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Artificial Intelligence and employment: a systematic review

Inteligência Artificial e emprego: uma revisão sistemática

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RESUMO: Este artigo apresenta uma revisão sistemática da literatura, com base em procedimentos bibliométricos, das obras (Economia Política), produzidas entre 2008 e 2020, sobre as relações entre Inteligência Artificial e emprego. Ele detecta uma tendência de crescimento de artigos publicados nesta área, especialmente a partir de 2019, e identifica quatro grupos principais de preocupações sobre o tema. Dentro desses grupos, pode-se notar uma prevalência de abordagens mais otimistas sobre as céticas e, especialmente, de abordagens econômicas ortodoxas sobre heterodoxas sobre o assunto. De maneira geral, é possível apreender que tanto os trabalhos quanto suas métricas são bastante dispersos e variados em escopo. Entre outras razões, isso se deve à falta de uma definição básica comum, no campo, do que é IA em primeiro lugar.
PALAVRAS-CHAVE: Inteligência Artificial; automação; trabalho.

ABSTRACT: This paper presents a systematic literature review, grounded on bibliometric procedures, of the (political economy) works, produced from 2008 to 2020, on the relations between *Artificial Intelligence* and *employment*. It detects a growing tendency of published papers in this field, especially from 2019, and identifies four main groups of concerns on this topic. Within these groups, a prevalence of more optimistic over skeptical accounts and, especially, of economic orthodox over heterodox approaches on the issue can be noted. Overall, it is possible to understand that both the reviewed works and their metrics are quite dispersed and varied in scope. Among other reasons, this is due to the lack of a common basic definition, within the field, of AI in the first place.
KEYWORDS: Artificial Intelligence; automation; work.
JEL Classification: J21; O33; P16.

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INTRODUCTION

A systematic review of literature aims to detect, classify, and theorize about the most relevant academic literature on a specific topic. This can be achieved by using replicable procedures and bibliometric criteria, which makes possible to enhance its quality and to access straightforwardly the pertinent works in the field. Applying it to research in political economy provides us with a background to better identify the dominant questions and approaches in a well-defined topic, in this paper, Artificial Intelligence (AI) and its consequences for employment.

With this aim, the use of a well-defined methodology provides the necessary rigor[1] for accessing the most recent and popular theoretical analysis and empirical enquiries in a given area. In this work, our bibliometric analysis was conducted following the basic procedures of the "Theory of the Consolidated Meta-Analysis Approach" (Mariano et al., 2019; Mariano and Rocha Santos, 2017) – Teoria do Enfoque Meta-analítico Consolidado (TEMAC), in Portuguese. Its main goal includes implementing a replicable, systematic, and integrating literature review, grounded on bibliometric principles, which is useful for mapping scientific knowledge.

The TEMAC approach uses different elements to select materials, such as quantities of citations by papers or by authors, keyword frequency, and bibliographic interrelations. All these tools are combined with the role of the reviewers themselves in selecting the pertinent works after the first initial filters. To reach this outcome, the methodology consists of three basic steps: 1) to prepare the research, 2) to present and link the data, and 3) to make the integrating model and the evidence-based validation (Mariano and Rocha Santos, 2017).

In this vein, the objective of this paper was to use a systematic review of the political economy of the AI and employment literature produced between 2008 and October 2020. For that, aside from this introduction and the final remarks, the paper was divided into three main sections according to the three basic methodological steps aforementioned. In the first step, we broadly present the reviewing methodology and its parameters. In the second, we present and evaluate data and its interrelations with a focus on the most prominent papers by their number of citations. Finally, we detail, integrate, and validate the systematic review by classifying the most significant publications within four areas obtained via cross-analysis, which are elucidative of the main research streams at the place: "AI and the future of market job"; "Polarization of jobs and wages"; "Disruptions in jobs demand, changes in education, and reorganization of the workplace"; and "Social controlling, surveillance, and ranking."

By that, we see a strong growing tendency of published papers in this field from 2019 onwards and learn that a major part of the relevant works is published in the United States. We also note a prevalence of more optimistic over skeptical accounts and, especially, of economic mainstream/orthodox over heterodox approaches. Over-

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[1] This rigor intends for reducing biases in the selection of the literature, which may be correlated with convenience, proximity, access barriers to texts and essays, as well as other distortions.

all, it is possible to understand that both the analyses and metrics are quite dispersed and varied in scope. Among other aspects, this is due to the lack of a common basic definition/conceptualization, within the field, of AI in the first place.

