Short Paper

Irina Vélez^{a,1,*}, Otto Palkama^{b,1}

^aBig Wig University, 1 main street, Gotham, 123456, State, United States
^bDepartment, A street 29, Manchester, 2054 NX, The Netherlands

Abstract

This is the abstract.

It consists of two paragraphs.

Keywords: keyword1, keyword2

1. 1. Introduction

The idea is to explore how the use of Large Language Models (LLMs) as General Purpose Technology (GPT) could reshape industries, considering the generalization capabilities of LLMs and the rapid adoption of these tools by the public and firms.

A. Background on the potential economic impact of Large Language Models (LLMs) as General Purpose Technology (GPT) B. Objective of the paper: Exploring how the use of LLMs as GPT could reshape industries and contribute to economic growth

Generalization of tools seems to be an important characteristic to leverage the potential of growth and development, because if a same tool could be broad use for different purposes, so the tool becomes in a very valuable tool.

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 (10^23 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.

On the other hand, the use of LLMs as a base technology of other tools, such as software-AI powered, open a new window and enveloped the potential of productivity improvements of the work-human force or human capital as it was mention by (Eloundou et al., 2023) telling that LLMs such as GPTs exhibit traits of general-purpose technologies, could have considerable economic, social, and policy implications.

So, the potential arising of emergent abilities and the wide use of LLMs as enablers of new tools (AI based-software) alongside the spread use of tools such as ChatGPT by a large amount of humans (here: million of users of chatGPT), it could signify a future unseen before by the human beings, because the expansion and pushing of new boarders and limits would be accelerated.

 $^{^* \\} Corresponding \ author$

Email addresses: alice@example.com (Irina Vélez), bob@example.com (Otto Palkama)

¹This is the first author footnote.

 $^{^2}$ Another author footnote.

2. Generalization Capabilities of LLMs as GPT

A. Examining the adoption rate of previous GPTs B. Key factors contributing to the widespread adoption of a technology as a GPT C. Reviewing the literature on the potential of AI as 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". 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.

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.

3. Assessing the Potential Economic Impact

Considering the potential of the AI as a new GPT, specifically the LLMs, assessing its potential economic impact to setting expectatives, it could be address based on a retrospective approach what it means that the behaviour of previous General Purpose Technology like internet, electricity or semiconductors, can give a more realistic answer to this question, given the current conditions of uncertainty of this time.

It is worth noting that the article by (Brynjolfsson et al., 2017) was written seven years before the launch of ChatGPT by OpenAI. This temporal context adds significance to the insights provided by (Brynjolfsson et al., 2017), as they were able to anticipate and discuss the potential impact of artificial intelligence (AI) technologies on productivity growth before the emergence of specific AI models like ChatGPT. Their analysis and observations offer valuable perspectives on the productivity paradox and the clash between expectations and statistical realities in the context of technologies with the potential to become GPTs.

This apparent incongruence relies on the time lag between invention and the full impact on the economy and society. It takes time to build the stock of the new technology, develop the necessary human capital skillset, undergo the re-engineering process of business process transformations, and develop complementary innovations for its full realization.

One example mentioned by (Brynjolfsson et al., 2017) is the call center industry, which had approximately 2.2 million agents 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.

The positive expectations surrounding new technologies driving development, economic growth, and generating profits are often accompanied by optimism from industry leaders, technology experts, and venture capitalists. This optimism leads to speculative investments and forecasts of future company wealth in the financial sector. However, as (Brynjolfsson et al., 2017) suggests, there is no inherent contradiction between forward-looking technological optimism and backward-looking disappointment. Both can coexist, particularly

³Available at: https://hai.stanford.edu/sites/default/files/2020-09/AI-Definitions-HAI.pdf

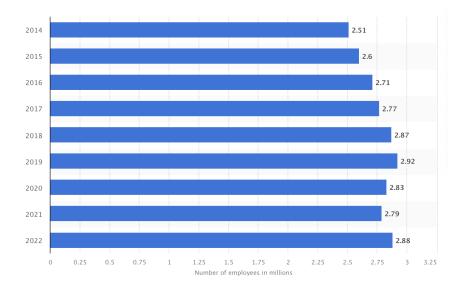


Figure 1: Number on contact center employees in the United States from 2014 to 2022.

during periods of transformative change. This can be attributed to human nature, as individuals desire to see their expectations fulfilled within their lifetime. However, it takes time for society to fully incorporate and benefit from new technologies, resulting in a slower pace of assimilation.

