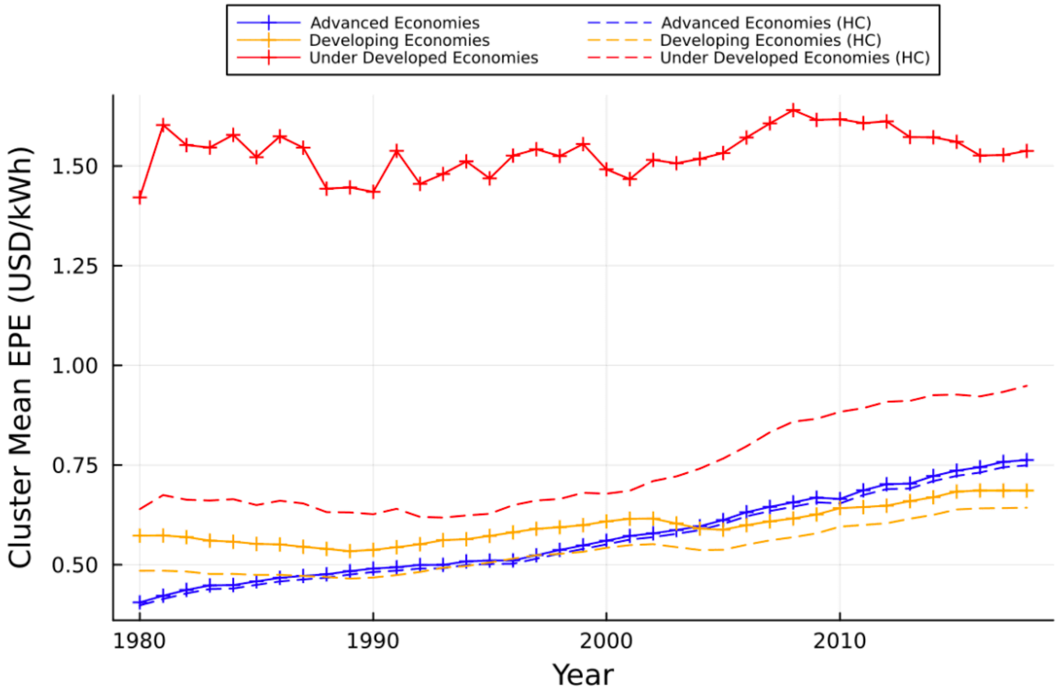
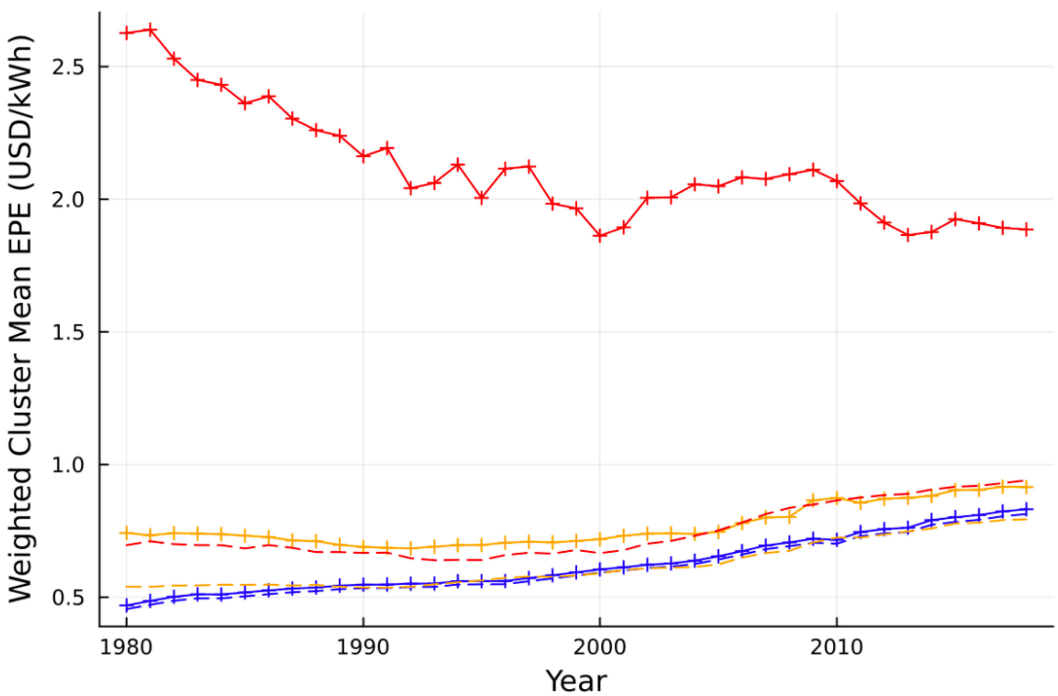