PREPARING THE RESEARCH

Following the aforementioned TEMAC method, in the first step, the researchers should select multiple databases and research descriptors (keywords), determine the fields and subfields of knowledge, and define the interest period. The databases selected are *Web of Science (WoS)*, *Scopus*, and *Google Scholar (GS)*. The three were selected to provide wide coverage in economics[2,3]. We have covered three languages, namely, English, Spanish, and Portuguese. In the second step, the measures of the works' relevance are collected. Finally, in the third step, the literature review itself takes place when the author selects and explores the best-fitting papers, identifies the research lines, and makes the evidence-based validation and the integrating model, which finally compares the distinct sources.

Once the databases, timeframe, and keywords are defined, the first step is then to prepare the research. In the *WoS*, *Scopus*, *and GS* databases, the keywords used for this study were "artificial intelligence" paired with "employment," "unemployment," "automation," "labor," "labor," "jobs," and "work" between 2008 and October 2020. In the Portuguese language inquiry, the expressions used were "*inteligência artificial*," "*emprego*," "*desemprego*," and "*automação*." The Spanish language descriptors were "*inteligencia artificial*," "*empleo*," "*desempleo*," and "*automatización*." This allows us to find the available papers about AI and, especially, the ones closely related to any word used to describe employment. It is worth noting that for the Latin languages, only GS presented significant outcomes.

Initially, we used additional filters to select the relevant areas. In *WoS*, the knowledge areas concern, direct or indirectly, economy, industrial production, and social sciences[4]. Then, 420 registers were founded. For *Scopus*, other areas were chosen owing to their particularities[5], even though some interchangeability may

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[2] For more details, see Alberto Martín-Martín, Enrique Orduna-Malea, Mike Thelwall, Emilio Delgado-López-Cózar (2019). Google Scholar, Web of Science, and Scopus: Which is best for me?. Available in: <https://blogs.lse.ac.uk/impactofsocialsciences/2019/12/03/google-scholar-web-of-science-and-scopus-which-is-best-for-me/>. Access in June 11, 2021.

[3] The database Web of Science and Scopus were accessed through the Brazilian source "Periódicos CAPES" <http://www.periodicos.capes.gov.br/> within institutional login provided by the University of Brasília, Brazil. The other software used in this paper permit free access.

[4] The subareas were business, business finance, development studies, economics, engineering manufacturing, humanities multidisciplinary, industrial relations labor, law, philosophy, political science, social issues, social sciences interdisciplinary, sociology.

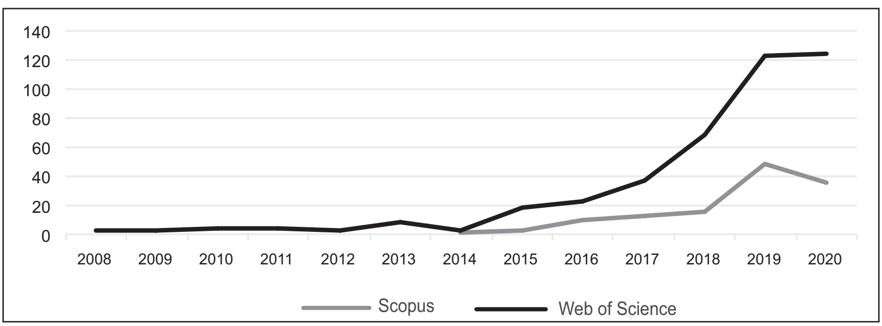
[5] The areas were wider than Web of Science's: art and humanities, business, management, and accounting, economics, econometrics and finance, multidisciplinary, and social sciences.

also be observed. This enabled the extraction of more complete data from the platforms. Thus, we found 131 results. Finally, with the help of the software *Publish or Perish* 7[6], the *GS* data was extracted. The findings in English and Portuguese returned 1000 works, equivalent to the *software*[7] capacity. For the Spanish, 995 titles were found. All queries were applied on October 10, 2020.

DATA PRESENTATION AND ITS INTERRELATIONS

In the second phase, the bibliometric criteria were used for the previous findings[8]. The first point to analyze was the number of publications per year[9]. A growing number of published papers in the field may be noticed as a relevant tendency. For example, in 2019, the quantity more than doubled in comparison with 2018 in both databases, as can be seen from Figure 1.

Figure 1: Total Publications by Year



Source: Scopus and WoS database. Elaborated by the authors

The production by countries of origin also configured an interesting piece of information[10]. In the platform *WoS*, researches from the United States were dominant, with 94 papers (18,3% of the total). For Scopus, the results were similar, where the United States host 41 (26.1%) of the articles, respectively. The data for the first 10 countries are presented in Figure 2.

