A view of the economic implications of AI as a potential General Purpose Technology

Irina Vélez[1,1,*], Otto Palkama[1,1]

Abstract

This paper explores the potential of artificial intelligence (AI) and Language Models (LLMs) as general-purpose technologies (GPTs) that can drive growth and development. The generalization of tools, particularly in the realm of AI, enhances the potential for productivity improvements and opens up new possibilities for value creation. However, there can be a discrepancy between optimistic expectations and actual outcomes, which is a natural aspect of transformative periods. The paper discusses the coexistence of forward-looking optimism and backward-looking disappointment and emphasizes the time required for society to fully integrate and benefit from new technologies. It concludes by highlighting the importance of grounded expectations and the value of intangible assets in the process of economic transition.

Keywords: General Purpose Technology, Artificial Intelligence, Creative destruction

1. 1. Introduction

The generalization of tools is a crucial factor in harnessing the potential for growth and development. When a tool can be widely used for various purposes, its value increases significantly. In the realm of artificial intelligence (AI), Language Models (LLMs) serve as a foundational technology for other tools, such as AI-powered software. This opens up new possibilities and enhances the potential for productivity improvements in the workforce. As mentioned by (Eloundou et al., 2023), LLMs like GPTs exhibit characteristics of general-purpose technologies, which can have profound economic, social, and policy implications.

The emergence of new capabilities and the widespread adoption of LLMs as enablers of new AI-based tools, coupled with the increasing number of users utilizing tools like ChatGPT, signifies a future that has not been seen before. This accelerated expansion and pushing of boundaries and limits hold the potential for transformative changes.

In light of these dynamics, it is important to recognize that while there may be optimism surrounding new technologies, there can also be a discrepancy between expectations and actual outcomes. This coexistence of forward-looking optimism and backward-looking disappointment is a natural aspect of periods of transformative change. It reflects the human desire to witness the fulfillment of expectations within their lifetime, while also acknowledging the time required for society to fully integrate and benefit from these innovations.

2. 2. Generalization Capabilities of LLMs as GPT

Investigating the adoption rate of various GPTs, (Chen, 2021) examined how worker mobility affects the likelihood of an establishment adopting a new general-purpose technolog]. By examining data from over 153,000 establishments between 2010 and 2018, it was observed how these establishments made decisions regarding the adoption of machine learning. The findings from the study showed a significant decline

*Corresponding author
Email addresses: irina.velezlopez@helsinki.fi (Irina Vélez), otto.palkama@aalto.fi (Otto Palkama)
[1]Exchange Student.

in adoption likelihood when there were facilitations in worker movements. According to the (Helpman and Trajtenberg, 1996), both historical evidence and theoretical models indicate that General Purpose Technologies (GPTs), like the steam engine and electricity, are pivotal for economic progress. The author further demonstrates that the stepwise adoption of a GPT across sectors leads to a dual-phase cycle, ultimately resulting in prolonged economic growth.

2.1. Key factors contributing to the widespread adoption of a technology as a GPT

General Purpose Technology is a transformative technology with a strong improvement process at the begining and eventually becoming widely adopted for its multiples uses, while producing many spillover effects (Brynjolfsson et al., 2017). As such, it have a pervasive impact on society as a whole, mainly due to its capability to redefine the ways in which businesses operate, improve productive and contribute to long-term economic growth. Some well-know examples are steam power, electricity, semiconductors, and internet.

The study by (feng Qiu and Cantwell, 2018) observes a trend towards internationalized innovation networks in multinational corporations. Through a U.S. patent database from 1969-1995, it's found that the development of general purpose technologies (GPTs) is tied to the globalization of corporate innovations. The observations are in line with (Chen, 2021), which further finds that actors such as establishment characteristics and industry conditions play a crucial role in this adaptation. Notably, establishments with greater size, more large establishments in their vicinity, and heightened experimentation with analytics technology exhibit a particularly healthy environment for the widespread adoption of a technology as a GPT.

Until now the abilities reached by the Large Languages Models LLMs have arisen to a certain level of computational power that might require scaling up past this threshold (10ˆ23 training FLOPs), meaning that they are able to perform multiple tasks related to Text Understanding and Generation,Problem Solving and Mathematics, Image and Data Classification, Text Analysis and Comprehension, and so on, but as (Wei et al., 2022) suggested for future works, it could be possible new abilities could emerge scaling up the models and understanding how emergence occurs would provide new insights into how to train more-capable language models. The emergence of these skills are one of the key factors of becoming in a GPT.

