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THE RELATIONSHIP BETWEEN AI AND LABOR PRODUCTIVITY – MYTH OR REALITY

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Abstract
Artificial intelligence (AI) is one of the latest technologies to raise the interest of mainstream media, world leaders and investors. In certain scenarios, AI is expected to augment human capabilities and, therefore, profoundly change macroeconomic labor productivity. Such a change would be greatly welcomed, considering that labor productivity in advanced economies has registered sluggish growth for many years. Despite these expectations, the reality remains disappointing. Even with continuous AI breakthroughs, labor productivity growth in the US, where world's leading AI companies operate, has remained lower in the period 2019-2024 than in the period 1990-2007. In essence, the relationship between AI and labor productivity is not yet visible in macroeconomic statistics. Consequently, we tried to find evidence in scientific literature. We performed a bibliometric analysis, employing two scientific databases: Scopus and Web of Science. Our main goal was to determine the number of scientific publications which established a clear relationship between AI and labor productivity, be it on a macroeconomic level or on a firm level. Our results showed that not many researchers investigated the link between AI and labor productivity. In this study, we provided statistics per authors, journals and countries. We also provided an overview per content and epistemological orientation, to describe the research status in this field.
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1. INTRODUCTION

The recent advent of big data, cheaper storage and faster processors hold the promise of incredible AI breakthroughs (Burgess, 2017). Knowing this, big tech companies are currently investing heavily in the development of AI models. Some big tech leaders promise that those AI models will be so powerful that they will be able to deeply change human societies (Knight, 2024; Eastwood, 2024; Hammond, 2024). Their promises seem to be believed by the members of the World Economic Forum who meet every year in Davos. During their 2024 meeting, AI was one the main topics of discussion and their expectations appeared to be high (Pomeroy & Meyers, 2024). Those high expectations are also visible in the case of stock investors, who have invested heavily in AI chipmakers. It should not come a surprise, therefore that the share price of the main AI chipmaker, Nvidia, has registered a threefold increase in June 2024, pushing its market capitalization to three trillion dollars and making it the most valuable company in the world (Solo-Lyons, 2024).

AI is a popular topic not only for big tech leaders, world leaders and stock investors, but also for researchers. By performing a simple search in one scientific database such as Scopus, approximately 2 million articles can be found on the topic of artificial intelligence. Some researchers are not so enthusiastic about AI; on the contrary, they are concerned that the AI technology is overhyped and that the grand promises made by big tech leaders will never materialize (Czarnitzki, Fernández & Rammer, 2023). Indeed, the macroeconomic indicators of US, where most AI companies are based, have been disappointing, and this may legitimize some researchers' concerns about AI. Up until August 2024, which is the moment of writing this paper, labor productivity growth in the US has remained rather sluggish, around the 1947-2024 average value of 2.17 (U.S. Bureau of Labor Statistics, 2024). As such, there is no sign yet that AI technology has impacted labor productivity on a macroeconomic level.

One of the explanations for this incongruity could be related to the fact that AI adoption is still limited. As it was the case for other general-purpose technologies, a longer period may be needed before AI is widely adopted and before its promised value becomes materialized (Rock, Brynjolfsson & Syverson, 2017). For instance, it took around 30 years for most US factories to become electrified after the invention of the polyphase alternate current; knowledge had to be built, complementary technologies, such as the electric motor, needed to be invented not to mention that new management ways had to be found before electrification became widely spread in US manufacturing companies (David, 1991 in Rock, Brynjolfsson & Syverson, 2017). In a similar manner, perhaps only a small number of companies have so far managed to understand and implement AI technology. Even though the link between AI and labor productivity is not yet visible at a macroeconomic level, there may therefore be companies or theorists who have already noticed the benefits of AI, including increases in labor productivity, which could justify the optimism regarding AI. Simply put, in this context of AI hype, we should be able to already find scientific publications which have linked AI to labor productivity.

As we could not find any bibliometric analyses on the publications that linked AI to labor productivity, we started by performing searches in Scopus and Web of Science to find such publications. The searches were based on the keywords relevant for each AI core domain (reasoning, planning, learning, communication, perception). Next, the publications were screened for suitability and quantified based on corresponding authors, journals or countries. Finally, they were classified on the basis of content and epistemological orientation.

