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Labor in the Age of Automation: Revisiting the 30-Year Debate on the 'End of Work' Prophecy

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This systematic review revisits the 30-year debate on Jeremy Rifkin's 'end of work' prophecy, which predicted that technological progress would reduce human labor demand, causing unemployment and social crises. We examine key contributions in the economic literature since 1995, focusing on arguments and evidence for and against Rifkin's thesis as well as proposed policies and indicators for monitoring economic transitions. The review reveals nuanced views on the response to technological level and automation on employment demand, with some studies suggesting that new tasks can foster employment levels, whereas others emphasise the need for public policies to balance the job landscape. Education and reskilling policies are the most recurrent proposals to support workers in adapting to evolving labor market supply. The study proposes a group of indicators for monitoring economic transformations driven by technological advancements, including employment trends by sector, wage growth, job quality, income distribution, and pace of technology adoption. In addition, this study advocates broader national and regional analyses and updates to theoretical frameworks explaining labor market dynamics. Future research should expand the scope of the analysis and develop robust monitoring systems to assess the multifaceted effects of automation on the economy and society.

Keywords: labor market, systematic review, employment, technological change, automation.

JEL Classification: J23.

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El empleo en la era de la automatización: 30 años de debate sobre la profecía del "fin del trabajo"

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Esta revisión sistemática retoma el debate de 30 años sobre la profecía del "fin del trabajo" de Jeremy Rifkin, la cual predecía que el progreso tecnológico reduciría la demanda de trabajo humano, provocando desempleo y crisis sociales. Examinamos las principales contribuciones de la literatura económica desde 1995, centrándonos en los argumentos y evidencias a favor y en contra de la tesis de Rifkin, así como en las políticas propuestas y los indicadores sugeridos para monitorear las transiciones económicas.

La revisión revela visiones matizadas sobre el impacto del avance tecnológico y la automatización en la demanda de empleo: algunos estudios sugieren que la aparición de nuevas tareas puede fomentar el empleo, mientras que otros subrayan la necesidad de políticas públicas que equilibren el panorama laboral. Las políticas educativas y de recualificación son las propuestas más recurrentes para apoyar a los trabajadores en su adaptación a un mercado laboral en evolución.

El estudio propone un conjunto de indicadores para monitorear las transformaciones económicas impulsadas por los avances tecnológicos, incluyendo las tendencias del empleo por sector, el crecimiento salarial, la calidad del empleo, la distribución del ingreso y el ritmo de adopción tecnológica. Además, se aboga por realizar análisis más amplios a nivel nacional y regional, así como por actualizar los marcos teóricos que explican la dinámica del mercado laboral. Se sugiere que futuras investigaciones amplíen el alcance del análisis y desarrollen sistemas de monitoreo sólidos para evaluar los efectos multifacéticos de la automatización en la economía y la sociedad.

Palabras clave: mercado de trabajo; revisión sistemática; empleo.

Clasificación JEL: J23.

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1. Introduction

In the thirtieth anniversary of the publication of 'The End of Work’ (Rifkin, 1995), economists find themselves at a new peak of concern regarding the consequences of technological innovations on the employment landscape. Economists hold mixed opinions on the ultimate impact of artificial intelligence (AI) on the number of available jobs and overall job market response (Webb, 2019). Throughout history, dilemmas surrounding the effects of technological advancements have been resolved by increased productivity, ultimately fostering growth, and the emergence of various new jobs and sectors (Bartel et al., 2007). New sectors can increase wages and prices, potentially overcoming wage stagnation and leading to "vacancy chains" in which workers migrate to more advanced occupations/sectors (Vermeulen et al., 2020).

The economic debate surrounding the impact of technological change on employment and working time has a long and rich intellectual lineage. In his 1930 essay Economic Possibilities for our Grandchildren, John Maynard Keynes foresaw a future of unprecedented productivity that would permit a drastic reduction in working hours and material scarcity, while warning of temporary “technological unemployment” as society adjusted to new modes of production (Keynes, 1930/2010). From a more structuralist perspective, Karl Marx analysed the relationship between capital accumulation and mechanisation, arguing that technological innovation, while increasing output, tends to displace labor and intensify exploitation unless accompanied by shifts in ownership and power structures (Marx, 1867/1990). Later, Joseph Schumpeter advanced the influential notion of creative destruction, describing how innovation continuously revolutionises the economic structure by dismantling old industries and giving rise to new ones (Schumpeter, 1942/2003). However, this dynamic view has been contested by authors such as Edmund Phelps, who emphasised the social fragmentation and delayed adjustment costs associated with innovation (Phelps, 2013). Meanwhile, Alfred Marshall already noted in the late 19th century that technological progress may not reduce labor demand if it triggers compensatory mechanisms through falling prices and rising demand (Marshall, 1890/2013). These classical insights provide a valuable theoretical lens through which to interpret contemporary debates on automation, inequality, and labor market transformation, and offer historical depth to the diverse empirical findings reviewed in this study.

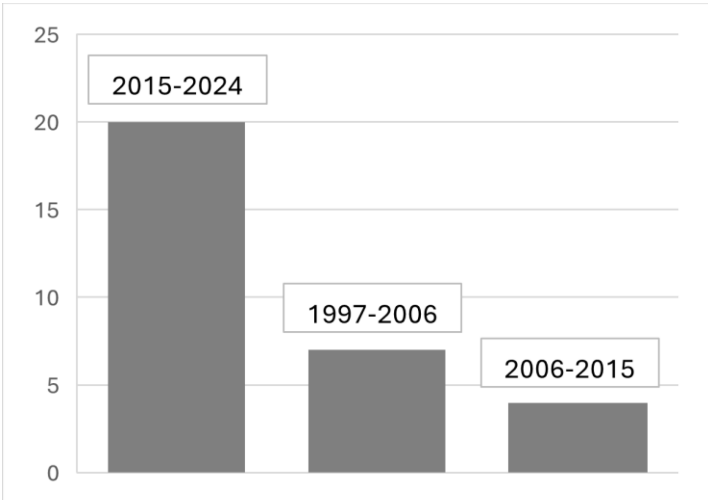
However, the current strength of automation driven by artificial intelligence has raised concerns about how economies can rapidly increase productivity and development without causing higher rates of unemployment and inequality (Domini et al., 2021). In addition, there are some significant debates related to different social sciences regarding how people modify their lives because of the new possibilities of reaching the highest levels of productivity. This includes the length of the labor week, basic income as a generalised policy, or the need for public investment in education and training to equip people with the necessary skills for the AI era (Frank et al., 2019; Furman & Seamans, 2019; Vermeulen et al., 2020; Webb, 2019). As a result of this concern, attention to the topic has grown significantly (Figure 1), with sustained interest in the term 'the end of work’, which has shown a continuous increase from 1920 to 2019. Since Rifkin's work was published, the last decade has been the most fruitful in this regard (Figure 2), aligning with Babina et al. (2024), who observed that AI investments were not specifically influenced by firm growth trends before 2010 according to data collected (Google Books Ngram Viewer, 2024). However, since then, the positive relationship between AI investments and firm growth has become robust, despite sectoral variations.

The prevailing paradigm of work, which has been dominant for the past 100 years, is shifting, and workers must continuously demonstrate their value to organisations in a changing job landscape (Biberman and Whitty 1997). This dynamic must also be understood within the broader interplay between labour supply and demand. From this perspective, the Beveridge curve serves as a useful conceptual and empirical tool to capture labour market mismatches, illustrating how periods of rising job vacancies may coexist with persistent unemployment due to skill gaps or spatial frictions—issues that become more pronounced in the context of rapid technological change (Blanchard & Diamond, 1989).

Figure 1. Google Trends for 'the end of work'.