Artificial intelligence a term coined by emeritus Stanford Professor John McCarthy in 1955, was defined by him as "the science and engineering of making intelligent machines".[2] These systems are designed to simulate human cognitive abilities, such as learning, reasoning, problem-solving, perception, and language understanding. Within the realm of AI, Large Language Models (LLMs) are a specific type of AI model that utilizes deep learning techniques, particularly neural networks, to process and generate human-like language. LLMs are trained on vast amounts of text data and can perform tasks like language translation, text summarization, and question answering.

In the past, computer programs were developed by painstakingly encoding human knowledge, following a precise set of instructions that mapped specific inputs to desired outputs. This approach required programmers to meticulously define every step of the process. However, machine learning systems operate differently. They utilize general algorithms, such as neural networks, which enable them to independently determine the appropriate mapping between inputs and outputs. This is achieved through exposure to extensive datasets containing numerous examples. By analyzing and learning from these examples, machine learning systems can identify patterns and make accurate predictions or classifications without explicit programming instructions.

3. 3. What is the potential economic impact of AI?

Considering the potential of AI as a new GPT, assessing its possible contribution to economic growth is worthwhile in times of dizzying change such as the present. The winds of uncertainty are blowing everywhere and it would be useful to set expectations. Given the conditions of uncertainty and the low accuracy of predictions, the assessment of its potential impact seems to be addressed only by a retrospective approach, which means that the performance of previous general-purpose technologies, such as steam power, electricity or the Internet, could provide a more realistic answer to this question.

[2]Available at: https://hai.stanford.edu/sites/default/files/2020-09/AI-Definitions-HAI.pdf

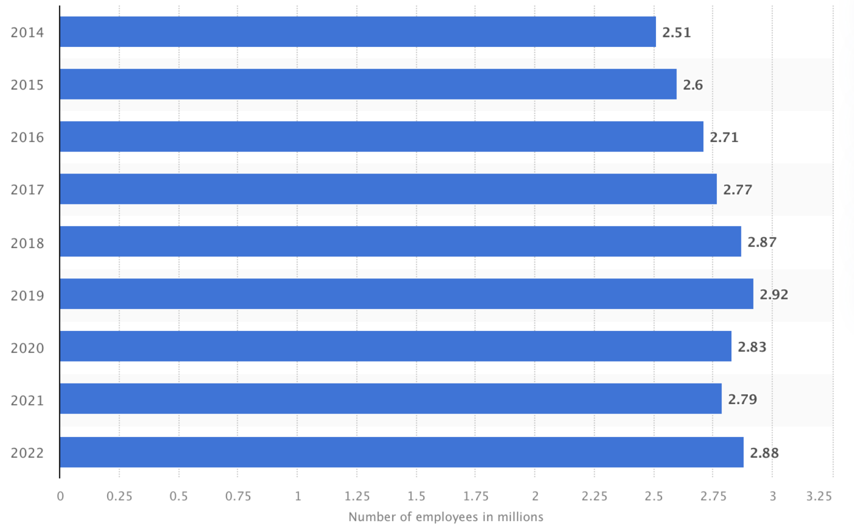

Figure 1: Number on contact center employees in the United States from 2014 to 2022.

However, this topic has already been addressed by (Brynjolfsson et al., 2017) and (Crafts, 2021), in a context where there are optimists and pessimists about technology and growth. A real dichotomy emerges between the higher profit expectations of forward-looking entrepreneurs and the poor growth performance reflected in retrospective statistics.

One example mentioned by (Brynjolfsson et al., 2017) is the call center industry, which had approximately 2.2 million agents in 2015 in the United States. It was plausible at that time to anticipate that voice recognition systems like IBM's Watson could potentially reduce the number of workers by 60%. However, in hindsight, it is evident that the expectations have not been fully met, as shown in Figure 1, which illustrates the statistics.

As (Brynjolfsson et al., 2017) explains, this apparent incongruity is due to the time lag between the creation of the technology and the full realization of its benefits in the economy and society. It takes time to build up the stock of the new technology, develop the necessary human capital skill set, undergo the process of re-engineering business process transformations, and develop complementary innovations for full realization in the real economy.