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2. LITERATURE REVIEW

2.1. A definition for the AI knowledge field

Multiple authors have tried to provide a definition for AI (Kaplan & Haenlein, 2019; Poole & Mackworth, 2017; Kaplan, 2016). Considering the multitude of definitions for AI, Samoili, López Cobo, Gómez, De Prato, Martínez-Plumed and Delipetrev have been assigned by the European Commission to create a single definition that manages to surprise the essence of AI. Samoili et al. (2020) have done this by critically reviewing previous definitions and by consulting AI specialists. The definition which resulted from their work is the following:

> Artificial intelligence (AI) systems are software (and possibly also hardware) systems designed by humans that, given a complex goal, act in the physical or digital dimension by perceiving their environment through data acquisition, interpreting the collected structured or unstructured data, reasoning on the knowledge, or processing the information, derived from this data and deciding the best action(s) to take to achieve the given goal. AI systems can either use symbolic rules or learn a numeric model, and they can also adapt their behaviour by analysing how the environment is affected by their previous actions. (Samoili, López Cobo, Gómez, De Prato, Martínez-Plumed & Delipetrev, 2020, p.4).

In addition to providing this definition, Samoli et al. (2020) have split the AI knowledge field into five AI core domains and three transversal domains. The same authors have also provided keywords for each AI domain. The core domains (reasoning, planning, learning, communication, perception) have been defined as "the fundamental goals of AI" (Samoili et al., 2020, p.11) whereas the transversal domains (integration and interaction, services and ethics and philosophy) refer to issues common to most technologies and not specifically to AI. Since our focus is the relationship between AI and labor productivity, and not the issues common for most technologies, this paper will solely concentrate on AI core domains. The definitions for each AI core domain are visible in the table below whereas the keywords per AI domain are visible in Appendix 1.

TABLE 1. DEFINITIONS FOR AI DOMAINS

AI domain	Definition based on goals
AI reasoning	Make inferences from data
AI planning	Organize and execute strategies
AI learning	Learn, predict or decide and relearn
AI communication	Understand and generate human-like messages
AI perception	Process audio or image

Source: Author's research based on Samoili et al. (2020)

2.2. AI and labor productivity

Ever since the beginning of AI's history, humans had high expectations (Burgess, 2017). For instance, in 1970, the founder of MIT's AI lab, Marvin Minsky, gave an interview in which he exposed his predictions that within eight years, machines would surpass human genius, by having incalculable powers and by being able to excel in many of the activities in which humans were engaging, such as playing office politics (Darrach, 1970).

> In from three to eight years we will have a machine with the general intelligence of an average human being. I mean a machine that will be able to read Shakespeare, grease a car, play office politics, tell a joke, have a fight. At that point the machine will begin to educate itself with fantastic speed. In a few months it will be at genius level and a few months after that its powers will be incalculable. (Darrach, 1970, p.59).

More than fifty years after that interview, Marvin Minsky's predictions failed to materialize, and humans are still on a quest to discover the AI models capable of surpassing the intelligence of a human genius (Hammond, 2024). Since Marvin Minsky's interview in 1970, however, AI has seen some important improvements. Humans have collected vast amounts of data, they have invented cheaper storage and faster processors (Burgess, 2017). All these improvements enabled humans to create AI models that managed to beat the world's champion at the board game Go, or which are now capable of writing emails or wedding speeches (Jarrahi, 2018; Paris & Buchanan, 2023).

These developments are making many employees afraid that AI will soon become so powerful that it will be able to replace them in their work (Arslan, Cooper, Khan, Golgeci & Ali, 2022; Rampersad, 2020; Zirar, Ali & Islam, 2023). Indeed, some researchers believe that some tasks currently performed by humans might be taken over by artificial intelligence, in arrangements in which humans are employed only on a short-term basis (Zirar, Ali & Islam, 2023; Braganza, Chen, Canhoto & Sap, 2021). Other researchers believe that such scenarios will not be possible any time soon, because AI has still limited powers (Jarrahi, 2018; Zirar, Ali & Islam, 2023). Instead of a scenario in which AI replaces humans, they propose a scenario in which humans work together with AI in a symbiotic relationship, in which AI is augmenting human capabilities (Jarrahi, 2018; Zirar, Ali & Islam, 2023).