Source: Google Trends. (n.d.). "The end of work". Retrieved September 30, 2024, from https://trends.google.es/trends/explore?date=2013-10-01%202024-09-30&q=%22the%20end%20of%20work%22&hl=en

Figure 2. Citations per year, by decade.



Source: The Authors from Table 1 data.

In this study, we examine key contributions in the economic literature regarding the fulfilment of Rifkin's prophecy. This analysis is crucial for understanding the paths of modern economies and for preparing economic and social policies to maintain living standards. The objectives are to differentiate the predominant stances on technological impact and to identify areas requiring further study to inform policies for sustainable development in advanced economies. In order to respond to this second challenge, this study provides an indicators panel that monitors the main derivatives of automation. Rifkin (1995) argues that technological progress will reduce human labor demand, causing unemployment and social crises. He suggests transitioning to a post-market economy through policies, such as reducing the workweek, creating social service jobs, and establishing universal basic income.

We conducted a systematic review of the most cited papers since 1995 on "the end of work", focusing on arguments and evidence for and against, as well as proposed policies and indicators for monitoring economic transitions. Recent literature reveals that the impact of automation on employment is complex and varies by technological change and the economic context. Acemoglu and Restrepo (2018) distinguished between the employment-reducing effects of automation and new task creation, which can stabilise jobs. Makridakis (2017) stresses balancing AI's benefits with job displacement risks, urging policymakers to mitigate the negative impacts of automation while creating new opportunities.

Education and skill development are crucial to adapting to these shifts, being the first policy mentioned by both sides authors. Autor and Salomons (2018) note that productivity growth has shifted employment towards high-skill workers, while Frey and Osborne (2017) emphasise the importance of acquiring less automatable skills. Arntz et al. (2016) advocate for task-specific training to prepare workers for technological advancements.

This review clarifies the diverse perspectives of the automation debate, stressing the need to reconcile theoretical and empirical approaches for effective policymaking. It addresses the research gaps highlighted by Dauth et al. (2021) and Grigoli et al. (2020) concerning labor market dynamics and the effects of automation on workers. Although robotisation is a subset of automation that specifically involves the use of robots, it is frequently addressed as the central piece of technological transition. For example, Klenert et al. (2023) noted contradictory findings on the impact of robot adoption on employment, while Acemoglu and Restrepo (2022) highlighted the overlooked link between demographic changes and automation. This study summarises the policies proposed by various authors, regardless of their alignment with Rifkin's thesis, and the indicators they suggest for monitoring economic transformations due to technological advancements.

2. Method

Given the identified gaps in the literature, our systematic review methodology aims to further elucidate the different positions and proposals regarding the impact of automation and technological changes on employment trends.

We adhered to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines as the foundational research method. PRISMA provides a comprehensive framework that enhances the quality and consistency of systematic reviews by offering a detailed checklist of essential reporting items (Moher et al., 2015). This adherence is crucial for several reasons: it ensures that all relevant aspects of the review process are meticulously documented, including search strategy, selection criteria, and data extraction methods. Following the PRISMA, we aimed to increase the reliability and reproducibility of our findings, thereby providing a clear and accurate representation of the evidence.

The search terms and keywords employed, 'end of work', blend articles from several topics from the economic field to the medical and health aspects of work, such as the study of fatigue in relation to the workday. Therefore, this literature research sequence based on the key term becomes contaminated when 'end of work' is used indiscriminately. Hence, it is necessary to combine the analysis of the three main bibliographic sources (Web of Science, Scopus, and Dimensions) with human filtering and the use of automated literature review applications (literature mapping) as follows:

1. Search strategy:

    Search for the term "the end of work" in the Web of Science (WOS) database among academic articles, book chapters, and conference proceedings. (https://www.webofscience.com/wos/woscc/summary/ea4a2999-5dd7-4bf4-bfe0-918c1668fe5d-937bae68/relevance/1) on January 16th, 2024.

    Articles that did not correspond to the study topic and originated from knowledge areas other than economics were excluded.

    Three literature mapping applications (LitMaps, ConnectedPapers, and Semantic Scholar) were used to identify second-order articles with multiple citations connected to the main list of articles on 16 January 2024.

    Complete a database of references by means of Scopus and Dimensions databases employing the same search terms and filters and eliminating the references with five citations or less on 16 January 2024.

2. Inclusion/Exclusion criteria:

We proceeded with abstract screening to ensure that each reference met the area of research. Finally, we read the full texts to confirm eligibility. Discrepancies between authors were resolved through discussion or consultation with a third party.

The combination of the search term 'end of work' restricted to the economics field of study did not make it necessary to employ further specific restrictions within economics, since all the references tackled the expected area of study by the authors (labor market, technological change, and social consequences) and ensured consistency in the screening process.

3. Data extraction:

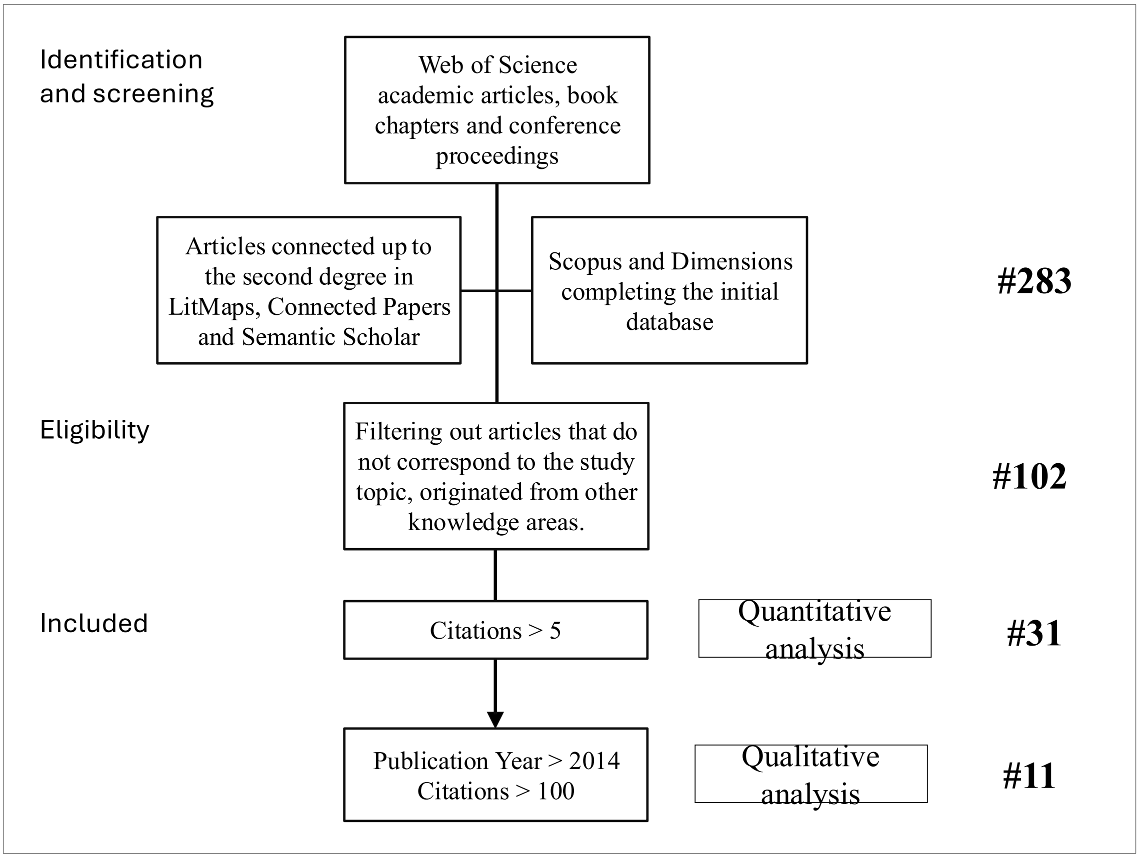
    Then, the authors created a spreadsheet file with a table including the accepted references, their publication year, number of citations on January 16th, 2024, authors, and publishers (accessible for review purposes).

