Technological Unemployment in Terms of Global Labor Market Imbalances: A Bibliometric Analysis

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Abstract: The current society, known as the supersmart society or Society 5.0, emerged in response to the Fourth Industrial Revolution. also known as Industry 4.0 (I4.0), which arose with the development of different technologies such as the Internet of Things (IoT), Artificial Intelligence (AI), Machine Learning (ML), and Big Data Analytics (BDA), among others. Based on the report "Future of Jobs Report 2023" the most affectin g macro trend in driving business transformation is the increased adoption of new and frontier technologies with an 86.2% rate. I4.0 significantly changed production processes and manufacturing systems, transforming firms into smart factories. One of the consequences of the I4.0 revolution is technological unemployment (TU). This paper aims to conduct a comprehensive evaluation of the literature on Industry 4.0 (I4.0) and Technological Unemployment (TU) within the 2015-2024 timeframe, with a particular focus on their impact on labor market imbalances (LMI). Through a bibliometric analysis, the study will assess performance metrics, including the publication and citation performance of authors, institutions, countries, and journals. Additionally, the research will visualize and critically examine bibliometric citation outcomes, including cited references. To achieve this, we adopted a quantitative approach and employed a confirmatory-explicative research method to elucidate Technological Unemployment (TU) within the context of Industry 4.0 (I4.0) transformations and confirm its implications on Labor Market Imbalances (LMI). Bibliometric analysis was used to discern data patterns, trends, and relationships within the literature. Our findings revealed several significant trends, notably job polarization, income inequality, and TU. We determined that the effects of I4.0 on employment are not universally negative; in some cases, technological investments enhance employment rates by creating new professions and job opportunities. Our analysis also indicated that occupations requiring human judgment, decision-making, creativity, and innovation exhibit resilience to technological advancements.

Keywords: Technological Unemployment, Labor Market Imbalances, Industry 4.0, Performance Analysis, Bibliometric Analysis.

1. Introduction

I4.0 is a subject that interests many people, particularly industrial and IT (Information Technology) specialists and business managers. Innovative businesses can benefit greatly from these changes, but those who are unable to adapt quickly and effectively risk suffering serious consequences. Job automation and job computerization are the focus areas from a human resources standpoint. Therefore, new positions and specializations with new knowledge sets and expertise are being elevated due to the impact of advanced digital technologies (Stachová et al., 2019).

Businesses are facing challenges due to the rapid changes of the fourth industrial revolution, which presents both risks and opportunities (Roblek et al., 2016; Strandhagen et al., 2017; Liboni et al., 2019). To adapt to Industry 4.0, companies must focus on human development and new practices (Stachová et al., 2019). John Maynard Keynes predicted in 1930 that technological advancements would lead to abundance but also to technological unemployment (TU) (Bertani et al., 2020). The McKinsey Global Institute forecasts that automation could displace 75-375 million workers by 2030, reflecting Keynes' concerns and supporting findings that rapid technological progress tends to increase unemployment (Bertani et al., 2020).

2. Literature Review

2.1 Industry 4.0 and Technological Unemployment:

The history of mankind in terms of social evolution consists of five different societies (1-the hunting society; 2-the agricultural society; 3-the industrial society; 4-the information society; 5-and the supersmart society (Society 5.0), which is currently emerging with I4.0) (Kurt, 2019). The 18th century saw a shift from human labor to machine power with the advent of steam, leading to reduced production costs and standardized, high-quality goods. Industry 2.0 and 3.0 introduced electricity and information technologies (Lasi et al., 2014; Li et al., 2017). Industry 4.0 builds on this with advanced technologies such as the Internet of Things (IoT), Cyber-Physical Systems (CPS), and additional innovations including cloud computing, big data analytics, AI, machine learning, cybersecurity, digital twins, augmented reality, additive manufacturing, and autonomous robots (Kerin & Pham, 2019).2011's Hannover Fair marked the debut of the phrase "I4.0" when Robert Bosch and Kagermann formed a working group to propose the fourth industrial revolution to the German Federal Government (Kurt, 2019; Sony & Naik, 2019). The I4.0 is now referred to in different ways, such as Society 5.0 in Japan, I4.0 in Germany and Turkey, and the Internet of Things in the US.