In such a symbiotic relationship, both humans and AI contribute with the best of their capabilities. AI contributes with large computation and analytical capacity and takes over the human tasks in predictable, predefined situations (Jarrahi, 2018). Humans contribute with their intuition and common sense in uncertain or unpredictable situations which cannot be handled by AI alone (Jarrahi, 2018). By bringing the best of AI and of humans in a symbiotic AI-human relationship, there is a high chance that human

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productivity will increase. When we mention labor productivity, we mean the "quantity of goods and services that can be produced by one worker or by one hour of work" (Hubbard & O'Brien, 2024).

Despite continuous impressive breakthroughs in the field of AI (Merchant, 2024), macroeconomic statistics do not provide any evidence for a potential relationship between AI and labor productivity (Rock, Brynjolfsson & Syverson, 2017). This is especially the case if we consider the macroeconomic labor productivity growth of the US (U.S. Bureau of Labor Statistics, 2024), which has been the cradle of AI and where the world's biggest AI big companies are incorporated (Ho & Wang, 2020; Lei & Lu, 2019).

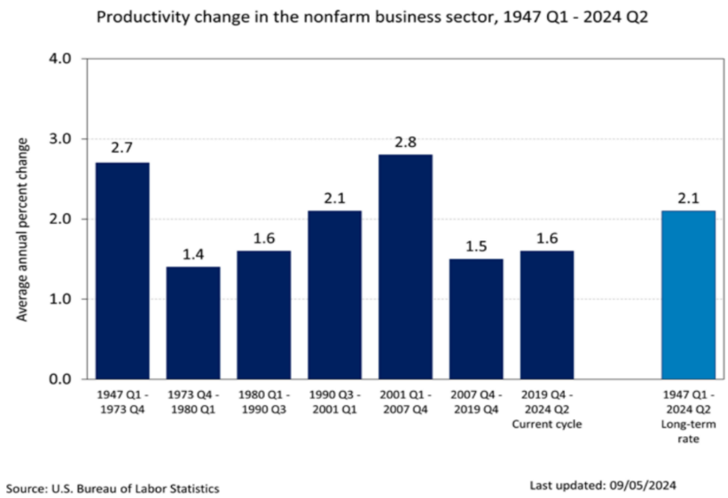

FIGURE 1. LABOR PRODUCTIVITY GROWTH IN US NONFARM SECTOR
Source: U.S. Bureau of Labor Statistics (2024)

This could be explained by the still limited implementation of AI. As for other general-purpose technologies, companies may need more time to gain knowledge and invent complementary technologies that would enable them to fully harness the power of AI (Rock, Brynjolfsson & Syverson, 2017). Nonetheless, considering the enthusiasm for AI visible in multiple segments of society, some early AI adopters or theorists may have already observed positive impacts of AI, including potential increases in labor productivity. Even though the relationship between AI and labor productivity is not visible yet on macroeconomic level, we would expect this relationship to already be visible on microeconomic level, in organizations or company departments that already adopted AI.

2.3. Previous bibliometric analyses on AI and labor productivity

Bibliometric analysis is a research method meant for analyzing the knowledge structure of a certain field (Donthu, Kumar, Mukherjee, Pandey & Lim, 2021). Some researchers have already conducted bibliometric analyses to determine the structure of the AI knowledge field. Ho and Wang (2020) are among those researchers who have performed a bibliometric analysis on publications that treated the AI technology. Their focus was on the studies published between 1991 and 2018. In their bibliometric analysis, the United States was designated as the leader in research on AI while neural networks and machine learning have emerged as the main research foci. Lei & Liu (2019) are other researchers who have performed a bibliometric analysis on the AI knowledge field. Their focus was on the publications between 2007 and 2016, and their results have confirmed the United States as the biggest producer of AI research and machine learning as the most important research area (Lei & Liu, 2019). The scope of both papers was broad and did not provide any indication on whether labor productivity was also considered in the studies which were part of the analysis.

Other researchers have narrowed the scope of their AI bibliometric studies, by concentrating on specific fields, such as education (Talan, 2021), tourism and hospitality (Knani, Echchakoui & Ladhari, 2022), health (Jimma, 2023; Zhang, Ling & Lin, 2022; Shen, Wu, Chen, Hu, Pan, Kong & Lin, 2022) or finance (Goodell, Kumar, Lim & Pattnaik, 2021). In other bibliometric analyses, the scholars have included studies on the links between AI and other constructs, such as sustainability (Bracarense, Bawack, Wamba, & Carillo, 2022) or human resources management (Kaushal, Kaurav, Sivathanu, & Kaushik, 2023; Palos-Sánchez, Baena-Luna, Badicu & Infante-Moro, 2022).