4. Performance analysis of the remaining list.

    References were prioritised according to the total number of citations of each work on January 16th, 2024. We also include the number of citations per year until 2022. This approach enabled us to focus on studies that exerted considerable influence within the academic community, reflecting their impact and relevance in the field of economics. By giving precedence to highly cited works, we ensure that the review incorporates key contributions that have shaped the current understanding and discourse, thereby providing a robust foundation for our analysis and conclusions.

Considering that most citations gather around a reduced number of works and authors, we opted for a systematic review methodology and focused on the main arguments exhibited in the selected references.

Figure 3. PRISMA diagram for the study on 'the end of work' with number of references at each step of the selection.



Source: The Authors.

3. Results and quantitative analysis

Table 1 gathers the list of articles selected in steps 1 to 4, since the publication of Rifkin (1995), by the methodological process followed. A total of 31 references added up to 22,782 citations. The median year of publication was 2,017. 22 years after the publication of Rifkin (1995). Frey and Osborne (2017) clearly hold the majority of the citations, and there are five other references with more than 100 citations per year, and the rest of the references keep 1,466 citations.

Table 1. Most cited articles about 'the end of work'.

Authors	Article Title	Publication Year	Times Cited	Citations per Year
Frey, C. B., & Osborne, M. A. *	The future of employment: How susceptible are jobs to computerisation?	2017	12,327	2,054.50
Autor, D. *	Why are there still so many jobs? the history and future of workplace automation	2015	3,636	454.5
Arntz, M., Gregory, T., & Zierahn, U. *	The Risk of Automation for Jobs in OECD Countries: A Comparative Analysis	2016	2,756	393.71

Makridakis, S. *	The forthcoming Artificial Intelligence (AI) revolution: its impact on society and firms	2017	1,314	219
Mokyr, J., Vickers, C., & Ziebarth, N. L. *	The history of technological anxiety and the future of economic growth: Is this time different?	2015	836	104.5
Acemoglu, D & Restrepo, P *	Robots and Jobs: Evidence from US Labor Markets	2020	447	149
Gregory, T., Salomons, A., & Zierahn, U. *	Racing With or Against the Machine? Evidence from Europe	2016	292	41.71
Autor D. & Salomons A. *	Robocalypse Now?	2017	164	27.33
Arntz, M; Gregory, T; & Zierahn, U. *	Revisiting the risk of automation	2017	157	26.17
Borland, J., & Coelli, M. *	Are Robots Taking Our Jobs?	2017	111	18.5
Klenert, D., Fernandez-Macias, E., & Anton, J. I. *	Do robots really destroy jobs? Evidence from Europe	2022	96	96
Strangleman, T	The nostalgia for permanence at work? The end of work and its commentators	2007	92	5.75
Biberman, J; Whitty, M	A postmodern spiritual future for work	1997	65	2.5
Nierling, L.	“This is a bit of the good life”: Recognition of unpaid work from the perspective of degrowth	2011	65	5.42
Vermeulen, B; Kesselhut, J; Pyka, A; Saviotti, PP	The Impact of Automation on Employment: Just the Usual Structural Change?	2018	49	9.8
Acemoglu, D; Restrepo, P	Demographics and Automation	2022	46	46
Coombs, C; Hislop, D; Taneva, SK; Barnard, S	The strategic impacts of Intelligent Automation for knowledge and service work: An interdisciplinary review	2020	44	14.67
Goos, M., Arntz, M., Zierahn, U., Gregory, T., Gomez, S. C., Vázquez, I. G., & Jonkers, K.	The impact of Technological innovation on the Future of Work	2019	39	9.75
Kapeliushnikov, R.	The phantom of technological unemployment	2019	36	9

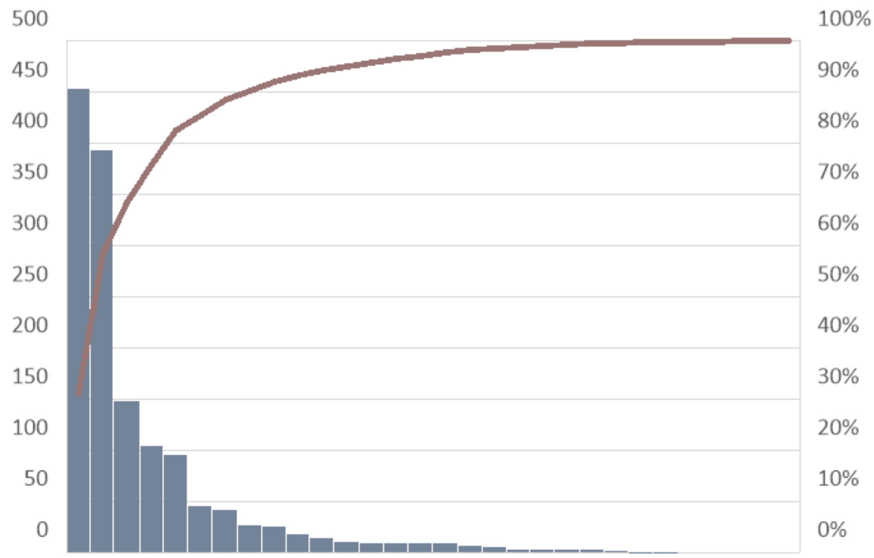
Grigoli, F; Koczan, Z; Topalova, P	Automation and labor force participation in advanced economies: Macro and micro evidence	2020	27	9
Nun, J	The end of work and the marginal mass thesis	2000	23	1
Nun, J	The future of employment and the thesis of the marginal mass	1999	22	0.92
Bowring, F	Post-Fordism and the end of work	2002	22	1.05
Domini, G; Grazzi, M; Moschella, D; Treibich, T	Threats and opportunities in the digital era: Automation spikes and employment dynamics	2021	21	10.5
Ben Vermeulen, Andreas Pyka, and Pier Paolo Saviotti	Robots, Structural Change, and Employment: Future Scenarios	2020	21	7
Buhr, D.	What about Welfare 4.0.?	2017	21	3.5
Appay, B	Economic concentration and the externalization of labour	1998	18	0.72
Moody, K	High Tech, Low Growth: Robots and the Future of Work	2018	14	2.8
Saint-Paul, G	Distribution and growth in an economy with limited needs: Variable markups and 'the end of work'	2006	9	0.53
May, C	Information society, task mobility and the end of work	2000	6	0.26
Meindl, B., Frank, M. R., & Mendonça, J.	Exposure of occupations to technologies of the fourth industrial revolution	2021	6	3

* Included in the qualitative analysis

Source: The Authors.

We observed a strong concentration of citations in the first two articles listed in Table 1 (Figure 4). Following these, there is a prominent group of 11 articles, each garnering over 90 citations and more than 10 citations per year, which we use for the qualitative analysis. While the majority of these articles mostly disagree with Rifkin’s thesis, those that largely agree occupy the first, fourth, and sixth positions (Table 3). Notably, Frey and Osborne (2017) account for more than 50 percent of the citations at the time of the study.

Figure 4. Articles ordered from left to right along the X-axis by the number of citations (Y-axis).



Source: The Authors from data on Table 1.

4. Discussion and qualitative analysis

Overall, the works included in the qualitative analysis (Table 3) indicate that automation has the potential to decrease employment in some degree and the proportion of labor in specific sectors, potentially causing a decline in wages. However, it can also generate employment opportunities in alternative industries and enhance overall productivity. This, in turn, might result in spillovers and indirect increases in employment and demand for labor in tasks that are not automated.