I4.0 describes various modifications to manufacturing systems that are primarily IT-driven (Lasi et al., 2014). Such as the progress in gene sequencing, nanotechnology, artificial intelligence, and renewable energy sources (Kurt, 2019). Therefore, I4.0 refers to the process of transforming organizations into smart factories. By using a wide range of technologies (Sony & Naik, 2019), These changes are also referred to as the Internet of Things (IoT), Internet of Services (IoS), Internet of People (IoP) (Zezulka et al., 2016), and internet of energy (IoE) (Khan et al., 2017). In addition, I4.0 significantly affects the nature of work, the identity of employees, and the relationship between employees and employers due to the intensive human-machine interaction (Kurt, 2019). These changes in the labor market and production processes are reducing the numbers of employed workers especially those in the working class (Kurt, 2019), resulting in large unemployment rates (Liboni et al., 2019).

TU is a negative consequence of automation (Lima et al., 2021), and the level of this latter is influenced by the digitalization strategy of each nation and the speed of its implementation, as well as the readiness of a particular country's education system to retrain susceptible groups in the labor market (Szabó-Szentgróti et al., 2021). Therefore, TU degrees differ from one country to another, and from small towns to large cities. Considering TU as a long-term economic shift, workers need to acquire new skills to meet the new occupations' needs (Lima et al., 2021). As mentioned by Autor (2022), At the top of the labor market, an increasing number of high-education, high-wage jobs provide promising career paths, rising lifetime wages, and considerable job stability.

3. Design & Method

3.1 Research Objectives and Questions

This study intends to conduct an in-depth review of the literature on I4.0 and TU and to explore their impacts on the LMI. To achieve this, we have established the following research questions:

- RQ1: how does the impact of I4.0 on the labor market differ from one country to another?
- RQ2: what are the intrinsic changes that occurred to the labor market in response to technological progress in the period of (2015-2024)?
- RQ3: what occupations remain resilient in the face of technological advancements?
- RQ4: on what basics does TU vary from one sector to another?
- RQ5: what are the anticipated impacts of TU on the LMI in the future?
- RQ6: what are the possible positive aspects of I4.0 on the labor market?

3.2 Data Collection

According to Noyons (2001), key elements commonly analyzed in bibliographic records are authors, their affiliations, keywords, publication year, and the source or journal. Our study focuses on keyword-based data, and the following table displays the keyword groups used to search for relevant articles in the Dimensions database.

Table 1: keyword groups used in the research

Groups	Keywords	Publication Years	Dimensions Database
Grp 1	("Industry 4.0" AND "technological unemployment")	2015 2016 2017 2018 2019 2020 2021 2022 2023 2024	92
Grp 2	("industry 4.0" AND "labor market")		54
Grp 3	("industry 4.0" AND "technological unemployment" AND "labor market")		68
Grp 4	("labor market" AND "technological unemployment")		231
Grp 5	(("industry 4.0" OR "technological advancement" OR "technological progress") AND ("technological unemployment" OR "unemployment") AND ("labor market" OR "labor market imbalances"))		389
Total	/	/	834

Source: Adapted from Dimensions database

This study uses the Dimensions database to gather bibliographic information on "Industry 4.0, technological unemployment, and labor market imbalances." With over 137 million publications and 209,000 source titles, the database offers extensive bibliographic and citation data. From the period 2015-2024, we identified 834 relevant publications. After removing duplicates with Zotero software and excluding non-English papers, 637 publications remained. Table 02 details the inclusion criteria used to filter and select the most pertinent research papers from the Dimensions database.

Table 2: Inclusion Criteria

	Search Type	Publication Years	Publication Type	Fields of Research	Journal List
Grp 1	Full data	2015 2016 2017 2018 2019 2020 2021 2022 2023 2024	Article, Edited Book, Chapter	Commerce, Management, Tourism and Services Strategy, Management and Organisational Behaviour Human Resources and Industrial Relations	DOAH ERIH PLUS ERA 2023
Grp 2	Title and Abstract		Article, Edited Book, Chapter	Commerce, Management, Tourism and Services Strategy, Management and Organisational Behaviour Human Resources and Industrial Relations	DOAH ERIH PLUS ERA 2023
Grp 3	Full Data		Article, Edited Book, Chapter	Commerce, Management, Tourism and Services Strategy, Management and Organisational Behaviour Human Resources and Industrial Relations	DOAH ERIH PLUS ERA 2023
Grp 4	Full Data		Article, Edited Book, Chapter	Commerce, Management, Tourism and Services Strategy, Management and Organisational Behaviour Human Resources and Industrial Relations	DOAH ERIH PLUS ERA 2023
Grp 5	Full Data		Article	Human Resources and Industrial Relations	DOAH ERIH PLUS ERA 2023