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[6] Available in <https://harzing.com/resources/publish-or-perish/>. Access in October 10, 2020.

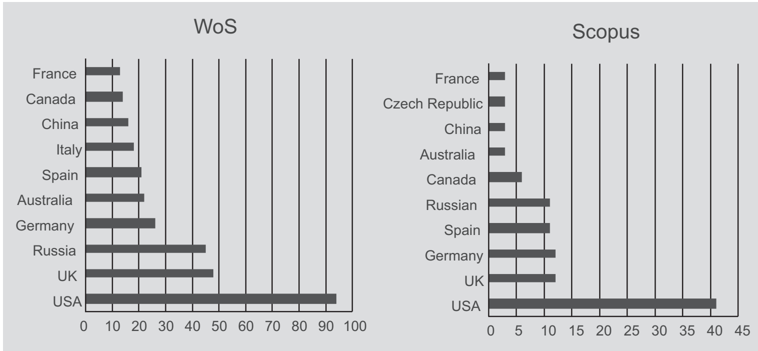
[7] Unlike other databases, Google Scholar permits an even wider search of content and sources, including non-formal works, books, webpages, etc. On the other hand, the platform does not offer detailed metadata in an efficient format to the following analysis. So, only restricted bibliometric evaluations were possible.

[8] For more details, see Mariano and Rocha Santos (2017).

[9] The data is presented by Web of Science and Scopus separately due to incompatibility between their respective databases. Therefore, some information may be in duplicate.

[10] It is worth noticing that Web of Science returns journals that accept papers fundamentally in English. Despite being a bit more varied on that aspect, Scopus also presents most of its papers in English.

Figure 2: Publications per country.



Source: WoS database. Elaborated by the authors.

Papers by the number of citations

Among the bibliometric data, the number of citations is the main landmark to verify the initial relevance of a paper. Despite multiple causes for a paper to eventually reach this position, a systematic review must include number of citations. Because the mentioned databases used distinct criteria to count citations, discrepancies may be observed in the numbers. Also, the most cited papers were presented[11]. The results in Spanish and Portuguese were condensed in one table (i.e., Table 4) due to the small number of related works. Furthermore, in this phase, just the content in a straight line with the aforementioned scope of our review was selected.

For *WoS*, the main references are as follows:

Table 1

Title	Author(s)	Contributions
Why Are There Still So Many Jobs? The History and Future of Workplace Automation	Autor, David H. (2015, 386 cit.)	Defends the idea that the past waves of innovations are not reliable parameters to analyze the new one. According to the author, there is a "polarization" of the employments, characterized by a shrinking of medium-skill jobs in comparison with the low – and high-skill jobs.
Artificial Intelligence in Service	Huang, Ming-Hui; Rust, Roland T. (2018, 135 cit.)	Develops a theory for the replacement of workers by AI in the service sector. They conclude that AI evolution accounts for a threat particularly for the jobs in the lower-intelligence categories.

[11] The complete list can be generated following the steps described above or directly contacting the authors.

Revisiting the Risk of Automation	Arntz, Melanie; Gregory, Terry; Zierahn, Ulrich (2017, 38 cit.)	Criticizes the previsions of replacement of workers for AI and robots, once they overestimate the automatable parts of jobs, disregard heterogeneity in tasks, and pay no attention to the adaptability of jobs to the digital transformations.

Source: *WoS*. Elaborated by the authors.

In *Scopus*, the most cited references are as follows:

Table 2

Title	Author(s)	Contributions
Revisiting the Risk of Automation	Arntz M., Gregory T., Zierahn U. (2017, 54 cit.)	Referred above.
Robots and Humans–Complements or Substitutes?	DeCanio S.J. (2016, 27 cit.)	The author uses Houthakker's model to analyze the effects of AI over wages in the United States. Keeping other things equal, the wages tend to fall regardless of whether the elasticity of substitution between human labor and AI is greater than 1.9.
Automated Pastures and the Digital Divide: How Agricultural Technologies Are Shaping Labour and Rural Communities	Rotz S., Gravely E., Mosby I., Duncan E., Finnis E., Horgan M., LeBlanc J., Martin R., Neufeld H.T., Nixon A., Pant L., Shalla V., and Fraser E. (2019, 23 cit.)	Evaluate the consequences of a "digital revolution" in agriculture. They investigate the impacts on rural labor, based on interviews with locals in Canada, and conclude that there is a possibility of increasing inequalities.