Even though bibliometric analyses on AI-related publications exist, we could not find any bibliometric analysis on the studies that address the relationship between AI with labor productivity. Consequently, our bibliometric analysis will have the following objectives:

2.4. Objectives

Objective 1: Identify and quantify the number of publications that link AI and its five core domains with labor productivity

Objective 2: Provide statistics by authors, journals and countries

Objective 3: Provide a classification of the publications based on their content and epistemological orientation

3. METHODOLOGY

Firstly, we consulted the literature for recommendations on which scientific databases are most suitable for conducting a bibliometric analysis. Multiple researchers indicated that Scopus and Web of Science are the most prestigious as they contain a significant population of good quality articles (Knani, Echchakoui & Ladhari, 2022; Donthu et al., 2021).

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Secondly, we performed searches in Scopus and Web of Science by using the keywords provided by Samoili et al. (2020) for each AI domain. An overview of those keywords can be found in Appendix 1. As it can be noticed in Appendix 1, next to using the keywords corresponding to each AI domain, we also used in one of our searches a broader term, namely "artificial intelligence", in case of articles which did not make any reference to a specific AI domain. We only searched for journal articles. All searches resulted in 720 publications.

Thirdly, we merged the search results from Scopus and Web of Science and removed the duplicates. We made sure that each publication is assigned an AI domain. In case a publication appeared in the search results for more than one AI domain, we kept only one record and we included it in a new category which we named "Multiple AI domains". Around 206 duplicates have been removed.

Fourthly, we evaluated the title, the keywords, the abstract and sometimes even the entire text of the paper to determine the suitability of each paper for our study. We only maintained articles which clearly addressed the relationship between AI and labor productivity. After performing these steps, we were left with 55 publications.

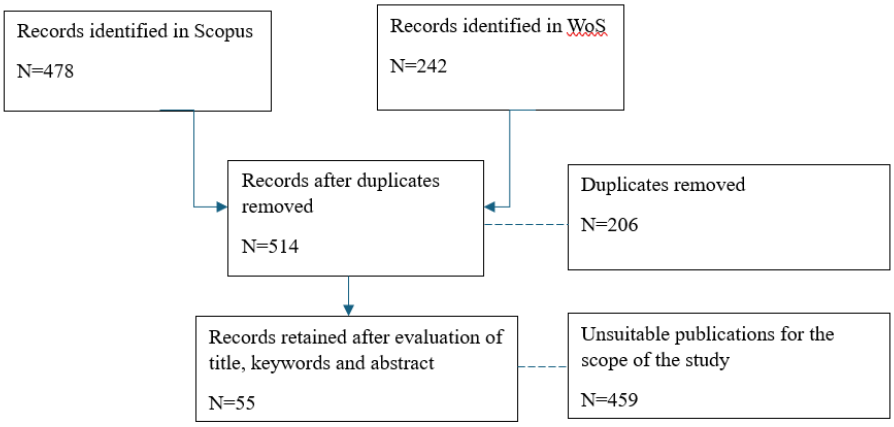

FIGURE 2. PREPARATION OF PUBLICATIONS TO BE INCLUDED IN ANALISYS
Source: Author's research

Fifthly, we determined the content classification and epistemological orientation by reading again the title, the keywords, the abstract and sometimes, the entire text of the paper. For epistemological orientation, we used as classification criteria the positivist epistemological categories and subcategories used in the papers of Barley (1988) and Bakker et al. (2005) and strongly recommended by Granados et al. (2011). The definitions for each epistemological category and subcategory are provided in the table below.

TABLE 2. DEFINITIONS FOR EPISTEMOLOGICAL ORIENTATIONS

Category	Subcategory	Definitions
Descriptive	Descriptive	Presents facts or opinions
Prescriptive	Instrumental	Provides ideas or potential solutions to various challenges, other than of an ethical nature
	Normative	Provides recommendations or courses of actions from an ethical point of view
Theoretical	Conceptual	Creates new hypotheses based on existing literature and without collecting new research data
	Exploratory	Creates new hypotheses after collecting new research data
	Predictive	Tests hypotheses based on new research

Source: Author's research based on Granados et al. (2011)

4. RESULTS

Not many researchers have investigated the connection between AI and labor productivity. We have found a total of 55 publications that addressed the relationship between AI and labor productivity. Even though the number of publications on this topic has increased in recent years, as can be noticed in the graph below, the number remains quite small in comparison with the millions of publications on artificial intelligence.