To support this explanation of the lag, the Schumpeterian growth model could offer another good perspective, taking as a starting point that the real contributions to growth are value creation and cost optimization, so AI should be at the service of these contributors to growth.

3.1. Assessing the potential economic impact of AI in terms of value creation and cost optimization.

From an economic perspective, one of the fundamental problems in understanding corporate behavior is the pursuit of profit maximization by firms. This objective drives economic growth and leads to two main objectives in the private business sector: adjusting the production function to obtain the right quantities to supply the market, while coping with constraints, often in the form of a limited budget.

The firm's goal of maximizing profits can be represented as follows:

$$Profit = Total\ Income - Total\ Costs : \Pi = PX - C(X)$$

$$Maximization\ Problem : \max_{x} \Pi(X) = PX - (wL + rK)$$

Where PX represents the revenue generated by production function X, and C(X) represents the corresponding costs associated with labor and capital costs. Thus, on one side of the coin, value creation contributes to increasing profits by adjusting the output of production function X, while on the other side, cost optimization aims to mitigate not only budget constraints but also resource constraints. Therefore, AI must be oriented towards achieving one or both of these objectives to promote growth.

To exemplify value creation through AI, consider the use of deep neural network systems in skin cancer diagnosis (Esteva et al., 2017), fraud detection and risk assessment in the financial sector, and inventory forecasting automation, as seen in Amazon's AI-powered inventory management product. On the other hand, from a cost optimization perspective, AI is used in predictive maintenance and quality control to anticipate equipment failures[3].

3.2. Shumpenter's concept of creative destruction

Creative destruction refers to the process of creating and developing new technology that continuously disrupt and replace the existing obsolete technology in order to drive economic progress and growth.[4].

Thus, let us consider two types of companies, those that are creators of new technologies and major investors in R&D, such as the big technology companies like Apple, Amazon, Meta or Google, called "creators" of technology, and on the other hand, companies that adopt and implement the new technology in order to maximize their profits through the greater added value created by their production functions and cost optimization, or both, called "adopters" of technology.

Knowledge or innovation is considered a **public good**, one you have invented something , it is almost free to spread it around the world. Thus, the first initial cost of producing the technology has to be covered through monopoly profits (Creators), because this has been the mechanism that the market system has found to cover the huge initial costs[5].

Once the new technology has been widely launched in the market at an almost affordable or even free price, as in the case of ChatGPT, the maturity level or readiness of the adopter must be high in order to take advantage of the full potential of the new technology. From the adopter's point of view, it takes time to evolve and incorporate the new technology into their business process in a way that is effective and beneficial to the business. This evolution requires developing new business processes, adjusting their production functions to add value to their bottom line, and reallocating skilled human capital to address the transformation.

Destruction is represented in the Schumpeterian Growth Model as the expected years that firms will remain in the market, if they do not adapt. And this adaptation process is mainly promoted by the creation of new ideas E[A]. This time expectation is represented by the following equation

$$Firm\ Lifetime : E[\tau] = 1/E[A]$$

$$Firm\ Lifetime : E[\tau] = 1/\gamma N$$

Where: New ideas corresponds to $E[A] = \gamma N$

The life of the company is reduced by the increase in productivity (γ) and the deployment of new technologies (N). This leads to two transition scenarios

1. If the adopter is not able to incorporate the new technologies or take advantage of them, its profit will be decreasing until a possible exit from the market, when its profits will be zero, and therefore, this company will not contribute to the growth of the economy.
2. If the adopting company is able to incorporate the new technology or take advantage of it, its profit will increase, which in turn will ensure its permanence in the market. However, this benefit is not immediately reflected in the aggregate accounting statistics. The adaptation process takes time, due to the development of new business processes, to the improvement of the qualification of its human capital, to the time required for the reallocation of more qualified human capital from less capable companies to companies with more potential for growth or success.