(a) Mean of the cluster (eq. (2))



(b) Mean of the cluster weighted by population (eq. (3))

Figure 2. Mean EPE for different clusters of countries over time, without (solid lines) and with (dashed lines) human energy consumption. The trend of the advanced economies is given by the blue curve, the

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developing economies by orange, and the underdeveloped economies by red.

We find that the mean EPE of the advanced economies has increased monotonically in the last 40 years in both Figure [mean efficiency cluster] and [mean efficiency weighted by pop] almost linearly. It can be observed from Figure [mean efficiency cluster] that around 2004 the mean EPE of the advanced economies surpassed the developing economies. The EPE of the latter exhibits a persistent growth only after around 2005.

Globally, world EPE grew monotonically in the last 40 years, and the growth was driven by the improvement of the EPE of the advanced economies. Furthermore, we find that the underdeveloped economies have the highest values of EPE. The nearly constant trend of the mean EPE of the underdeveloped economies in Figure [mean efficiency cluster] suggests that, overall, the cluster's ability to generate GDP relative to its energy consumption has remained stable over time. Nevertheless, in Figure [mean efficiency weighted by pop], we observe that when weighted by countries' populations, the average EPE is generally higher and exhibits a decreasing trend. That means that countries with relatively low values of energy consumed and GDP with respect to their population have typically higher values of EPE. If we assume that the GDP of the underdeveloped countries is produced mainly by human work, the data suggests that, in general, organized human work at a societal level requires less energy to generate the same amount of income as industrial machines.

In order to account for the energy consumed by human labour, we modify the measure of energy consumption in a country by adding a term proportional to the country's population. Considering a daily energy use per individual of $2500\,\mathrm{kcal/day} = 2.9 \quad kWh$[30], we modify the measure of energy consumption as follows:

$$E_i' = E_i + 2.9 \cdot 365 \cdot Pop_i,$$

where E_i' denotes the total energy accounting for human consumption, and E_i is the energy consumed by machines. The value of 2.9 kWh per day is based on the world average energy consumed by a human being. We emphasis that, this correction does not restrict the added term to the working-age population, as every individual, regardless of age, consumes energy for basic biological functions. The goal is to account for the total societal metabolic energy, not just the economically productive share. The impact of incorporating human energy consumption is illustrated by the dashed lines in Figure 2, where one observes a significant decrease in the mean EPE for underdeveloped economies. The perturbation is more pronounced for underdeveloped and developing economies, whose GDP and energy consumption values are lower, while the EPE of advanced economies remains almost unchanged. Taking human energy consumption into account, we find that the EPE of the three clusters generally exhibits less dispersion, demonstrating that equation [ene_pop_with human] provides a robust definition of energy consumption. Finally, we note that these results are not highly sensitive to the specific measure chosen.

3. AI and Economic Growth

Several reports from business consulting companies such as the McKinsey Global Institute 2018[31], 2019[32], and 2023[33], the Goldman Sachs Economics Research report 2023[34], and PWC[35] have made predictions of the overall impact of AI on the economy globally. These consulting firms make use of expert surveys (i.e., experts in AI, economics, and other fields to provide insights into the different ways that AI is likely to impact the economy) or econometric models to estimate the impact of AI on GDP by simulating the effects of AI on productivity, economic growth, and job creation. Additionally, they use case studies of specific industries and companies to see how AI is being used to improve productivity, reduce costs, and create new products and services.

It was estimated in[34] that the annual US labor productivity due to generative AI could grow by about 1.5 percentage points over a 10-year period following widespread adoption. This leads to double the recent 1.5% average growth pace, roughly the same-sized boost that followed the emergence of prior transformative technologies like the electric motor and personal computer. Additionally, at the global level, there will be an economically significant boost to labor productivity, and it is estimated that AI could eventually increase annual global GDP by 7%. A 2-3 percentage point increase in labor productivity growth on average following AI adoption was found in[33][36][37][38][39][40]. However, it is important to note that the growth attributed to AI can exhibit highly non-linear patterns, heavily influenced by the rate of adoption[32][41], akin to the delayed effects observed with personal computers on labor productivity growth. While personal computers were invented in 1981, their impact on productivity only became significant in the late 1990s[34].