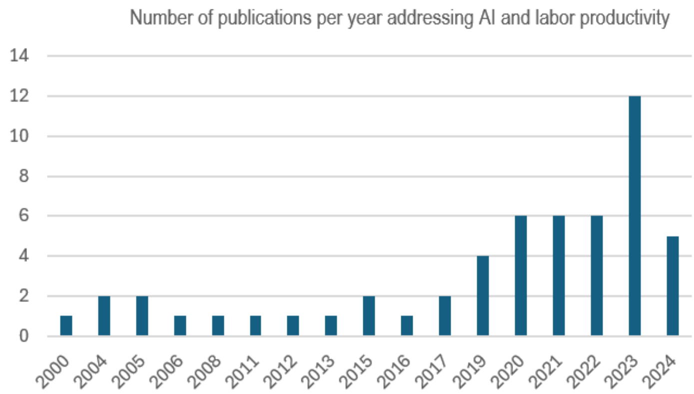

FIGURE 3. NUMBER OF PUBLCATIONS ADRESSING AI AND LABOR PRODUCTIVITY
Source: Author's research based on SCOPUS and WoS

For determining the statistics per authors and countries, we counted all authors related to all publications. We did not employ proportional counting, but full counting. Not unsurprisingly, considering the small number of publications, only 169 authors have investigated the relationship between AI and labor productivity. The majority have contributed to literature with only one article. The exceptions, who have published more than two articles, are mentioned in the table below:

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TABLE 3. MOST PROLIFIC AUTHORS

Author	Documents	Citations
Fayek, Aminah Robinson	4	130
Ebrahimi, Sara	2	15
Goldfarb, Avi	2	14
Moselhi, Osama	2	125
Nasirzadeh, Farnad	2	48
Sumati, Vuppuluri	2	15

Source: Author's research based on SCOPUS and WoS

Most authors have been associated with universities and only a few have been associated with governmental institutions. The articles have been published in 44 journals, mostly in the field of construction or engineering. In total, 117 universities from 29 countries have been involved in studying the relationship between AI and labor productivity, with 24% of the articles being the result of international collaborations. Most international collaborations have been between Western countries, such as Canada and the United States. These countries are also the ones which have contributed the most (25%) to literature so far, being closely followed by Asian countries such as China and India.

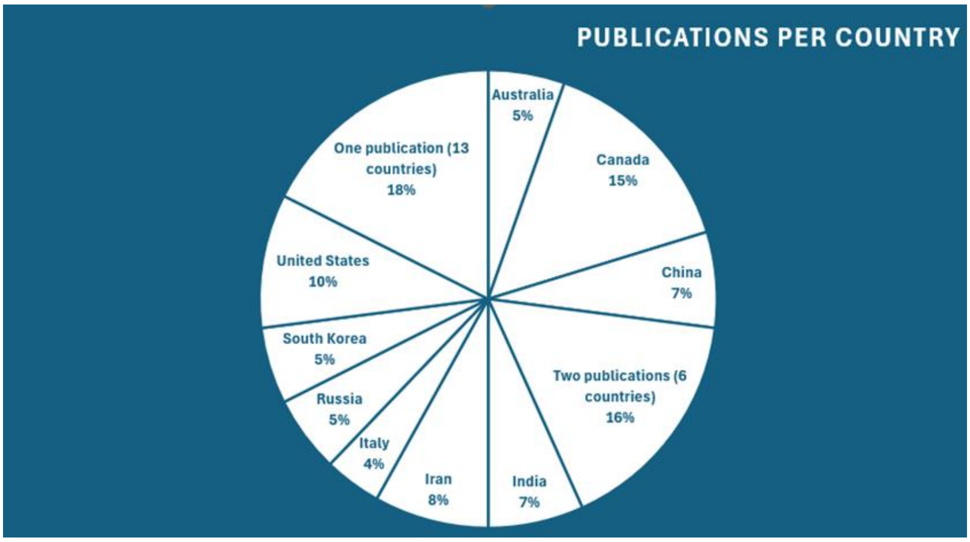

FIGURE 4. PUBLICATIONS PER COUNTRY
Source: Author's research based on SCOPUS and WoS in VOSviewer