[3]Available at: https://www.ge.com/research/project/predictive-maintenance
[4]Definition created with the help of ResearchGPT
[5]Insights taken from this Bilkent Üniversitesi lecture

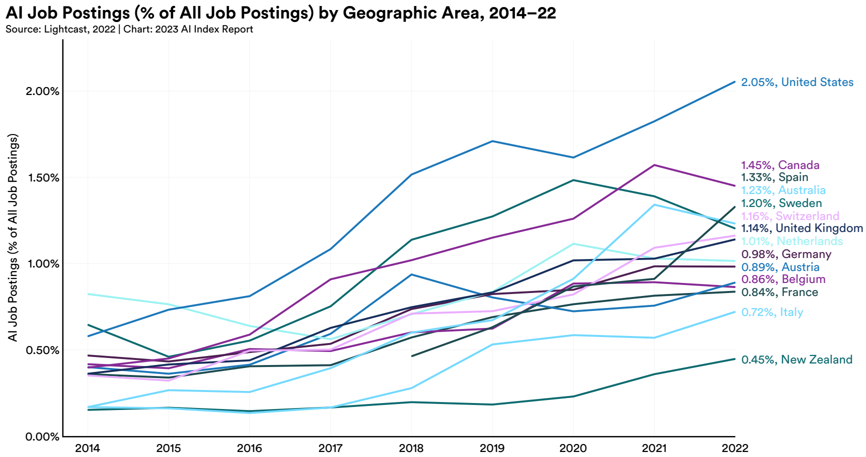

Figure 2: Percentage of all job postings that require some kind of AI skill by Geographic Area, 2014 to 2022.

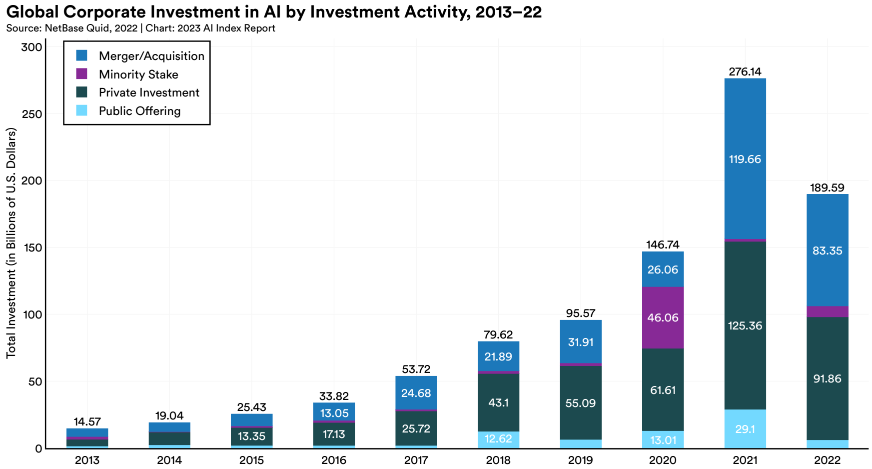

Figure 3: Global Corporate Investment in AI by Investment Activity, 2013 to 2022.

This reallocation of human capital can be seen in one of the key statistics in the labor market: Job postings.The number of AI related job postings has increased on average from 1.7% in 2021 to 1.9% in 2022 according to (Maslej et al., 2023). This increased trend can be seen in Figure 2. In 2022, the top three countries with the higher percentage of AI job postings were the United States (2.1%), Canada (1.5%), and Spain (1.3%).

Thus, in times of structural change such as the present, it is difficult to see the results of these new technologies, as the contributions to growth that successful firms might make are offset by the declining profits of outgoing firms. Therefore, it is reasonable to think that the statistics do not yet reflect the potential benefits of using AI.

This can be illustrated by reviewing the investments in AI over the last decade and the historical behavior of the Multiple Factor of Productivity. Figure 3 shows an upward trend in global AI investments over the last decade, with the exception of 2022, when, for the first time since 2013, global business investment in AI has declined.

However, these investments are not yet paying off in increases in the productivity multiple factor, as can be seen in Figure 4 and Figure 5.