Source: *Scopus*. Elaborated by the authors.

The main references obtained from *GS* are as follows:

Table 3

Title	Author(s)	Contributions
The Future of Employment: How Susceptible Are Jobs to Computerization?	CB Frey, MA Osborne (Frey e Osborne, 2017)	They realize an analysis of susceptibility to computerization of 702 occupations in the United States. For the authors, 47% of the jobs are in the high-probability category of automation, with 70% or more of automation risk.
Trends in US Wage Inequality: Revising the Revisionists	DH Autor, LF Katz, MS Kearney (2008, 2,696 cit.)	The paper examines the growth of wage inequality in the United States since 1963, which presents a pattern variation in 1980. Looking for a complete analysis, they study the role of information technologies in wage changes. In conclusion, the authors theorize about the "polarization" of the job market.

The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market	H David, D Dorn (2012, 2,500 cit.)	Having the paper by Autor, Katz, and Kearney (2008, above) as a starting point, the authors add a model of spatial equilibrium to evaluate the impacts over salaries. They obtained evidence that the effects of "polarization" guide workers from medium skills and routine tasks to the service sector, less subject to robotization.
Job Polarization in Europe	M Goos, A Manning, A Salomons (2009, 1,380 cit.)	The authors estimate the job "polarization" between 1993 and 2006 in 16 European countries caused by the routine-task automation allowed by the recent technological advances.
The Risk of Automation for Jobs in OECD Countries	M Arntz, T Gregory, U Zierahn (2016, 1,200 cit.)	Evaluates the chances of future reduction of jobs as a result of automation and digitalization. However, the authors argue this as unexpected regardless of whether the analysis is conducted based on tasks and not on the occupations, which have a high level of aggregation.
Robots and Jobs: Evidence from US Labor Markets	D Acemoglu, P Restrepo (2017, 967 cit.)	Analyzes the growth of the use of "industrial robots" in previous human-executed tasks in the United States between 1990 and 2007. According to the authors' estimation, one robot more per thousand workers may reduce the employment–population ratio by 0.18%–0.34% and wages by 0.25%–0.50%.

Source: Google Scholar. Elaborated by the authors.

The main Portuguese and Spanish language references obtained from *GS* are:

Table 4

Title	Author(s)	Contributions
Industria 4.0: fabricando el futuro	A Inés-Basco, G Beliz, D Coatz, P Garnero (2018, 39 cit.)	Analyzes the impact of the new technologies on manufacturing, workplace, and global chains of value. In addition, it presents some evaluations about Argentina and Brazil.
Las transformaciones tecnológicas y su impacto en los mercados laborales	J Weller (2017, 20 cit.)	Evaluates the current transformations in the labor market and argues that the impacts of the technical change depend largely on policy choices made by the relevant players.

Economía de plataformas y empleo:¿ Cómo es trabajar para una app en Argentina?	J Madariaga, C Buenadicha, E Molina, C Ernst (Madariaga et al., 2019)	The aim is to classify and analyze the platform work in Argentina. Some alleviations of unemployment were identified as well as challenges for labor regulation and worker protection.
Nuevas tendencias en el empleo: retos y opciones para las regulaciones y políticas del mercado de trabajo	G Bensusán (2016, 17 cit.)	A discussion about the expansion of precarious jobs, especially in Latin America. Furthermore, the report outlines some public policy to deal with this question.
Desempleo tecnologico: una aproximacion al caso latinoamericano	A Aguilera, MG Ramos Barrera (Aguilera e Ramos Barrera, 2016)	The main goal is to analyze the relations between science and technology, innovation, and unemployment rate in seven Latin America countries (1996–2011). The paper concludes that there is no evidence, until now, that technology investments reached the level to increase unemployment.
Las transformaciones tecnológicas y sus desafíos para el empleo, las relaciones laborales y la identificación de la demanda de cualificaciones	G Bensusán Areous, W Eichhorst, JM Rodríguez (2017)	The book gathers three studies related to technological transformations and labor market. They are broadly interested in the education processes and productivity questions as well as their implications in the economics of developing countries.
Na era das máquinas, o emprego é de quem? Estimação da probabilidade de automação de ocupações no Brasil	PH Albuquerque, CAPB Saavedra, RL de Morais (2019, 6 cit.)	The report estimates the automation probabilities of occupations in Brazil, applying the same methodology used by Frey & Osborne (2017). High and very high automation probabilities are found in 54.45% of the formal workers.