FIGURE 5. RESEARCH COLLABORATIONS
Source: Author's research based on SCOPUS and WoS in VOSviewer

As far as the content and epistemological orientation are concerned, our results were surprising. Around 67% of the articles mentioned the difficulty of measuring labor productivity and consequently suggested ways in which AI can be used to measure labor productivity. Other articles prescribed ways of using AI in different situations for improving labor productivity. Both types of articles were considered to have an instrumental prescriptive orientation. Finally, some articles reported facts or opinions or theorized on the link between AI and labor productivity. These were having either a descriptive or a theoretical predictive orientation.

TABLE 4. CONTENT CLASSIFICATION

Content classification	No. of articles	Frequency (per cent)
Propose AI models to measure labor productivity/identify factors influencing labor productivity	37	67
Report facts or opinions	2	4
Propose AI uses and measures the resulting labor productivity	5	9
Theorize on the connection between AI and labor productivity	11	20
Total	55	100

Source: Author's research based on SCOPUS and WoS

TABLE 5. EPISTEMOLOGICAL ORIENTATION

Category	Subcategory	No. of articles	Frequency (per cent)
Descriptive	*Descriptive total*	2	4
Prescriptive	Instrumental	42	76
	Prescriptive total	42	76
Theoretical	Conceptual	1	2
	Exploratory	3	5
	Predictive	7	13
	Theoretical total	11	20
Total		55	100

Source: Author's research based on SCOPUS and WoS

As far as the classification per AI domain is concerned, most articles focused on machine learning technology as a way of measuring or increasing labor productivity. Other articles presented use cases based of AI perception or AI reasoning and measured the resulting labor productivity. Surprisingly, considering the popularity of chatbots such as ChatGPT, the AI domain with the fewest search result was the AI communication domain. Most theoretical articles focused on AI in general, without a particular reference to a specific AI domain.

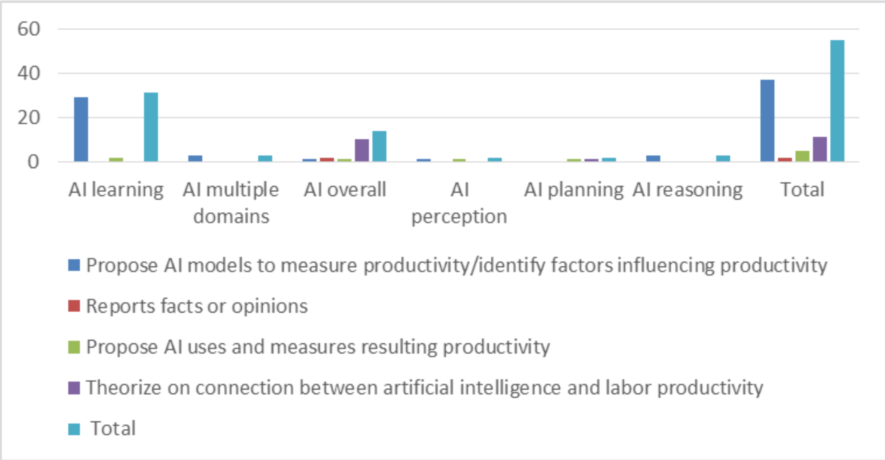

FIGURE 6. ARTICLES CATEGORIZED PER AI DOMAIN AND CONTENT
Source: Author's research based on SCOPUS and WoS

5. DISCUSSION

AI is yet to leave a mark on human society. Its impact has not been visible yet at the level of macroeconomic labor productivity. At the same time, our study, which is the first bibliometric analysis on the topic of AI and labor productivity, showed that the number of scientific publications which have linked AI to labor productivity is rather limited. There could be three potential explanations for these results.

A first explanation could be related to the limited implementation of AI. It may be that not many companies have implemented AI, making it difficult for more researchers to find data and evidence for the link between AI and labor productivity (Czarnitzki, Fernández & Rammer, 2023). The limited implementation of AI may be caused by limited knowledge of the technology or limited availability of complementary technologies (Rock, Brynjolfsson & Syverson, 2017). Indeed, our results showed the prevalence of instrumental prescriptive articles, which are in fact use cases for AI, suggesting that knowledge on AI is still in its infancy in many segments of society.