##

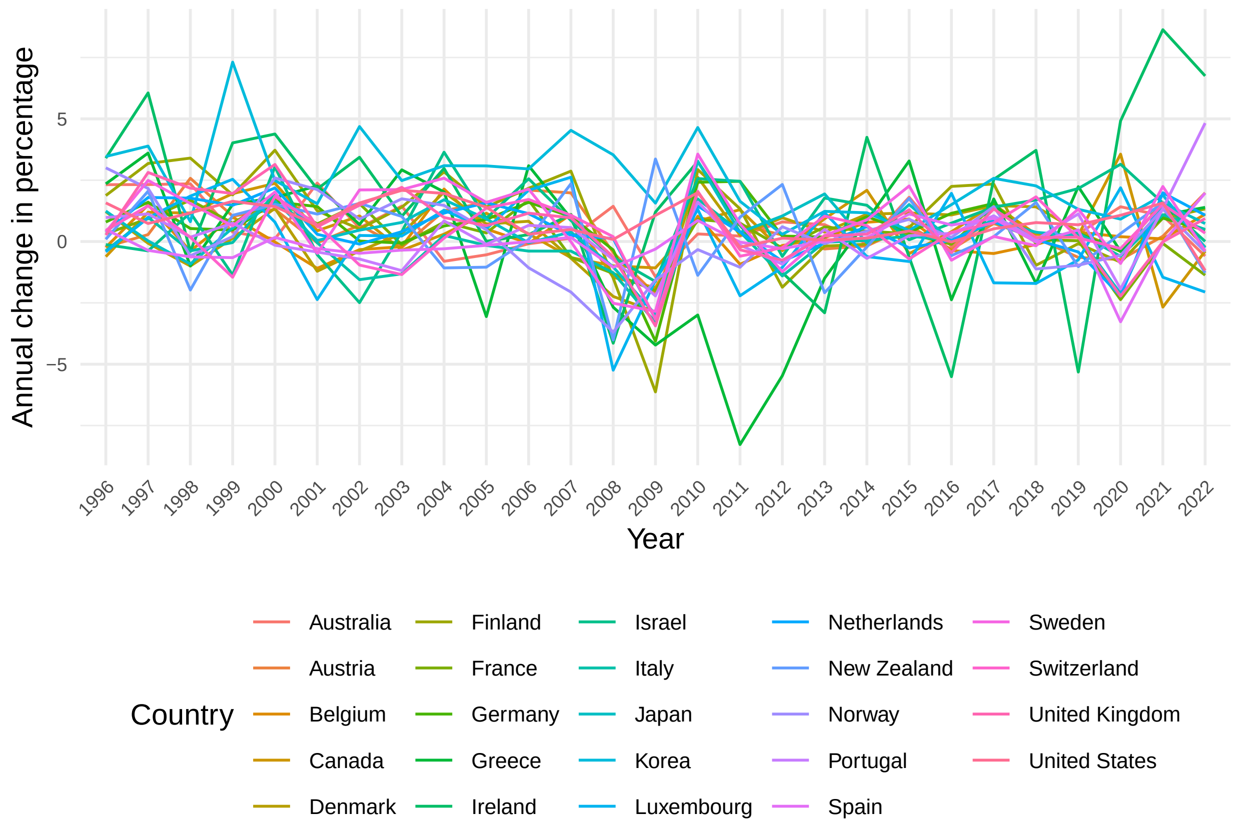

Figure 4: Annual change of Multi Factor Productivity by OECD Country, 1996 to 2022.

```
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
##
##     filter, lag

## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

Figure 5 shows a decreasing trend in multifactor productivity since 1996, but this trend has not changed despite investments in AI since 2013. Therefore, this is an indicator that new technologies such as AI has not yet reflected its benefits in the economy.