Source: Google Scholar. Elaborated by the authors.

DETAILING, INTEGRATING MODEL, AND THE EVIDENCE-BASED VALIDATION

In the third phase, we selected the papers narrowly related to the topic, indicating the research streams, and then compared the results of the distinct sources (Mariano and Rocha Santos, 2017). Then, we used two bibliometric indices — co-citation and bibliographic coupling. The software VOSviewer[12], version 1.6.15, was

[12] Available in:<https://www.vosviewer.com/>. Accessed on June 11, 2021.

used,[13] and closely related themes were represented by a cluster constructed by a parameter resolution[14] (Van-Eck and Waltman, 2014).

The "co-citation" evaluation identifies the papers cited pairwise by the selected articles in the first step. Therefore, if paper, say, A cites paper X and Y, then the pair (X, Y) is co-cited. This indicates similar approaches of research and, therefore, makes it possible to detect relevant studies older than the period selected for the review. On the other hand, the "bibliometric coupling" considers distinct papers that cite the same source, which may indicate the configuration of a research stream measured by the congruence between their references. For example, if papers A and B cite paper X, then the pair (A, B) will be a node in bibliometric coupling.

The co-citation identified in the *WoS* database shows the works usually cited in pairs, indicating similar contents. Setting a minimum of eight citations, we found three distinct clusters. In the *Scopus* database, we identified six clusters but for a minimum of two citations, which was necessary due to the smaller number of the results. For the bibliometric coupling analysis, as long as it identifies the most recent fronts of research, we evaluated the papers produced from 2017 to October 12, 2020. The results for *WoS* were 354 papers. Applying the criteria of a minimum of 6 citations, we found 31 papers, divided into 6 clusters. Only clusters closely related to this review focus are presented below. Finally, the bibliographic coupling applied to the results of the *Scopus* database returned four clusters when a minimum of three-time cited papers is considered.

With the aim of identifying and referencing the clusters through the analysis, we called each cluster by its source, bibliometric procedure, and number (*n*) of the cluster, in this order. Then, the four categories were WoS_ccit_*n* and Scopus_ccit_*n* for the co-citation clusters and WoS_bibc_*n* and Scopus_bibc_*n* for the bibliometric coupling.

AI and the future of the job market

The future of the job market was the main question identified in the most cited works, co-citation analysis, and bibliographic coupling. Some papers have evaluated the state of the art of technological change and its relations with employment. The common purpose was to develop a framework able to accurately predict the probabilities of jobs or tasks being totally or partially substituted by machines. In consonant with some of the most cited authors, the clusters that belong to this topic are:

- *WoS_ccit_1*[15]: It is composed of economic mainstream/orthodox authors

[13] The reviewers of this paper suggested the removal of the network graphs demonstrating the connection among the references, as they have a supplementary character. Images can be accessed by e-mail request to authors.

[14] The clustering process is presented in detail by Waltman, van-Eck, and Noyons (2010).

[15] Composed by Autor (2015), Autor, Levy, and Murnane (2003) Brynjolfsson & McAfee (2014), Ford

that have predicted the impacts of AI on jobs. In most cases, they have evaluated the aggregate impact of innovations as positive;

- *Scopus_ccit_2*[16]: Joins authors that have predominantly investigated the job market transformations generated by modern innovations and the future impact on distinct occupations;
- *WoS_bibc_2*[17]: Gathers papers about the applications of AI to replace tasks previously done by humans;
- *Scopus_bibc_1*[18]: The papers have addressed the distinct effects of AI over the workforce, focusing on the unemployment issues; and
- Scopus_bibc_4[19]: Joins papers about economic transformations in the knowledge economy and consumer's perception.

A significant fraction of the references is dedicated to the characterization of this new era of innovations based on AI. Brynjolfsson and McAfee (2014) have discussed the impacts of the "*Second Machine Age*," grounded on the digitalization of jobs, Economy, and social life. They have indicated an inflection point similar to the introduction of the steam engine during the first Industrial Revolution. Therefore, they argued that society must mitigate negative consequences to inequality and unemployment in this new phase that promises prosperity, welfare, and freedom.

Nick Bostrom (2014) has argued for the prospect of what he called "superintelligence". This would be the development of machines that surpass the human brain in practically all domains. Makridakis (2017) has compared the predictions made to the industrial and digital revolutions and, by that, has hypothesized that the outcomes of AI applications in the next 20 years on life, society, jobs, and business will be several times greater than both digital (1995–2015) and the Industrial Revolution.