A second explanation could be related to the file drawer effect (Rosenthal, 1979). It may be that more researchers have studied the link between AI and labor productivity without finding any relationship between AI and labor productivity. This may have led them to decide against publishing those results. The reasons for not finding any evidence for the relationship between AI and labor productivity may be related to over-inflated expectations (Burgess, 2017; Rock, Brynjolfsson & Syverson, 2017) or to the difficulties faced when measuring the labor productivity (Burgess, 2017; Rock, Brynjolfsson & Syverson, 2017). Indeed, many publications included in our study mentioned the difficulty of measuring labor productivity.

A third explanation could be the fact that AI provides more value by replacing humans than by augmenting their capabilities (Zirar, Ali & Islam, 2023; Braganza, Chen, Canhoto & Sap, 2021). Researchers may have conducted more studies on AI's capability of replacing humans than on AI's impact on labor productivity. This could be proven if other researchers are to conduct a bibliometric analysis of the publications on AI's capability of replacing humans and compare their results with the results from our bibliometric analysis.

When considering the statistics per country, authors and journals, we notice the clear dominance of the academic literature from the Western world. We consider that more practitioners should be included in the research, since they may have more practical knowledge and more access to scarce AI research data. Moreover, we notice that researchers have conducted more studies on machine learning than on other types of AI.

5.1. Limitations and future research directions

The first limitation of this bibliometric analysis is the fact that it was based on only two scientific databases: Scopus and Web of Science. There may be more authors who have investigated the relationship between AI and labor productivity, however, those may have published their results or conclusions in journals which are not indexed in Scopus or Web of Science. Regardless of this, Scopus and Web of Science are some of the most respected scientific databases, with a good representation of high-quality scientific articles, on which solid bibliometric analyses could be performed (Donthu, Kumar, Mukherjee, Pandey & Lim, 2021).

The second limitation is related to the qualitative judgements employed for determining the suitability of each article and the epistemological orientation. To overcome this limitation, we used strict evaluation criteria. Only articles which have as the central focus of research the link between AI and labor productivity were included in our study. The criteria used for determining the epistemological orientation was the positivist one used in other previous bibliometric analyses (Bakker et al., 2005; Granados et al., 2011).

This bibliometric analysis showed that not many researchers have studied the link between AI and labor productivity. This could be explained by at least three potential reasons: 1) limited availability of research data because of limited implementation of AI, 2) file drawer effect and 3) researchers' view on AI as more capable of replacing humans than by augmenting their skills. Our results showed that research on AI and labor productivity is mostly conducted by academia, without involvement from practitioners, so we strongly encourage researchers to include practitioners in research projects as they may provide access to much-needed data and practical knowledge on AI. At the same time, we encourage researchers to try to publish their results, even though those do not include any evidence on the relationship between AI and labor productivity. This type of study may help both researchers and practitioners form informed opinions on the relationship between AI and labor productivity. Finally, we recommend researchers to conduct a bibliometric analysis of the publications on AI's capability of replacing humans and to compare their results

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with the results from our bibliometric analysis. This may provide insights into how the scientific world views AI: as a replacement for or augmenter of human capabilities.

5.2. Managerial implications

We recommend managers or practitioners to collaborate with academia on research projects from which both could benefit. From such a collaboration, managers could gain more knowledge on AI and on various AI use cases whereas academia may gain access to much needed data. Moreover, we recommend managers not to overlook the power of machine learning. We found more scientific studies on the positive effects of machine learning than studies on chatbots such as ChatGPT.

6. CONCLUSION

On a macroeconomic level, labor productivity growth has remained sluggish, despite continuous advancements in the field of AI. By performing a bibliometric analysis, it was shown that even in the scientific world, there are not many publications which have established a direct connection between AI and labor productivity, be it on a macroeconomic level or on a firm level. This study could be limited by the fact that it was conducted on only two scientific databases: Scopus and Web of Science. Nevertheless, Scopus and Web of Science are scientific databases with a good reputation in the scientific community. The explanations for the limited number of publications on the link between AI and labor productivity could be diverse: 1) limited availability of research data because of limited implementation of AI, 2) file drawer effect and 3) researchers' view on AI as more capable of replacing humans than by augmenting their skills. Researchers are strongly encouraged to continue investigating the link between AI and labor productivity, to bring more light on AI's impact, or lack thereof, on human societies.

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