```
## `geom_smooth()` using formula = 'y ~ x'
```

However, this result may not be entirely accurate, as the measurement tools available to us today may not be capturing the real impact of these technologies. Mainly because multifactor productivity growth is measured as a residual, i.e., the part of GDP growth that cannot be explained by growth in labor and capital inputs. Traditionally, TFP growth has been considered to reflect technological progress, but in practice this does not mean that this parameter reflects all the benefits.

To exemplify this, let's think that a country with an amount R of resources can allocate part of them (Creators) to do R&D, while others (Adopters) to produce a certain level of activity or result X.

Figure 5: Mean and median of Multifactor Productivity by year, 1996 to 2022. The dashed black lines represent the mean and median trend line

Creators: Proportion n does R&D: nR. Adopters: The remainder goes to produce X: $(1-n)R$.

If we think of these companies as a composite of human capital, creators are individuals with the necessary skills to create new technologies, while adopters are individuals with sufficient skills to produce X in the traditional business model. Now, adopters need to acquire new skills in order to incorporate the benefits of technology, creating new business processes and successfully transitioning their production from the old schemes to the new schemes. These adopters are investing in intangible assets that the metrics are not reflecting. More importantly, adopters need the help of creators to facilitate the adoption process in their industries, because it stands to reason that creators are the most skilled human capital part of the available resources.

This similar approach of dividing efforts into doing R&D and producing the product should be adopted by adapting firms, in the sense that those doing R&D are actually the ones leading the company's successful transition to a new business model. In practical terms, from the perspective of an adopting company:

Business Transformers: The ratio n avoids exiting the market: nR. Change assimilators: This ratio continues to maximize profit in the new business model: $(1-n)R$.

Since consumers are not part of the production process, they have been left out of this analysis. However, their acceptance towards the consumption of AI-based products and their expected increase in the consumption of AI-based services will have a positive impact on economic growth.

Thus, the intangible assets associated with the transformation process are not yet quantified and in the last wave of computerization their value was about ten times greater than the direct investments in the computer hardware itself (Brynjolfsson et al., 2017). Thus, it is plausible that the intangibles associated with AI are of comparable or greater magnitude.

4. 4. LLMs vs. Artificial General Intelligence (AGI)

4.1. Understanding the difference between LLMs and AGI

Large Language Models (LLMs) and Artificial General Intelligence (AGI), represent distinct approaches to AI. Understanding their differences and how they link together is crucial in navigating the evolving landscape of AI research and applications. AGI, as defined by (Zhou et al., 2023) is a highly autonomous entity with the remarkable capacity to comprehend, learn, and apply knowledge across an extensive array of tasks and domains. Unlike narrow AI systems, AGI aims to replicate the breadth of human cognitive abilities. This ambition makes AGI the pinnacle objective within the field of artificial intelligence. One of the key distinctions between LLMs and AGI lies in their scope of intelligence. LLMs are specialized, focusing solely on language-related tasks. Another critical difference is in learning and adaptation. AGI systems, are designed for continual learning and adaptation. As described by (Wang and Goertzel, 2012) AGI's ability to be generalized on fundamentally new areas.

4.2. Exploring whether AGI is the real General Purpose Technology

The question of whether AGI can be considered the real General Purpose Technology is soon to become more relevant, as AGI has not yet reached its full potential and audience. While advanced LLM models like OpenAI's ChatGPT have undoubtedly revolutionized the way people work in a wide range of tasks, they represent just a glimpse of what AGI could ultimately achieve. AGI, with its aspiration to replicate human-like general intelligence across various domains, holds the promise of transcending the limitations of narrow AI and becoming the ultimate tool for problem-solving and innovation. Paper by (Mikki, 2023) introduces the intriguing idea that achieving AGI may necessitate noncomputable systems. This concept challenges conventional thinking in AI by encouraging us to expand our understanding of AGI's potential. It suggests that AGI might require unconventional approaches beyond traditional computational frameworks. While AGI has not yet fully realized its capabilities, it holds the promise of reshaping the technological landscape. Mikki's proposal of noncomputable systems, when integrated with other development ideas, offers a tantalizing glimpse into the future of AGI, where its transformative power knows no bounds.

5. 5. Acknowledging Benefits and Limitations of LLMs as GPT