Source: Adapted from Dimensions database

4. Bibliometric Analysis

In the next phase of our research, we reviewed the titles and abstracts of the collected papers to verify their relevance. We excluded 197 articles that were either irrelevant or duplicates. After a thorough examination of the remaining 637 papers, 28 articles were selected for the final qualitative assessment. For details on our methodological approach, refer to Fig 01.

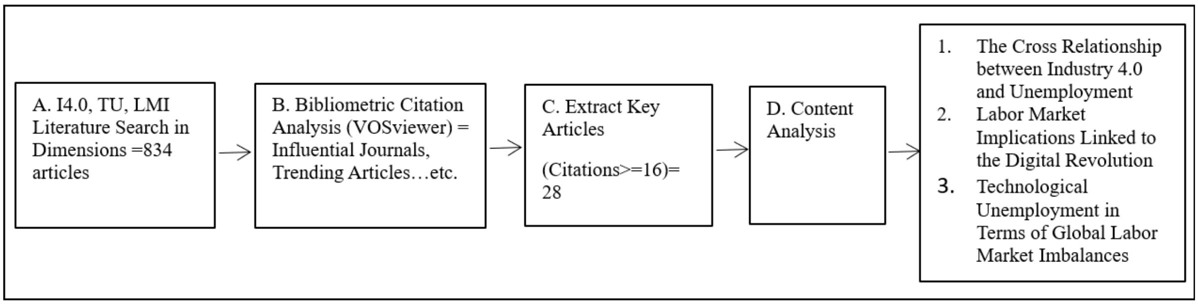

Figure 1: Methodological approach.

Source: Prepared by researchers

We utilized analytical visualization software (VOSviewer) to identify the citation linkages of the 637 identified papers. VOSviewer is a tool of data analytics that can be used to analyze and visualize direct and indirect citation relationships between articles by simply revealing who cited whom (Pasadeos et al., 1998).

4.1 Most Influential Papers in the Literature of "I4.0, TU, and LMI"

In this part, we conducted a performance analysis, by evaluating the "publication" and "citation" performances of authors, institutions/universities, countries, and journals (Öztürk et al., 2024) to determine whether our dataset is effective in the relevant field or not. To set the scientific value of the papers, scholars have used various bibliographic analyses, for instance, the methodology of Alon et al. (2018) was to identify the total global citation (TGC) and the total local citation (TLC) of their sample. TGC indicates how often an article has been cited according to the full count in the ISI Web of Science database.

4.1.1 Institutions and Universities

Technological advancements, particularly in Industry 4.0, have primarily originated in developed countries with advanced industries. To understand the impact on the labor market and technological unemployment, we began by examining the institutions and countries associated with our sample papers. Our analysis focuses on the influence of research from various countries, with the table highlighting the most cited institutions, such as Old Dominion University (809 citations), University of Colorado Boulder (561), University of Colorado Denver (561), and Catholic University of the Sacred Heart (491), among others.

Table 3: Most influential institutions.

Organizations	Documents	Citations	Citation per document
Auckland University of Technology	4	470	117.5
Catholic University of the Sacred Heart	12	491	40.9
Institute for the Study of Labor	10	366	36.6
Institute of Economics Agriculture, Volgina, Belgrade, Serbia	1	376	376
Massey University	6	400	66.6
Old Dominion University	2	809	404.5
Ovidius University	1	376	376
Petroleum & Gas University of Ploieşti	1	376	376
Sant'anna School of Advanced Studies	6	289	48.2
United Nations University – Maastricht Economic and Social Research Institute on Innovation and Technology	6	329	54.8
University of Colorado Boulder	1	561	561
University of Colorado Denver	1	561	561

Source: Adapted from the VOSviewer software

In our analysis of institutional contributions to Industry 4.0, the United States led with the highest number of papers (88), followed by the United Kingdom (60), Italy (52), China (42), Germany (41), Australia (35), India (31), Poland (27), and both the Netherlands and Spain (25 each). When evaluating the quality of contributions based on citations, the United States also had the greatest impact with 3417 citations, followed by the United Kingdom (1370), Italy (1301), Germany (1205), and the Netherlands (1004).