Ford (2015) has evaluated the impacts over jobs and inequality caused by technical change. On these grounds, he has proposed that new technologies can automatize not only "repetitive" tasks, often related to low-skilled workers, but also the "predictable" tasks, which can be executed based on historic standards as, for example, the analysis of medical exam images. Similarly, Agrawal, Gans, and Goldfarb (2019a) have evaluated the impact of machine learning in jobs whose tasks demand predictions and, as a consequence, decision-making processes.

Other researches have handled estimations of automation in the next years.

(2015), Frey and Osborne (2017), Schwab (2016), Susskind and Susskind (2015), and World Economic Forum (2016).

[16] Formed by Acemoglu and Autor (2011), Autor, Levy and Murnane (2003), Brynjolfsson & McAfee (2014), and Spitz-Oener (2006).

[17] Composed by Bechmann and Bowker (2019), Huang and Rust (2018), and Singh et al. (2019).

[18] Constituted by Arntz, Gregory and Zierah (2017), Berg, Buffie and Zanna (2018), Bruun and Duka (2018), Frank et al. (2019), Furman and Seamans (2018), and Tubaro and Casilli (2019).

[19] Formed by Ivanov, Webster, and Seyyedi (2018) and O'Donovan (2020).

Benedikt-Frey and Osborne (2017) have indicated that in the United States, 47% of the jobs fulfill the high-risk category of automation by computerization (those with 70% or more chance of automation in the following period). Albuquerque et al.. (2019) have used the same model to Brazil and, by that, estimated 54.45% of the formal jobs at a high-risk level. Conversely, Aguilera and Ramos Barrera (2016) have not yet found pieces of evidence of technological unemployment in Latin America.

The effects of increased use of robots and computational technologies to replace human occupations in the United States were evaluated by Acemoglu and Restrepo (2017) from 1990 through 2007. According to their estimations, one more robot by a thousand workers reduces the employment–population ratio between 0.18% and 0.34% and wages by 0.25% and 0.50%, a pattern that may deppen. Nica, Manole and Stan (2018) have presented estimations of probabilities of automation, and Huang and Rust (2018) have measured possible impacts on the service sector. Lastly, DeCanio (2016) has estimated the substitution elasticity between human jobs and machines.

The working-class conditions are also a topic of interest. Berg, Buffie, and Zanna (2018) have developed four macroeconomic models on the impact of AI on inequality and growth, questioning optimistic assumptions related to this new wave of innovations. They have concluded that automation increases both economic growth and inequality. Furthermore, the wages should be reduced in the short run and a long-run augmenting is possible, although this may take too long. Besides, Bensusán (2017) has investigated the probable (technologically based) precarization of jobs in Latin America. Rotz et al. (2019) have ventured into the possible increase in countryside inequality. As a reaction to this scenario, Weller (2017) has defended the minimization of negative impacts through correct policy choices by key actors.

Lastly, these predictive analyses have suffered important criticisms. Frank et al. (2019) have identified some difficulties in previsions, such as lack of high-quality data and fragile understanding of the dynamics of innovations and institutional mechanisms. David Autor (2015) has questioned the application of past experiences to evaluate this new wave of innovation. Acemoglu and Autor (2011) have considered that models based on two main categories of workers (high/low skills) are insufficient to explain the last 30 years of empirical results. Therefore, they have developed a model with endogenous skills and considered technical changes that could replace human labor. Finally, Arnts Gregory and Zierahn (2016) have criticized the methodological use of a representative employee and emphasized distinct tasks in the same occupations.

Polarization of jobs and wages

The "polarization" of jobs and wages configures a constant theme in discussions about recent technological change and employment. Moreover, this theory offers elements to predictive researches discussed in detail above. Some of the most cited articles have debated such a thesis, as well as *Scopus_ccit_1*[20] and *Scopus_ccit_5*[21].

The main hypothesis was that the demand and supply of skills had a central role in the growth of wage inequality, reducing the jobs and wage share of the median group (Autor, Katz and Kearney, 2008). This occurred because such technologies complement occupations with high skills, replace medium-skilled laborers that perform routine tasks, and have little effect on low-skilled employees (Goos and Manning, 2007; Goos, Manning and Salomons, 2009; Michaels, Natraj and Van-Reenen, 2010). Michaels, Natraj and Reenen (2010) have found evidence of a "polarization" in the United States, Japan, and nine European countries. Goos and Manning (2007) have tested a similar hypothesis exclusively to Great Britain. Other studies about this topic, with similar approaches, are those of Frey and Osborne (2017); Acemoglu and Autor (2011); Autor, Levy and Murnane (2003); and Autor and Dorn (2012).