Acemoglu & Restrepo (2020) affirm that automation can reduce employment and labor share in industries where it is implemented, potentially leading to lower wages in a static economic model with fixed capital and exogenous technology. The displacement effect of automation, where capital replaces labor in tasks, tends to reduce labor demand and the labor share, but this can be counterbalanced by the creation of new tasks that favor labor demand (Gregory et al., 2016).

For Borland and Coelli (2017), while automation directly displaces employment within industries, this can be offset by indirect employment gains in customer industries and increases in aggregate demand, although labor share losses are not typically recovered in the short term. The impact of automation on employment can be seen as a structural change, with job losses in some sectors being compensated for by job creation in others, particularly in new, labor-intensive sectors such as food service, cleaning, and hospitality (Autor & Salomons, 2017; Klenert et al., 2022).

Goos et al. (2019) affirm that the effect of automation on employment can vary depending on the elasticity of demand within industries; it may initially boost job growth but later lead to job losses as demand becomes satiated. There is growing concern about the potential threat of automation to workers with low and medium-skill levels, leading to a need for policies that address the increasing importance of non-cognitive skills and digital proficiency.

For Autor (2015) the use of automation technologies can reduce labor but may also enhance employment trends when complemented by human capital and new management methods in the long term. A higher risk of automation can reduce job-finding probabilities for unemployed workers, but labor market training can mitigate this impact. At the firm level, automation can increase total employment and lead to skill upgrading, with a stronger productivity effect than the displacement effect in manufacturing firms (Klenert et al., 2022).

On the grounds of empirical studies, advocates of Rifkin’s thesis are challenged by other studies that deny a dystopian view. For instance, Frey and Osborne’s (2017) concerns about polarisation based on occupation data in the US are countered by Arntz et al. (2017), who re-estimate the share of jobs at risk of automation for twenty-one OECD countries using a task-based approach and find a much lower risk of automation (9%). Similarly, Gregory et al. (2016) and Autor and Salomons (2017), employing data from European countries and OECD databases respectively, respond to Makridakis (2017) by highlighting the potential positive net labor demand effects of technological change, as well as the heterogeneity of employment effects across sectors. Finally, the conclusions of Acemoglu and Restrepo (2018), who use data from the International Federation of Robotics to measure the penetration of industrial robots across US industries and commuting zones indicating the adverse effects of automation, are challenged by Gregory et al. (2016), whose comprehensive dataset analyses the impact of routine-replacing technological change (RRTC) on labor demand across a broad geographical and temporal scope within Europe.

a. Authors’ stances in the analysed articles

Authors who mostly support Rifkin’s thesis argue that technological advancements, particularly automation, adversely affect employment and wages. Acemoglu and Restrepo (2022) concluded that the spread of industrial robots as part of automation has led to a decrease in employment and wages across commuting zones in the US, with a shortage of middle-aged workers specialised in manual production tasks. Similarly, although Autor and Salomons (2017) take a critical stance towards Rifkin’s thesis, they recognise that while productivity growth has not reduced jobs overall, it has skewed the distribution of employment towards high-skill workers at the expense of middle-skill workers, contributing to employment polarisation. Frey and Osborne (2017) estimate that 47% of jobs are at high risk using an occupation-based approach. Finally, Mokyr et al. (2015) express concern over the potential dehumanising effects of technological progress, as illustrated in Rifkin's thesis. They acknowledge the fear of a world in which the elimination of work itself leads to dehumanisation and emphasise the need to recognise the fundamental human satisfaction that comes from distribution.

On the other hand, authors who mostly reject Rifkin’s thesis present evidence that automation may not have a uniformly negative impact on employment. Klenert et al. (2022) find a positive correlation between robot adoption and total employment in Europe, suggesting that sectors with high levels of automation have been more resilient in terms of employment. Borland and Coelli (2017) conclude that there is no indication of decreasing aggregate employment in the Australian labor market, with total hours worked per capita remaining stable. Similarly, Arntz et al. (2017) use a task-based approach to estimate that only 9% of jobs across OECD countries are at a high risk of automation.

These studies collectively underscore the complex interplay between automation and employment, highlighting the need for nuanced policy interventions to mitigate adverse outcomes.

Given the ambiguous findings observed in the reviewed literature, it is essential to identify the key factors that influence whether technological change leads to net job losses or gains. One determinant is the type of technology: studies focused on industrial robots (e.g., Acemoglu & Restrepo, 2020; Klenert et al., 2023) often report labor-displacing effects, while those exploring AI or digital tools (e.g., Makridakis, 2017) highlight complementary potentials. The skill level of workers is also central: Frey & Osborne (2017) stress the vulnerability of low-skill occupations, while Autor (2015) and Arntz et al. (2017) emphasize polarization and the relative resilience of high-skilled roles. The elasticity of demand emerges in Goos et al. (2019) and Gregory et al. (2016), who note that labor effects may depend on product market dynamics and spillovers. The presence of public policies, especially those supporting reskilling and labor transition, is a recurring element in Makridakis (2017), Arntz et al. (2017), and Frey & Osborne (2017), who all stress that institutional support can mitigate automation risks. In methodological terms, occupation-based approaches such as Frey & Osborne's tend to yield higher automation risk estimates than task-based approaches like Arntz et al. (2017), which better capture within-job heterogeneity. Finally, the regulatory and institutional context matters: Borland & Coelli (2017) and Gregory et al. (2016) suggest that more flexible labor markets and adaptive institutions can absorb automation shocks more effectively.

Also, mechanisms through which technological change affects employment (Table 2) allow to synthesise the diverse insights emerging from the literature. Although most of the studies reviewed do not adopt general equilibrium models explicitly, this framework offers a coherent lens to capture both direct and indirect effects across the economy. Table X summarises six key mechanisms, the relevant indicators (as described in Appendix 1), and the specific articles that support each pathway. This classification helps clarify how automation and related innovations operate through substitution, productivity spillovers, reallocation dynamics, institutional responses, and changing labour preferences.

Table 2. Mechanisms through which technological change affects employment.

Mechanism	Relevant Indicators (from Appendix 1)	Transmission Channel	Articles Supporting This Mechanism
Direct substitution of labor by capital (automation)	Jobs at risk, automation level, technological unemployment, robot adoption, capital/labor ratios	Productivity of capital rises; firms replace human labor with technology, reducing labor demand in routine or automatable tasks. Can generate structural unemployment if labor reallocation is insufficient.	Frey & Osborne (2017); Acemoglu & Restrepo (2020, 2022); Autor & Salomons (2017); Arntz et al. (2017); Borland & Coelli (2017)
Creation of new tasks and sectors	Employment demand by sector, job patterns, spillovers on production, new job categories	Technological progress creates new goods and services; increased productivity and spillovers lead to job creation in emerging sectors and roles, especially in non-automatable domains.	Gregory et al. (2016); Autor (2015); Klenert et al. (2023); Vermeulen et al. (2018); Makridakis (2017)
Productivity increase and aggregate demand expansion	Productivity, value-added growth, employment-to-population ratio, total employment demand	Higher productivity lowers prices or raises real incomes, increasing consumption and production. Labor demand rises in complementary or	Autor (2015); Autor & Salomons (2017); Goos et al. (2019); Acemoglu & Restrepo (2020); Makridakis (2017)

		expanded sectors depending on demand elasticity.	
Intersectoral and structural reallocation	Revenue distribution by sector, labor force participation rate, external shocks	Technology shifts economic structure, reallocating resources across sectors. Efficient reallocation depends on labor mobility and market flexibility; otherwise, mismatches and regional unemployment arise.	Gregory et al. (2016); Borland & Coelli (2017); Klenert et al. (2023); Vermeulen et al. (2018)
Institutional and public policy channels	Education and reskilling, active labor market policies, public job provision, basic income	Policy interventions influence labor supply and wages through education, subsidies, public jobs, or income support, modifying equilibrium employment and allocation.	Makridakis (2017); Arntz et al. (2017); Autor (2015); Frey & Osborne (2017); Goos et al. (2019)
Social preferences and cultural transformation	Meaningful employment, social discourse on work, gig economy volume, voluntary job proportion	Technology alters participation decisions and labor preferences. People may shift toward part-time, gig, or voluntary jobs, or prioritize work-life balance, affecting labor supply and job structure.	Mokyr et al. (2015); Bailey et al. (2019); Nierling (2012); Strangleman (2007); Klotz (2021)

Source: The Authors.

b. Points at discussion.