Table 4: Most influential international contributions.

Country	Documents	Citations
Australia	35	959
China	42	583
Germany	41	1205
India	31	317
Italy	52	1301
Netherlands	25	1004
Poland	27	267
Spain	25	335
United Kingdom	60	1370
United States	88	3417

Source: Adapted from the VOSviewer software

4.1.2 Influential Journals

Among the 336 journals in our sample, six have published 10 or more articles related to Industry 4.0 and technological unemployment between 2015 and 2024 (see Table 5).

Table 5: Most influential journals in terms of published documents (>=10 documents).

Source	Abbreviations	Documents	Citations
International Journal of Environmental Research and Public Health	IJERPH	15	349
International Journal of Manpower	IJM	17	206
International Labour Review	ILR	14	109
New Technology Work and Employment	NTWE	12	504
Sustainability	-	32	889
Technological Forecasting and Social Change	TFSC	15	1351

Source: Adapted from the VOSviewer software

Among the 336 journals, 12 journals surpassed the threshold of 200 citations (see Table 6). When merging both criteria of the number of documents (D) and citations (C) of each journal, we found that five journals have the most influence over the literature of I4.0 and TU, which are IJERPH (15D., 349C.), IJM (17D., 206C.), NTWE (12D., 504C.), Sustainability (32D., 889C.), and TFSC (15D., 1351C.). Our analysis indicates that the Sustainability journal is the most influential in the I4.0 and TU studies due to its high focus (Documents=32), while TFSC has the highest impact on this literature set (Citations=1351).

Table 6: Most influential journals in terms of document quality (>= 200 citations).

Source	Abbreviations	Documents	Citations
Annual Review of Organizational Psychology and Organizational Behavior		1	561
International Journal of Environmental Research and Public Health	IJERPH	15	349
International Journal of Manpower	IJM	17	206
Journal of Economic Surveys	JES	4	300
Journal of Management & Organization	JMO	1	343
Journal of Vocational Behavior	JVB	5	306
New Technology Work and Employment	NTWE	12	504
Research Policy	RP	9	326
Sustainability	-	32	889
Technological Forecasting and Social Change	TFSC	15	1351
The Economic and Labour Relations Review	TELRR	4	220
Work and Occupations	WO	4	255

Source: Adapted from the VOSviewer software

4.1.3 Influential Research Papers

To understand the development of the I4.0 and TU literature, it is important to identify the most influential works. We analyzed citation trends to highlight the key articles that have shaped this field. Table 07 presents the top 10 most impactful articles, with the most influential being Li (2018), followed by Cascio (2016), Sima (2020), Brougham (2017), and Stanford (2017) for the period 2015-2024.

Table 7: Most influential articles in the I4.0 and employment.

Author and Year	Citations	Article Title
Stanford (2017)	196	The resurgence of gig work: Historical and theoretical perspectives
Pfeiffer (2016)	155	Robots, Industry 4.0 and Humans, or Why Assembly Work Is More than Routine Work
Brougham (2017)	343	Smart Technology, Artificial Intelligence, Robotics, and Algorithms (STARA): Employees' perceptions of our future workplace
Dachs (2019)	157	Bringing it all back home? Backshoring of manufacturing activities and the adoption of Industry 4.0 technologies
Cascio (2016)	561	How Technology Is Changing Work and Organizations
Dengler (2018)	193	The impacts of digital transformation on the labor market: Substitution potentials of occupations in Germany
Sima (2020)	376	Influences of the Industry 4.0 Revolution on Human Capital Development and Consumer Behavior: A Systematic Review
Fleming (2018)	177	Robots and Organization Studies: Why Robots Might Not Want to Steal Your Job
Liboni (2019)	176	Smart industry and the pathways to HRM 4.0: implications for SCM
Li (2018)	770	China's manufacturing locus in 2025: With a comparison of "Made-in-China 2025" and "Industry 4.0"