B. Evaluating the potential economic impact in terms of value creation and cost optimization 1. Real cases of successful implementations of LLMs for value creation 2. Real cases of successful implementations of LLMs for cost optimization

Value Creation	Cost Reduction	Reference
Deep neural network system matches the diagnostic performance of 21 board certified dermatologists in detecting skin cancer.		(Esteva et al., 2017)
Row 2 Value 1 Row 3 Value 1 Row 3 Value 1	Row 2 Value 2 Row 3 Value 2 Row 3 Value 2	Row 1 Value 2 Row 1 Value 2 Row 1 Value 2

Total Factor Productivity should reflect the exceptional technological advance

Review data: CBInsights - Labour Productivity Growth vs Global Investment focused on AI - OECD Productivity Growth - Real Median income has stagnated since the late 1990s

Both capital deepening and total factor productivity (TFP) growth lead to labor productivity growth, and both seem to be playing a role in the slowdown

The old adage that "past performance is not predictive of future results" applies well to trying to predict productivity growth in the years to come, especially in periods of a decade or longer. Historical stagnation does not justify forward-looking pessimism. Taken from Paradox

C. Intangible capital - capital may not be reflected in the measurements of economic growth AI developing skills: Perception and cognition

4. LLMs vs. Artificial General Intelligence (AGI)

A. Understanding the difference between LLMs and AGI B. Exploring whether AGI is the real General Purpose Technology

5. Acknowledging Benefits and Limitations of LLMs as GPT

A. Discussing the potential benefits of LLMs as GPT B. Addressing the limitations and challenges associated with LLMs as GPT

6. Conclusion

A. Summarizing the main points discussed in the paper B. Emphasizing the potential of LLMs as GPT in reshaping industries

7. Bibliography styles

Here are two sample references: Feynman and Vernon Jr. (1963; Dirac, 1953).

By default, natbib will be used with the authoryear style, set in classoption variable in YAML. You can sets extra options with natbiboptions variable in YAML header. Example

natbiboptions: longnamesfirst,angle,semicolon

There are various more specific bibliography styles available at https://support.stmdocs.in/wiki/index.php?title=Model-wise_bibliographic_style_files. To use one of these, add it in the header using, for example, biblio-style: model1-num-names.

7.1. Using CSL

If citation_package is set to default in elsevier_article(), then pandoc is used for citations instead of natbib. In this case, the csl option is used to format the references. Alternative csl files are available from https://www.zotero.org/styles?q=elsevier. These can be downloaded and stored locally, or the url can be used as in the example header.

8. Equations

Here is an equation:

$$f_X(x) = \left(\frac{\alpha}{\beta}\right) \left(\frac{x}{\beta}\right)^{\alpha-1} e^{-\left(\frac{x}{\beta}\right)^{\alpha}}; \alpha, \beta, x > 0.$$

Here is another:

$$a^2 + b^2 = c^2. (1)$$

Inline equations: $\sum_{i=2}^{\infty} {\{\alpha_i^{\beta}\}}$

9. Tables coming from R

Tables can also be generated using R chunks, as shown in Table 2 for example.

Table 2: Caption centered above table

	mpg	cyl	disp	hp
Mazda RX4	21.0	6	160	110
Mazda RX4 Wag	21.0	6	160	110
Datsun 710	22.8	4	108	93
Hornet 4 Drive	21.4	6	258	110
Hornet Sportabout	18.7	8	360	175
Valiant	18.1	6	225	105

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