According to[34], AI will boost GDP by increasing productivity directly by increasing labor quality and indirectly by increasing labor automation and, thus, through worker re-employment in other sectors. AI will impact different sectors differently[34]. Nevertheless, the predictive analysis generally does not take into account in their estimation the potential of AI creating new sectors. On the other hand, among the

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several limitations of such predictions, survey answers depend on the knowledge and perceptions of respondents, and the sample of customers of the business consulting firms may be biased towards early movers, thus overestimating the impact of AI[31][32][33][34].

Importantly, the studies predict a gap between developed and developing countries in terms of AI-driven growth and labour productivity[31], highlighting how AI boosts mainly the economies of developed countries. Indeed, adoption in developed countries is enforced by the need to increase productivity. As wages are high, there is an incentive to substitute a human workforce. Nevertheless, countries like China established national strategies to become global leaders in the field[42]. AI may also widen the gaps between companies (gap between front-runners on one side and slow adopters and non-adopters on the other) and workers (ones with digital skills and ones doing repetitive labours)[31]. The PWC report[35] predicts a boost to the GDP due to AI by 2030 of (% of the current GDP): 26.1% for China, 14.5% for North America, 9.9%, 11.5%, and 10.4% respectively for Northern Europe, Southern Europe, and developed Asia, 5.4% for Latin America, and 5.6% for the rest of the world.

The AI revolution is not in its infancy, but the majority of the economic impact is yet to come (step-change improvements in computing power and capacity, explosion of data, progress in algorithms). Indeed, after the advent of large language models (e.g., ChatGPT) and in general generative AI, the estimations of AI's impact on GDP and productivity have been revised to include a further addition of 0.1–0.6 percentage points to the annual growth of productivity from 2023 to 2040, according to the McKinsey Global Institute[33].

4. The Energetic Impact of AI

Artificial intelligence (AI) is poised to revolutionize various domains, rivaling the impact of the internet's emergence. However, this breakthrough in AI comes with a significant drawback: the substantial energy consumption and associated carbon footprint, for which there is an increasing concern (see[43]). For instance, research by the University of Washington[44] and others[13] has shown that AI models like OpenAI's ChatGPT can consume enormous amounts of energy, equivalent to that used by tens of thousands of households.

These AI models, such as ChatGPT, rely on extensive computational resources, comprising large networks of processing units housed in data centers. Unlike conventional cloud computing workloads, which are less computationally intensive, AI models require massive amounts of computation during

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training and inference phases. This computing demand necessitates data center infrastructure, leading to substantial electricity consumption.

Training a single large language model, like ChatGPT-3, can consume up to 10 gigawatt-hours (GWh) of power, equivalent to the yearly electricity consumption of over 1,000 U.S. households[13]. Moreover, a significant portion of AI-related energy consumption stems from inference, with Google reporting that 60% of energy usage from 2019 to 2021 was during the inference phase. The training phase for ChatGPT uses approximately 1,287 MWh in total and 564 MWh per day for its inference phase (1 MWh = energy provided by an electric power of 1 Watt for 1 hour). Other models of generative AI have different energetic impacts than ChatGPT, which nowadays has the largest market.

Today there are hundreds of millions of daily queries on ChatGPT, Google's Brad, Bloom and others[45]. This many queries can cost around 1 GWh each day, which is the equivalent of the daily energy consumption for about 33,000 U.S. households. Alphabet's chairman indicated in February 2023 that interacting with an LLM could likely cost 10 times more than a standard keyword search (see Figure 1 of[13] for data on energy per query for Google without AI, ChatGPT, Bloom and estimations for Google search with AI).

Tech giants like Google, Microsoft, and Amazon have recently signed agreements for production of energy with nuclear power[46][47][48][49]. Moreover, efforts are underway to mitigate AI environmental impact, striving to achieve sustainability goals, including carbon neutrality and reliance on renewable energy sources[50][51][52][53][54], as well as investments in nuclear fusion research[55].