Source: Adapted from the VOSviewer software

4.2 Visualization and Examination of Bibliometric Citation Outcomes

In this section, we employed data analytics visualization and co-citation mapping to analyze our sample of articles, uncovering the evolution of research in I4.0, TU, and the labor market by highlighting key concepts from highly cited papers. Co-citation mapping revealed development trends, main theories, and key topics through citation patterns. We concentrated on articles cited at least 16 times from 2015 to 2024. A content analysis of the 28 most cited articles was performed by two researchers to ensure reliable results and identify key research streams (Alon et al., 2018; Gaur & Kumar, 2018).

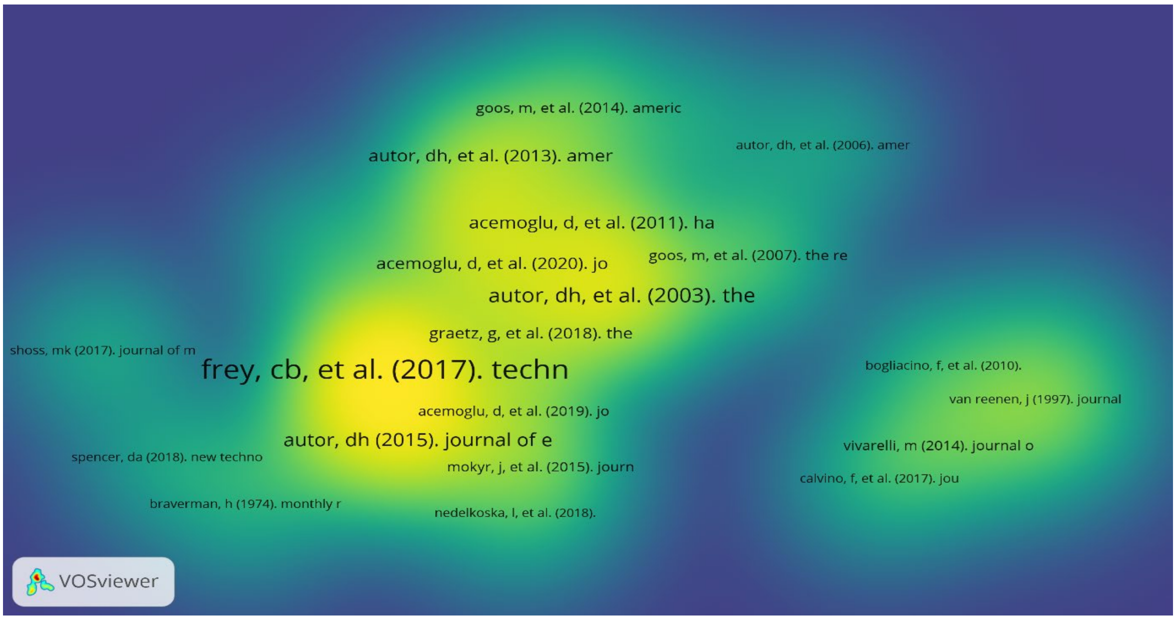

Figure 2: Density visualization

Source: Adapted from the VOSviewer software

4.2.1 Industry 4.0 and Unemployment: Unraveling the Cross-Relationship, Labor Market Dynamics and Global Imbalances in the Digital Revolution

I4.0 technologies, encompassing AI, robotics, nanotechnologies, 3D printing, and bioengineering, are reshaping industries and labor markets worldwide. While these advancements create new job sectors, they also render traditional roles obsolete, contributing to TU (Bogliacino et al., 2012; Hall, 2001). Automation leads to job polarization, where high-skill and low-skill jobs increase while middle-skill positions decline, exacerbating wage inequality and labor market disparities, particularly in advanced economies (Acemoglu & Autor, 2011; Frey & Osborne, 2017). Despite demographic and financial motivations driving automation adoption, there's a heightened risk of job displacement, especially for lower-skilled workers, underscoring the necessity for lifelong learning policies to mitigate these challenges (Pouliakas, n.d.; Acemoglu & Restrepo, 2017).