The central debate revolves around the impact of technological change on employment in automation. While some research highlights negative effects on jobs (Frey & Osborne, 2017; Mokyr et al., 2015; Acemoglu & Restrepo, 2020), other studies offer a more nuanced view, suggesting that automation may not immediately result in mass job losses (Autor, 2015; Arntz et al., 2017; Makridakis, 2017). These contrasting findings highlight the complexity of predicting the long-term effects of automation on employment.

Several scholars have emphasised the potential risks of automation, including job displacement and wealth inequality. Makridakis (2017) warned that coming AI could disrupt society without proper intervention, while Gregory et al. (2016) raised concerns about the adequacy of new job creation to offset job losses. Meanwhile, Battina (2020) and Brynjolfsson et al. (2019) stressed the need for a detailed sectoral analysis, noting that technological adoption often occurs slower than anticipated, requiring substantial resources for industry transformation.

Klenert et al. (2023) challenge the narrative of robots destroying jobs, showing a positive correlation between robot adoption and employment in Europe. This contrasts with Acemoglu and Restrepo's (2020) findings of reduced employment and wages in U.S. regions affected by industrial robots. Similarly, Borland and Coelli (2017) found no evidence of job destruction in Australia, while Autor and Salomons (2017) argue that although productivity growth hasn't reduced overall employment, it has contributed to job polarization by favoring high-skill workers.

Finally, the debate extends to broader questions regarding the future of work. Some advocate allowing market forces to replace lost jobs naturally, as in past technological waves, while others suggest rethinking the role of work altogether. This could involve adjusting regulatory frameworks to embrace voluntary work and universal basic income, as proposed by Šarapovas et al. (2024), leveraging AI-driven productivity gains for societal benefits.

Table 3. Summary of main stances over Rifkin's thesis.

Sorted by number of citations	ARTICLE	Predominant STANCE about Rifkin's thesis	POLICIES ADVOCATED subsequent to their stance
1	Frey & Osborne (2017).	In favor	• investing in education and reskilling to adapt to changing job requirements • retraining programs for displaced workers • fostering job creation in emerging sectors
2	Autor (2015).	Against	• guaranteed minimum income for each family • government as the employer of last resort for the hard-core jobless • two years of free education in community or vocational colleges • fully administered federal employment service • individual Federal Reserve Bank sponsorship in area economic development free from the Fed's national headquarters
3	Arntz at al. (2017).	Against	• upskilling and reskilling programs for workers • labor market policies that support employment transitions
4	Makridakis (2017).	In favor	• investment in retraining programs • fostering innovation in new industries • creating regulatory frameworks to ensure equitable distribution of AI-driven benefits
5	Mokyr et al. (2015).	Against	• policies that consider the moral implications of technological progress for human welfare • recognition of fundamental human satisfactions that come from meaningful work • policies that preserve the humane aspects of employment amidst technological advancement
6	Acemoglu & Restrepo (2020).	In favor	• observed negative effects of robots on employment and wages, measures to support affected workers, potentially through retraining programs and labor market interventions • targeted economic development strategies for regions facing adverse impacts from robot adoption.

7	Gregory et al. (2016).	Against	• policies to foster product demand and support local demand spillovers may help mitigate the potential negative effects of routine-replacing technological change on labor demand • targeted policies to ensure that gains benefit the labor force
8	Autor & Salomons (2017, June).	Against	• promoting workforce skills and adaptability in response to technological changes • policies that support innovation and the diffusion of technology across sectors can help balance productivity gains with employment growth
9	Arntz et al. (2017).	Against	• tailored policies that address the specific impact of automation on different tasks within occupations • policies related to retraining and upskilling workers, • promoting innovation and technological adoption, and creating targeted support for industries facing significant automation challenges
10	Borland & Coelli (2017).	Against	• policies to facilitate the adjustment and re-employment of workers who are displaced due to technological change • a safety net for those who are temporarily or permanently disadvantaged by job loss due to new technologies
11	Klenert et al. (2023).	Against	• policies promoting the continued adoption and integration of industrial robots • policies that support the resilience of country–sector pairs with high levels of automation to ensure continued employment growth despite labor-saving technical progress.

Source: The Authors.

5. Implications, policies and indicators.

Whether or not the authors agree with Rifkin's thesis, they all propose or mention specific policies that must be considered for enhancing social transformation, facilitating economic transition derived from evolving technological advances, and alleviating potential social problems.

In addition, the authors highlight a significant need to monitor the evolution of societies and economies to ensure that the benefits of increased productivity are shared across all societal groups, thereby preventing polarisation (Autor, 2022). Thus, it is also critical to count the corresponding indicators that form the dashboard to track the consequences of technological advances and social conditions (see Appendix 1).

a. Policies, adapting to automation's impact.

The most recurrent policy proposed by the authors in the analysed articles was education and reskilling, mentioned in three out of four articles in the qualitative analysis (Table 4). They suggest that education and reskilling policies will support workers in adapting to changing labor market demands and acquiring new skills that align with evolving job requirements. Additionally, it underscores the significance of lifelong learning and skill development to prepare the workforce for the challenges and opportunities arising from technological change. Goos et al. (2019) remark the idea that education and reskilling policies play a critical role in mitigating the potential negative effects of technological advancement on polarization and facilitating the transition to new and evolving job opportunities

Vermeulen et al. (2018) summarise the necessary public responses in three policy types of interventions: social initiatives, economic aspects, and changes in the regulatory framework. Social initiatives seek to ensure or alleviate the adverse effects of automation. Here, we find active labor market policies and human welfare policies, such as a safety net, the implementation of basic income, and public job provision.

The proposals centered on economic aspects point out to foster new industries capable of absorbing the remaining displacement labor supply from other sectors. They emphasise the need for policies that support the growth and development of new and emerging sectors, particularly those that are likely to create employment opportunities in the face of disruptive technological advancements (Makridakis, 2017; Arntz et al., 2017). They underscore the relevance of fostering an environment conducive to the growth of innovative industries and emerging sectors, which could involve targeted investments, regulatory frameworks, and incentives aimed at promoting the expansion of new and potentially job-rich areas of economic activity. As described by Domini et al. (2021), automation spikes represent a significant disruption in the way firms produce, thereby impacting their employment dynamics and structure. Their effect is positively correlated with the preceding and contemporaneous growth in employment due to the lower separation rates of investing firms, leading to net employment growth at the firm level.

Most authors identify the type of intervention (e.g., education and reskilling, active labor market policies, safety nets), but few offer specific design features such as eligibility criteria, institutional responsibilities, or evaluation frameworks. Even less frequent is the discussion of financial feasibility or funding sources for these policies. Only a minority of contributions, such as Makridakis (2017) or Frey & Osborne (2017), allude in general terms to public investment or state-supported training schemes, without entering into fiscal planning or implications for redistribution.