Arijit Sengupta, CEO of Aible, an enterprise AI solution company, warns that AI adoption is only at 1% of its potential, highlighting the looming energy crisis if corrective measures are not implemented[44]. Suggestions include optimizing AI models and machines to minimize carbon footprints and incorporating emissions considerations into machine learning papers to incentivize environmental responsibility[56]. In any case, the rapid adoption and development of AI models underscore the urgent need for energy-efficient solutions to prevent an impending energy crisis.

5. Conclusions and Perspectives

In this work, we provide a new perspective on the potential impacts of the AI revolution, combining economic growth and environmental sustainability through the defined measure of *Economic Productivity of Energy* (EPE). The latter measures the income generated by a unit of energy used, at a country or group of countries level. Our central aim has been to understand how EPE has evolved over time and across different economic clusters, and to assess what future scenarios may emerge under the influence of AI technologies. Our choice to focus on EPE, rather than the more conventional energy intensity, reflects a conceptual inversion: instead of asking how much energy is needed to generate income, we ask how much income can be extracted from a fixed energy budget. This shift provides a sharper lens for examining energy efficiency in the age of constrained resources. EPE, as the inverse of energy intensity, is also directly related to the Kaya identity, which decomposes CO_2 emissions into population, GDP per capita, energy intensity, and carbon intensity. While we do not apply the Kaya framework explicitly in this paper, our results offer indirect insight into the energy-efficiency component of that identity.

We are interested in its historical and recent trends; specifically, we investigate the behaviour of the EPE for different groups of countries divided according to their degree of economic development. We find that the advanced economies have monotonically increased their aggregate EPE in the last 30 years (see Figure 2), and their EPE is currently higher than that of the developing economies and converse when weighted by the population. Nevertheless, the economies that generate more income per unit of energy are those of underdeveloped countries. Furthermore, by interpreting historical data during the first industrial revolution in England and Wales and in Italy[12], we deduce that at the start of the revolution, EPE drastically lowers and starts growing only when the revolution is more mature.

This is very much of interest if we notice that the AI revolution, like the first industrial revolution guided by heat or steam engines, is *pre-scientific*, in the sense that the technological development arrives before a deep scientific understanding. For the first industrial revolution, the building of the steam engine came decades before the discovery of the second law of thermodynamics. For the AI revolution, while large language models are already at work, the scientific community is currently deeply involved in understanding the new thermodynamic of learning[57]. The relevance of fundamental research oriented toward pure science is a must within this context[58]. A different path has been followed by other industrial revolutions where technology has followed science. For example, the second industrial revolution guided by electricity in the late 19th century is post-scientific: the technologies developed at the time are applications of the consolidated Maxwell's theory of electromagnetism. Another example of a post-scientific revolution is the one based on quantum mechanics, which led to the construction of micro-electronic devices, the building blocks of modern computer science.

The lack of a scientific understanding would lead to the diffusion of suboptimal technologies, even from an energy perspective. Thus, if the analogy to the first industrial revolution holds also in terms of the EPE

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(the AI is extremely energy-consuming; see section 4), we may face a period of unsustainable growth when the AI adoption is profitable at any energetic cost, the energetic impact is disregarded, and the EPE lowers. Moreover, economic growth is not infinite, even with highly efficient machines, as it is constrained by fundamental thermodynamic limits that may become more significant in the future. For example, waste heat, the byproduct of all energy use (including "clean" energy from renewable sources or nuclear fusion), is currently negligible but could pose a threat as energy-demanding technologies proliferate[59].

However, the good news is *(a)* that AI can help in optimizing industrial processes and economic and societal organization, and *(b)* that nowadays there is a strong pressure from the public opinion towards a more sustainable economy, especially in the advanced countries. Indeed, AI has the potential to improve energy systems by enhancing its integration and management. The advanced countries are those that will experience the largest AI-driven boosts (see section 3) and are also the ones with the largest influence on global EPE.

While our analysis does not yet segment AI by application or energy profile due to data limitations, we recognize the importance of this step. Once more granular data becomes available, our framework can serve as a foundation for tracking the differentiated impact of various AI technologies on EPE and sustainability.

Will this be enough to keep or even improve the current positive trend of EPE in every stage of the actual or upcoming AI era? This remains an open and pressing question. The historical analogy suggests a risk of decline in EPE during the early phase of rapid AI adoption, but the outcome will depend on technological choices, policy interventions, and societal priorities. Future data analysis of EPE trends, when AI adoption becomes significant, will provide valuable insights to evaluate the direction in which we are heading.

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Declarations

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