5.1. Discussing the potential benefits of LLMs as GPT

One of the significant advantages of incorporating LLMs as GPT is the potential for substantial productivity gains. LLMs excel in natural language understanding and generation, making them valuable tools for automating tasks that involve processing and generating text. From content generation to customer support automation, LLMs can streamline processes, reduce labor costs, and boost efficiency. By automating routine language-related tasks, they free up human resources to focus on more creative and complex endeavors. In fields such as finance, healthcare, and market analysis, LLMs can assist in extracting valuable insights from unstructured data, leading to better-informed decisions and strategies.

5.2. Addressing the limitations and challenges associated with LLMs as GPT

While LLMs offer significant potential as GPT, it is essential to acknowledge the limitations and challenges associated with their widespread adoption. The use of LLMs raises ethical concerns, particularly in content generation and manipulation. LLMs rely on large datasets for training, often containing sensitive information. Safeguarding data privacy and ensuring compliance with data protection regulations is an ongoing challenge that must be addressed to harness the full potential of LLMs.

6. 6. Conclusion

Positive expectations around new technologies that drive development, economic growth and profit generation are often accompanied by optimism on the part of industry leaders, technology experts and venture capitalists. This optimism leads to speculative investments and forecasts of future corporate wealth in the financial sector. However, as (Brynjolfsson et al., 2017) suggests, there is no inherent contradiction between forward-looking technology optimism and backward-looking disappointment. The two can coexist, especially in periods of transformational change. This can be attributed to human nature, as individuals want to see their expectations fulfilled during their lifetime. However, it takes time for society to fully incorporate and benefit from new technologies, resulting in a slower rate of assimilation.

Although we are not concluding anything new to what has been mentioned before by several authors, it has been worthwhile to review especially the position of (Brynjolfsson et al., 2017) from the vision of the Schumpeterian growth model, and some metrics such as the Multifactor productivity and investments in AI, which allow us to have more grounded expectations of these new technologies, without ignoring the value of the intangible assets that are part of this process of economic transition.

References

Erik Brynjolfsson, Daniel Rock, and Chad Syverson. Artificial intelligence and the modern productivity paradox: A clash of expectations and statistics. Working Paper 24001, National Bureau of Economic Research, November 2017. URL `http://www.nber.org/papers/w24001`.

Ruyu Chen. How does labor mobility affect business adoption of a gpt? the case of machine learning*. 2021. URL `https://api.semanticscholar.org/CorpusID:247582628`.

Nicholas Crafts. Artificial intelligence as a general-purpose technology: an historical perspective. *Oxford Review of Economic Policy*, 37(3):521–536, 09 2021. ISSN 0266-903X. doi: 10.1093/oxrep/grab012. URL `https://doi.org/10.1093/oxrep/grab012`.

Tyna Eloundou, Sam Manning, Pamela Mishkin, and Daniel Rock. Gpts are gpts: An early look at the labor market impact potential of large language models, 2023.

Andre Esteva, Brett Kuprel, Roberto A. Novoa, Justin Ko, Susan M. Swetter, Helen M. Blau, and Sebastian Thrun. Dermatologist-level classification of skin cancer with deep neural networks. *Nature*, 542(7639):115–118, January 2017. doi: 10.1038/nature21056. URL `https://doi.org/10.1038/nature21056`.

Ran feng Qiu and John A. Cantwell. The international geography of general purpose technologies (gpts) and internationalisation of corporate technological innovation. *Industry and Innovation*, 25:1 – 24, 2018. URL `https://api.semanticscholar.org/CorpusID:157506117`.

Elhanan Helpman and Manuel Trajtenberg. Diffusion of general purpose technologies. *IRPN: Models of Diffusion (Topic)*, 1996. URL `https://api.semanticscholar.org/CorpusID:109412507`.

Nestor Maslej, Loredana Fattorini, Erik Brynjolfsson, John Etchemendy, Katrina Ligett, Terah Lyons, James Manyika, Helen Ngo, Juan Carlos Niebles, Vanessa Parli, Yoav Shoham, Russell Wald, Jack Clark, and Raymond Perrault. Artificial intelligence index report 2023, 2023.

Said M. Mikki. Artificial general intelligence and noncomputability: A dynamical framework. *J. Artif. Intell. Conscious.*, 10: 71–101, 2023. URL https://api.semanticscholar.org/CorpusID:256686011.

Pei Wang and Ben Goertzel. Chapter 1 introduction : What is the matter here ? 2012. URL https://api.semanticscholar.org/CorpusID:11570569.

Jason Wei, Yi Tay, Rishi Bommasani, Colin Raffel, Barret Zoph, Sebastian Borgeaud, Dani Yogatama, Maarten Bosma, Denny Zhou, Donald Metzler, Ed H. Chi, Tatsunori Hashimoto, Oriol Vinyals, Percy Liang, Jeff Dean, and William Fedus. Emergent abilities of large language models, 2022.

Juexiao Zhou, Xiuying Chen, and Xin Gao. Path to medical agi: Unify domain-specific medical llms with the lowest cost. *ArXiv*, abs/2306.10765, 2023. URL https://api.semanticscholar.org/CorpusID:259203619.