Nevertheless, some authors think that this tendency in the job market may change in the coming years. According to Autor (2015), despite the continuous reduction of medium-skilled jobs, the wages are not following the same pattern, and the labor share is presenting a global decline (Karabarbounis and Neiman, 2014). One possible explanation is the complementarity between human tasks and robots even in the median occupations. Otherwise, the service sector automation – including sales professionals (Singh et al., 2019) – may experiment greater levels of automation (Wirtz et al., 2018), affecting, even more, the wage and occupation structures.

Disruptions in job demands, changes in education, and reorganization of the workplace

The profound alterations on various dimensions performed by AI indicate another field of interest for researchers. Both applying a historic perspective and analyzing socioeconomic consequences, distinct approaches have attempted to understand the actual impacts of AI on social reproduction. The related clusters are as follows:

- *WoS*_ccit_3[22]: The researchers analyze AI itself and its relations with society. Sociological, philosophical, and economic questions are treated under distinct views;

[20] Composed by Acemoglu and Autor (2011), Autor and Dorn (2012), Autor, Levy & Murnane (2003), Frey & Osborne (2017), Goos and Manning (2007), Michaels, Natraj & Reenen (2010), and Wirtz et al. (2018).

[21] Formed by Autor (2015), Frey & Osborne (2017), and Karabarbounis and Neiman (2014).

[22] Composed by Bostrom (2014), Dreyfus (1992), Kaplan and Haenlein (2019), Kurzweil (2005), Searle (1980), and Turing (1950).

- Scopus_ccit_3[23]: Looks upon issues about digital transformations on laborer's life and economic consequences;
- Scopus_ccit_4[24]: The cluster tries to evaluate AI in a broader social and economic context;
- Scopus_ccit_6[25]: Gathers works concerning technology and the productive system;
- WoS_bibc_1[26]: Deals more directly with threats from robotization to jobs;
- Scopus_bibc_2[27]: Allocate papers about the reorganization of employment, especially as a function of new skills demanded by the current wave of innovation; and
- Scopus_bibc_3[28]: Joins analyses about the demand for labor skills.

Kurzweil (2005) has developed the hypothesis of "Singularity" caused by an accelerated technological development capable of a profound and irreversible change in human life. Therefore, "Singularity" would allow human beings to surpass body and brain limitations. In a similar line, it is discussed the post-humanist possibility (Hayles, 1999) and a profound change in human life (Markoff, 2016) by these means. The capacity to achieve this stage may depend on the imitation of the human brain and, consequently, the development of rationality by machines (Searle, 1980, 1982). Otherwise, AI is not a monolithic term, and this variety leads to different potentialities and risks (Kaplan and Haenlein, 2019).

These developments are commonly treated by some as the Fourth Industrial Revolution, whose social consequences would be subject to political and institutional decisions (Schwab, 2017). Such a process raises questions about interfaces between key technologies and correlated markets as well as the possibilities of a decentralized economy to explore its entire potential (Bresnahan and Trajtenberg, 1995). The current phase, it is said, will demand readjustments from entrepreneurs and business models (Silva et al., 2018). Moreover, the educational demands for the working class establish challenges for almost all countries, such as for Latin Americans (Bensusán, Eichhorst and Rodríguez, 2017).

The workers' conditions are likewise appreciated. Graham, Hjorth, and Lehdon-

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[23] The following are part of this cluster: Autor (2015), Schwab (2017), and Graham, Hjorth and Lehdonvirta (2017).

[24] Formed by Bresnahan and Trajtenberg (1995), Markoff (2016), and Zurcher and Rust (1987).

[25] Composed by Chesbrough (2007), Chui, Manyika and Miremadi (2015), and Fuchs (2010).

[26] Joins papers from Agrawal, Gans, and Goldfarb (2019b), Berg, Buffie and Zanna (2018), Boyd and Holton (2017), Estlund (2018), Wajcman (2017), and Wright and Schultz (2018).

[27] Aggregates Iphofen and Kritikos (2019), Kenney and Zysman (2020), Lloyd and Payne (2019), Means (2018), Padios and Rohn (2018).