Finally, there are proposals based on a regulatory framework. We find here those regarding an equitable family and regional distribution of AI-driven benefits and suggestions to ensure that all workers count on meaningful work that provides them with satisfactory jobs (Arntz et al., 2017; Wike & Stokes, 2018).

It should be noted that none of the most cited articles explicitly proposed the implementation of reducing the workweek, as Rifkin advocated. Frank et al. (2019) pointed out the increasing fear of mass technological unemployment and called for policy efforts to address the consequences of technological change. Overcoming these problems requires improvements in the longitudinal and spatial resolution of data, as well as refinements to data on workplace skills to enhance the decision framework.

Table 4. Summary of policy proposals in the 11 articles examined in the qualitative analysis.

group	policies	count	% of analysed papers
HUMAN CAPITAL		8	
	education and reskilling	8	73%
ECONOMIC		6	
	foster new industries	6	55%
SOCIAL		10	
	active labor market policies	5	45%
	human welfare policies	2	18%
	basic income	1	9%
	public job provision	1	9%
	safety net	1	9%
REGULATION		4	
	equitable distribution of AI-driven benefits	2	18%
	equitable regional distribution of AI-driven benefits	1	9%
	meaningful work	1	9%
total		28	

Source: The Authors.

b. Indicators, summoning a dashboard to monitor the transformation

As automation continues to transform industries, it is crucial to capture a comprehensive view of its effects on various dimensions. A well-designed dashboard allows policymakers, businesses, and researchers to track not just employment rates but also the quality of jobs, wage distribution, workforce skills, and sectoral shifts.

First, automation's impact is not uniform; it varies across different industries, job types, and regions, as mentioned by Acemoglu and Restrepo (2020) for the US labor market. A multifaceted dashboard can reveal these disparities by incorporating indicators such as employment trends by sector, changes in job roles, shifts in the demand for specific skills, and different impacts by region. This detailed insight helps identify which segments of the labor market are most vulnerable to automation, enabling targeted interventions.

Second, beyond employment, automation influences wage structures, job satisfaction, and economic inequality, as pointed out by Makridakis (2017). Indicators that track wage growth, job quality, and income distribution are essential for understanding the broader socioeconomic impact of automation. For instance, Autor (2015) indicates that a rise in low-wage jobs alongside the decline of middle-skill jobs may indicate increasing polarisation, which could have long-term implications for social stability.

Moreover, a dashboard can integrate forward-looking indicators, such as the pace of technology adoption (Makridakis, 2017) and the preparedness of the workforce (Autor, 2015). By monitoring educational attainment, retraining efforts, and the alignment of skills with emerging job opportunities, stakeholders can proactively address skill gaps and support workers in transitioning to new roles.

Appendix 1 presents and describes the fifty-eight indicators employed by the authors in the qualitative analysis. These indicators are built by employing different raw indicators from renowned entities. A raw indicator refers to low-processed or basic data, such as the total number of hours worked per week or number of employees. This is a direct measurement provided by a statistical source. In contrast, the indicators employed by the authors in the qualitative analysis can take this raw data and process it to provide more insight.

We identified twenty-two raw indicators (Table 5) that can be grouped into six sorts. First, several articles mention data related to the job structure of the economy or sectors. They include indicators focusing on the composition and characteristics of jobs and the technological skills to be performed. Here, we find indicators such as jobs-at-risk, occupation automation level, or job patterns. The second group is the most numerous and includes the indicators related to the labor market: total employment demand and by sector, productivity, labor supply, labor force participation rate, unemployment rate, technological unemployment, and wages. A third group of indicators considers the weight of the different sectors in the economy and how the sector structure changes along with technological transformation: revenue distribution by sector, spillovers on production, and external shocks. The fourth group measures social sensitivity regarding the social impact of automation, including aspects related to income distribution and human welfare. There is a fifth group concerned about the independent variables associated with the introduction of technological advancements and investment in automation/robotisation. Finally, social preferences sort evolves in parallel with the habits and cultural characteristics of societies, where work becomes a source of enjoyment rather than merely a means to provide for oneself and one's family.

We must also indicate many mentions related to the postwork society and the existence of meaningful jobs (Bailey et al., 2019), although the approach of the study is oriented to the economic field. Moving into the interdisciplinary scheme that Coombs et al. (2020) advocate, there is space for indicators that measure the different social aspects of work that technological transition entails (Klotz, 2021): hours worked, voluntary job proportion, social sector proportion in the economy, employees in part-time or short-term jobs, remote jobs, gig-economy volume, satisfaction at work, social discourse on work, or employees quitting. Nierling (2012) concluded that unpaid work, such as providing care, community services, and subsistence, can significantly contribute to an individual's well-being. She also suggests that a transition towards a society not triggered by income requires a shift in the normative paradigm concerning work. The optimism for this utopia is not generalised. Strangleman (2007) emphasises the need to recognise the structure of feeling and nostalgia for stability, denying the transformative power of human agency and highlighting the sociological strength of finding meaning and stability in the contemporary habit of work.

Table 5. List of the main raw indicators employed by the authors.

indicator	count	group
Jobs at risk	10	Jobs structure
Automation level	8	Jobs structure
Employment demand by sector	5	Labor Market
Productivity	4	Labor Market
Labor supply and demand	4	Labor Market
Technological advancements	3	Technology

Employment demand	3	Labor Market
Labor force participation rate	3	Labor Market
Technological unemployment	2	Labor Market
Technological investment	2	Technology
Spillovers on production	2	Economic
Income distribution	2	Income distribution
Revenue distribution by sector	1	Economic
Wages	1	Labor Market
Human welfare	1	Income distribution
Meaningful employment	1	Social preferences
Employment demand by region	1	Labor Market
External shocks	1	Economic
Unemployment rate	1	Labor Market
Raise earnings	1	Income distribution
Jobs patterns	1	Jobs structure
Labor demand	1	Labor Market
total	58	

Source: The Authors.

6. Conclusions

This study examines the economic literature on the impact of technological progress on employment, as predicted by Jeremy Rifkin in his 1995 book "The End of Work". It identifies the predominant economic perspectives on the new technological wave, main arguments, and the policies needed to ensure sustainable development in advanced economies. We reveal nuanced views on the impact of automation on employment, with some studies suggesting that new tasks can foster employment levels, while others emphasise the need for education and skill development to adapt to the changing job landscape. Without a clear winner from the debate, we clarify the distinct mainstream within the ongoing debate to ensure a more coherent understanding and effective application of the findings in shaping future economic and social policies.

This article also proposes a classification of employment impact mechanisms based on a general equilibrium logic, offering a structured synthesis of the theoretical and empirical insights gathered from the most influential studies.

Our study effectively enriches the understanding of the response of the labor market to technological progress. This approach responds directly to the ambiguity surrounding public concerns about labor market impacts and technological advancements. In addition to exploring these research gaps, our study provides a comprehensive summary of the policies proposed by various authors, irrespective of their alignment with Rifkin's thesis. We have also systematically outlined the indicators deemed essential for monitoring economic transformation driven by recent technological advancements. Furthermore, this study identifies both explicit and implicit suggestions for tracking potential shifts in the economy. By consolidating these policy recommendations and indicators, our study contributes to a more informed and practical understanding of how to navigate the evolving landscape of labor and technology.

Although this study offers valuable insights into the debate inspired by Rifkin's work, it is important to acknowledge certain limitations. These include the need for broader national and regional analyses of the impact of automation and updates to the theoretical frameworks explaining labor market dynamics and their societal effects. In addition, we have focused on developed countries, which have a wide scope of implications in those economies where automation level and technological sophistication are lower. Future research should address these gaps by expanding the scope of analysis and developing robust monitoring systems to assess the multifaceted effects of automation. This will involve creating a comprehensive set of indicators based on the contribution of this study to improve economic management worldwide. It will also enhance the adjustment of the main theoretical frameworks (Neoclassical, Keynesian, Institutional, Human Capital, Search and Matching, etc.) on the labor market, revising, when necessary, a new formulation of their analytical foundations.