[28] The papers are Agrawal, Gans, and Goldfarb (2019), Agrawal, Gans and Goldfarb (2019a), and Prüfer and Prüfer (2020).

virta (2017) have evaluated the consequences of the digital work and "gig economy" over the laborers' conditions and the economic implications of a workforce distributed globally (Ho et al., 2012; Suri, Goldstein and Mason, 2011). The "microworkers," which work on AI improvement, may consolidate an international "open-border" labor market, geographically distributed (Tubaro and Casilli, 2019), although even this kind of jobs can be subject to automation (Lei et al., 2016). This can also be a problem for the peripheral countries (Inés-Basco et al., 2018; Madariaga et al., 2019). In this vein, Estlund (2018) has elaborated suggestions to protect workers replaced by machines, whose rights are threatened. Finally, some argue on a reconfiguration of capitalism, whereas others propose necessary revision of the class notion (Fuchs, 2010).

This group of approaches is also subject to criticisms, such that the unprecedented social and economic transformations foreseen may not exist in the first place, once the common assumptions ignore limits and uncertainties about robot developments (Boyd and Holton, 2017).

Social controlling, surveillance, and ranking

Social controlling, surveillance, and ranking represent another topic and have recently received more attention. Threats to democracies and privacy right violations are associated with incomprehension about potentialities and uses of digital tools such as machine learning and big data. Along with some of the most cited articles, the clusters are as follows:

- WoS_ccit_2[29]: Gathers papers about the complex relations between AI, ethics, inequality, and privacy;
- WoS_bibc_3[30]: Joins papers about the decision-making process in public services as well as privacy questions;
- WoS_bibc_5[31]: Represents great social transformations in economic and communication managements made possible by AI; and
- WoS_bibc_6[32]: Collects papers about public budget control and auditing.

As a structure of control, the wide social ranking has become possible, thanks to AI systems (Citron and Pasquale, 2014). Furthermore, there are social and privacy risks caused by the information access allowed by big data, especially without clear rules, robust transparency (Katyal, 2019; Pasquale, 2015) and biases inherited from the existing social relations (Barocas and Selbst, 2016; Levendowski,

[29] Gathers papers from Barocas and Selbst (2016), Burrel (2016), Kroll et al. (2012), Lecun, Bengio and Hinton (2015), Mittelstadt et al. (2016).

[30] Constituted by Katyal (2019) and Levendowski (2018).

[31] The papers are Kaplan and Haenlein (2020), and Popkova and Parakhina (2019).

[32] It is formed by Moll and Yigitbasioglu (2019) and Kokina and Davenport (2017).

2018), with potential discrimination at place (Bechmann and Bowker, 2019). This situation worsens with the opacity of these technologies (Burrell, 2016) and ethic doubts (Mittelstadt et al., 2016). One example is given by the digital availability of prison records and racial discriminations (Sweeney, 2013).

Other concerns about this scenario refer to political consequences for formal democracy. Recent technological developments, it is said, may have contributed to the emergence of populist practices. Moreover, these developments may enhance job insecurity. The new uses of technologies evolve the long-run perception of unemployment and the threats to workers' living conditions (Nam, 2019). For this, basic income, as well as training programs, are pointed out as a possible solution (Bruun and Duka, 2018).

CONCLUDING REMARKS

Our systematic literature review has detected a growing tendency of published papers in this field, especially from 2019, when the quantity more than doubled in comparison with 2018. The major part of these relevant works was published in the United States. In addition, we identified and analyzed four main groups of concerns about the relations between *Artificial Intelligence* and *employment*: "AI and the future of market job"; "Polarization of jobs and wages"; "Disruptions in jobs demand, changes education, and reorganization of the workplace"; and "Social controlling, surveillance, and ranking." They are elucidative of the main research streams in place. Within these groups, a prevalence of more optimistic over skeptical accounts and, especially, of economic mainstream/orthodox over heterodox approaches on the issue can be noted. Overall, it is possible to understand that both the works and their metrics are quite dispersed and varied in scope. Among other reasons, this is due to the lack of a common basic definition/conceptualization of AI within the field.

Finally, it is worth mentioning that relevant questions remain unanswered or insufficiently considered in terms of a political economy of these processes. In the first place, the papers do not properly address broad socioeconomic tendencies and consequences for capitalism as a system, i.e., in its macro-structural dimensions. Second, and more importantly, the considerable differences between forecasts for job markets take us to some fundamental problems: how solid or reliable are they? Does the "polarization" thesis offer valid explanations, for example, for developing economies? How these so economically heterogeneous countries would face this situation? These and other related aspects may demonstrate some weakness of the approaches collected by this review and thus call for further investigations.

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