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Appendix

Appendix A. Description of the main indicators employed by the authors in their research.

ARTICLE	INDICATORS
Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs	**Probability of computerization**: P(z* | X*, D), where z* denotes the probability of computerization, X* represents the test features, and D consists of the training data used for prediction.

ARTICLE	INDICATORS
to computerisation?. Technological forecasting and social change, 114, 254-280.	These features include variables such as educational attainment, wage levels, and specific job attributes. On the other hand, D consists of the training data, which is used to train the Gaussian process classifier. This data would likely include historical information about occupations and their respective levels of computerization, serving as the basis for making predictions about new, unlabelled test data. In addition to that, they complementary use the **number of jobs at risk**, **relationship between an occupation's probability of computerization, wages, and educational attainment**.
Autor, D. H. (2015). Why are there still so many jobs? The history and future of workplace automation. Journal of economic perspectives, 29(3), 3-30.	The **employment-to-population** ratio is a measure of the proportion of a country's population that is employed. The author likely used historical data on this ratio to assess trends in employment levels relative to the overall population. **Fluctuations in the unemployment rate** refer to changes in the percentage of the labor force that is unemployed. By analysing historical unemployment rate data, the author gains insights into the cyclical patterns of joblessness and assess the impact of automation on overall employment levels. **Technology investment data**, such as **private fixed investment in information processing equipment** and **software as a percentage of Gross Domestic Product (GDP)**, provide insights into the level of capital investment in technologies that may affect labor demand and productivity. **Business cycle effects** refer to the impact of economic cycles, such as recessions or expansions, on the labor market. By considering **how business cycles coincide with technological advancements**, the author assesses the influence of economic conditions on employment dynamics. **Global events**, specifically **the rise of import penetration from China**, is assessed using **trade data**, **import/export statistics**, and economic indicators to understand the impact of international trade on domestic labor markets. **Changes in occupational patterns** may involve analysing data on **job categories**, **wage trends**, and the **distribution of employment across**

ARTICLE	INDICATORS
	industries and sectors to identify **shifts in the types of jobs available** and **the skills in demand**. The complementarities between automation and labor that increase **productivity**, **raise earnings**, and augment **demand for labor** is supported by economic models, empirical studies, and analyses of specific industries or occupations to demonstrate the ways in which technology interacts with labor to enhance overall economic output and employment opportunities.
Arntz, M., Gregory, T., & Zierahn, U. (2017). Revisiting the risk of automation. Economics Letters, 159, 157-160.	The indicators employed by the author for technological advancement include measures of **automation adoption rates**, **investment in digital technologies**, and **advancements in artificial intelligence and robotics**. For job displacement, the author uses indicators such as **layoffs due to automation**, **shifts in occupational employment**, and **retraining programs for displaced workers**. In terms of employment trends, the author looks at changes in **employment rates across different industries**, **shifts in the demand for specific skills in the labor market**, and the **development of new job categories as a result of technological advancements**.
Makridakis, S. (2017). The forthcoming Artificial Intelligence (AI) revolution: Its impact on society and firms. Futures, 90, 46-60.	Historical Trends in Technological Revolutions: These indicators involve examining historical data on the impact of past technological revolutions, such as the Industrial and Digital revolutions, on **employment patterns**, **economic restructuring**, and **wealth distribution**. This provides a basis for understanding the potential implications of the upcoming AI revolution. Susceptibility of Different Occupational Activities to be Replaced by Machines and Robots: The author utilizes studies and reports, such as those by McKinsey and other experts, that assess the **susceptibility of various occupational activities to automation**. This includes data on the **percentage of tasks within different professions that are highly susceptible, less susceptible, and least susceptible to automation**. Employment Statistics: The author incorporates quantitative data on **employment trends across different sectors, including agriculture, manufacturing, and services**. This includes information on the **decline in certain sectors and the growth in others**, providing insight into the shifting landscape of employment.

ARTICLE	INDICATORS
	Automation Projections: The author considers projections and estimates regarding the potential impact of AI and automation on jobs and industries. This involves data on the **expected rate of job displacement, the types of tasks that are likely to be automated, and the timeline for these changes**. Industry-Specific Data: The author likely examines industry-specific data to understand how AI technologies are being adopted and integrated across different sectors. This involves analysing trends in **AI investment, the development of AI applications in industries such as healthcare, finance, and manufacturing, and the potential effects on job roles within specific sectors**. Wealth Distribution: The author considers data related to **wealth distribution**, such as **income inequality trends**, **wealth accumulation among different demographic groups**, and the **potential impact of AI on wealth distribution patterns**. This involves referencing economic studies, reports, and **historical wealth distribution trends**.
Mokyr, J., Vickers, C., & Ziebarth, N. L. (2015). The history of technological anxiety and the future of economic growth: Is this time different?. Journal of economic perspectives, 29(3), 31-50.	Labor Market Dynamics: This encompasses various aspects such as **trends in job creation**, **job destruction**, **labor force participation rates**, and **shifts in the composition of the workforce**. Monitoring these dynamics allows the authors to assess the impact of technological progress on employment patterns and the overall structure of the labor market. Income Inequality: Examining **trends in income distribution and disparities** within the labor force provides insights into how technological advancements may influence economic inequality, particularly in relation to the **potential displacement of certain workers or the creation of highly specialized, high-income roles**. Human Welfare: Measuring **human welfare indicators**, such as access to meaningful work, job security, and overall well-being, offers a holistic view of the societal impact of technological progress on individuals and communities, beyond purely economic considerations. Technological Unemployment: Tracking **instances of technological unemployment**, where individuals lose their jobs due to technological

ARTICLE	INDICATORS
	advances, provides a specific measure of the influence of technology on labor market dynamics and potential displacement of workers. Satisfaction and Meaning Derived from Work: Assessing subjective measures of **job satisfaction, fulfilment, and meaning in work** can offer insights into the human experience of employment and the potential effects of technological progress on the quality of work and life satisfaction. Qualitative Assessments of the Impact of Technology on the Nature of Employment: Utilizing qualitative research methods, the authors may capture firsthand accounts and **narratives that depict the evolving nature of work**, the challenges posed by technological advancements, and the broader implications for individuals and society.
Acemoglu, D., & Restrepo, P. (2020). Robots and jobs: Evidence from US labor markets. Journal of political economy, 128(6), 2188-2244.	Exposure to robots: The authors construct a **measure of exposure to robots using data from the International Federation of Robotics (IFR)** on the increase in robot usage across industries. The exposure to robots measure is defined as **APRi**, the adjusted penetration of robots computed from European countries. They also exploit variation in industry-level adoption of robots in the US and European countries, such as the **adjusted penetration of robots between 1993 and 2007** to uncover the effects of the spread of robots on US labor markets. Robot usage across industries: The authors use counts of the **stock of robots by industry, country, and year from the International Federation of Robotics (IFR)** to measure robot usage across industries. This data allows them to examine the penetration and adoption of robots within specific sectors and analyse the relationship between robot usage and various labor market outcomes. Instrumental variable estimates and regression analyses: The authors employ instrumental variable (IV) estimates and regression analyses to quantify the **relationship between exposure to robots and its impact on employment and wages across commuting zones**. They use statistical methods to estimate the causal effect of robot exposure on labor market outcomes while addressing potential endogeneity and omitted variable biases. These methods involve specifying the relationships between exposure to robots and labor market variables, estimating the parameters of these relationships using statistical

ARTICLE	INDICATORS
	techniques, and **drawing inferences about the impact of robot exposure on employment and wages**.
Gregory, T., Salomons, A., & Zierahn, U. (2016). Racing with or against the machine? Evidence from Europe. Evidence from Europe (July 15, 2016). ZEW-Centre for European Economic Research Discussion Paper, (16-053).	Labor Demand Effects of RRTC: The authors estimate the labor demand effects of routine-replacing technological change (RRTC) using a task framework of **regional labor demand in tradable and non-tradable industries**. They use empirical data for 238 European regions over the period 1999-2010 to quantify the impact of RRTC on labor demand. Direct Substitution of Capital for Labor in Task Production: The paper considers the **direct substitution of capital for labor in task production** as a channel through which technological change affects labor demand. This involves analysing how advancements in technology lead to a shift towards capital inputs in the production processes of firms. Compensating Effects Operating through Product Demand and Local Demand Spillovers: The authors also distinguish **compensating effects operating through product demand and local demand spillovers as additional channels through which technological change affects labor demand**. They model how declining capital costs incentivize firms to substitute capital for routine labor inputs and to restructure production processes towards routine task inputs, while also considering the increase in product demand and local labor demand resulting from these changes.
Autor, D., & Salomons, A. (2017, June). Robocalypse now: Does productivity growth threaten employment. In Proceedings of the ECB Forum on Central Banking: Investment and Growth in Advanced	Data on Employment: The author employs measures such as the **number of employed workers and the ratio of employed workers to the working-age population to capture the level of employment across different industries and countries**. This data helps in understanding the dynamics of workforce participation and the impact of productivity growth on overall employment levels. Labor Productivity: This is measured as **real output per worker**, capturing the efficiency of labor in various industries. The author analyses how changes in labor productivity relate to changes in employment, particularly examining **whether productivity growth leads to job losses or job gains**.

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Economie (pp. 45-118).	Value-added Growth: The study considers indicators of **value-added per worker** as well as the impact of total factor **productivity** on value-added growth. This helps in understanding the added value generated by each worker and the overall efficiency of production processes in different sectors. Relationship between Productivity Growth and Employment Growth: The author investigates the **relationship between productivity growth and employment growth**, examining how changes in productivity levels correspond to changes in overall employment. This analysis allows for the assessment of whether productivity gains have led to job creation or job displacement. Spillover Effects of Productivity Growth: The study explores how **productivity growth in one sector can influence employment growth in other sectors**, capturing the spillover effects of technological advancements. This analysis helps in understanding how changes in productivity in one industry can have wider implications for employment across the economy. Changes in Workforce Skills: The author considers how changes in the **skill composition of the workforce**, particularly in response to technological diffusion, influence the employment implications of productivity advancements. This includes examining the **demand for high-, middle-, and low-educated workers** in the context of changing productivity levels. Technological Diffusion: The study investigates how the **spread of technology across sectors** influences the employment implications of productivity advancements. This helps in understanding how technological advancements impact job opportunities and skills requirements across different industries.
Arntz, M., Gregory, T., & Zierahn, U. (2017). Revisiting the risk of automation. Economics Letters, 159, 157-160.	The paper employs specific **task analyses within occupations** by examining detailed task data to understand the specific activities and responsibilities that make up different jobs. This allows the researchers to assess the variation in tasks within occupations and how they contribute to the overall automation potential. Technological feasibility studies involve evaluating the current and potential **technological capabilities related to automating specific**

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	tasks within occupations. This assessment helps determine which tasks are more susceptible to automation based on the existing technological landscape. Assessments of the **adaptability of tasks to automation** involve considering how easily certain tasks within occupations could be replaced by automated technologies. This analysis considers factors such as the complexity of tasks, the potential for technological advancements, and the potential for workers to adapt to changes in task requirements.
Borland, J., & Coelli, M. (2017). Are robots taking our jobs?. Australian Economic Review, 50(4), 377-397.	Total work available: The author likely used measures of **aggregate hours of work** to assess whether the total amount of work available has decreased following the introduction of computer-based technologies. These measures would provide insight into the overall volume of work in the labor market. Pace of structural change and job turnover: The authors have utilised data on **job churning rates, industry composition changes, and the frequency of job turnover** to evaluate the pace of structural change and job turnover in the labor market. These indicators would help assess whether the application of computer-based technologies has accelerated these dynamics. Impact of computer-based technologies on employment: The author reviewed recent studies and employed **empirical evidence to evaluate the specific impact of computer-based technologies on employment**. This assessment involves considering various job categories, sectors, and skill levels to understand the nuanced effects of technology adoption on employment dynamics. **Historical data on technological advancements and their effects on employment**: To provide a comprehensive analysis, the authors have examined historical trends in technological advancements and their impact on employment. This historical perspective would contribute to understanding the long-term patterns and precedents in labor market adjustments to technological changes.

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Klenert, D., Fernandez-Macias, E., & Antón, J. I. (2023). Do robots really destroy jobs? Evidence from Europe. Economic and Industrial Democracy, 44(1), 280-316.	Industry-level data on employment by skill type: This indicator involves **data that categorises employment within industries by skill type**, which allows for the analysis of how the adoption of robots affects different skill levels within the workforce. Data on robot adoption: This refers to quantitative measures of the **adoption and deployment of industrial robots within various industries and sectors in Europe**, providing insight into the prevalence and impact of robotic technologies. Different sets of fixed-effects techniques: Fixed-effects techniques are used to control for unobserved heterogeneity and are essential in panel data analysis. The authors employ various **fixed-effects models to account for specific assumptions**, indicators, and parameters and to identify the specific factors driving their results. Capital/labor ratios: These ratios provide insights into the **capital intensity of production processes** and are likely employed to understand how changes in robot adoption may relate to the relative use of capital and labor in different sectors. Capital formation: This indicator typically refers to the process of increasing the **amount of capital within a country's economy** by engaging in activities such as investment in machinery and equipment. The authors employ this as a control variable to account for broader economic and technological trends that are independent of robot adoption.

Source: The Authors.

Appendix B. Definitions of Policy Measures in Table 4

Policy Category	Extended Description
Education and reskilling	Programs aimed at equipping workers with new technical or digital skills, often through public investment in vocational training, upskilling initiatives, or partnerships with educational institutions. These policies seek to reduce skill mismatches and prepare the workforce for evolving job requirements.
Foster new industries	Policies designed to stimulate the development of emerging sectors likely to absorb displaced labor, such as green technologies, care services, or digital platforms. Instruments may include tax incentives, startup subsidies, or infrastructure investment.
Active labor market policies	Measures that support job search, matching, and employability, such as job placement services, mobility grants, wage subsidies, and individualized employment plans.
Human welfare policies	Broader social protection mechanisms aimed at supporting individuals affected by labor market disruptions, including healthcare, housing support, or child care.
Basic income	Unconditional cash transfers to all citizens as a form of income support in response to potential large-scale job displacement. Often discussed as a radical response to automation-related risks.
Public job provision	Direct employment by the state in socially valuable but often underfunded areas such as education, elder care, environmental maintenance, or cultural programs.
Safety net	Minimum income guarantees or unemployment insurance schemes to cushion transitions and ensure a baseline of economic security.
Equitable distribution of AI-driven benefits	Policy frameworks ensuring that the economic gains from automation and AI are fairly distributed across income groups and regions, potentially through taxation, regional investment, or inclusive innovation strategies.
Equitable regional distribution	Targeted policies aimed at supporting regions that are more vulnerable to automation shocks, often through tailored investment programs or employment guarantees.
Meaningful work	Initiatives that promote job quality, autonomy, and social value in employment, beyond the quantitative dimension of job creation.