The impact of I4.0 on employment varies across countries and sectors, influenced by differences in robot adoption rates and the intricate interplay between automation and labor demand (Vivarelli, 2014; Graetz & Michaels, 2018). While technological progress contributes to wage inequality and job polarization, it also presents opportunities for job creation through product innovations and enhanced productivity (Calvino & Virgillito, 2018; Spencer, 2018). To counterbalance the negative effects of labor-saving technologies, new technologies must create fresh occupations, enhance productivity, and complement human workers, thus stimulating labor demand (Arntz et al., 2017). Adaptable education systems, vocational training, and robust social policies are essential for economies to adjust to these shifts and maintain employment levels (Arntz et al., 2017; Mokyr et al., 2015; Hall, 2001).

While technological advancements have led to job creation, efficiency gains, and skill enhancement, they've also spurred job polarization and income inequality (Van Reenen, 1997; Autor et al., 2006). The rise of high-skill and low-skill jobs at the expense of middle-skill positions has reshaped employment structures within and between industries, exacerbating income disparities (Goos et al., 2014). Moreover, the digital revolution, characterized by AI and robotics, has led to job displacement, particularly affecting low-skilled workers while benefiting high-skilled ones (Spencer, 2018; Harrison et al., 2014). This has underscored the importance of investing in education, skills training, and adaptable labor market regulations to address the evolving demands of the digital era (Acemoglu & Restrepo, 2019; Hall, 2001).

TU, driven by automation and AI, poses significant challenges to global labor markets, intensifying imbalances and disproportionately affecting middle- and low-skilled jobs (Arntz et al., 2017). Historical economic theories highlight how technological innovation while stimulating economic growth, can also lead to unemployment (Spencer, 2018). The impact of these innovations varies by country, with some experiencing substantial reductions in labor demand while others face less severe effects (Harrison et al., 2014). To mitigate these challenges and address global labor imbalances, policy interventions such as adaptive education, vocational training, and robust social security measures are imperative (Arntz et al., 2017; Pouliakas, n.d.). These interventions aim to balance automation with job creation and ensure a smooth transition for workers in the face of technological disruptions (Acemoglu & Restrepo, 2017; Autor, 2015).

5. Discussion

Over the past decade, technological progress has significantly impacted the labor market. Automation and AI have displaced routine jobs while increasing the demand for digital skills. The gig economy and remote work have expanded due to advances in communication technologies, changing traditional employment patterns. Job polarization has occurred, with a decline in middle-skill jobs and growth in low-skill and high-skill roles. There has been a stronger emphasis on upskilling and reskilling to adapt to new technologies, and job creation has shifted towards tech-driven and innovative industries. Additionally, AI has become increasingly important in workforce management and decision-making.

I4.0 has various effects on the labor market across countries due to differences in economic development, workforce skills, government policies, sectoral composition, and cultural attitudes towards technology. Advanced economies with strong education systems and proactive policies, like Germany and Singapore, are better positioned to benefit from I4.0, experiencing growth in high-tech jobs and smoother transitions. In contrast, developing countries or those with less strategic planning may face challenges such as job displacement and a widening skills gap, leading to more disruptive effects on their labor markets.

The impact of automation, as highlighted by Graetz & Michaels (2018) and Spencer (2018), varies significantly across different sectors—some experience labor substitution, while others see labor complemented by technology. Therefore, TU varies by sector due to differences like tasks' nature, the degree of automation feasibility, adoption rates, skill requirements, investment levels, and market dynamics. For instance, I4.0 has led to a decline in routine-intensive jobs due to routine-biased technological change (RBTC), increasing unemployment in these sectors.

Technological advancements in I4.0 raise concerns about unemployment, even for high-skilled workers, highlighting the need for new technologies to create jobs, boost productivity, and complement human labor. The Future of Jobs 2023 report predicts significant employment shifts from 2023 to 2027, with growth in roles like Agricultural Equipment Operators, Heavy Truck and Bus Drivers, and Vocational Education Teachers. In contrast, jobs such as Data Entry Clerks, Administrative Secretaries, and Accounting Clerks are expected to decline, accounting for over half of the projected job losses.

Substantially, the technological advancements in I4.0 offer numerous positive impacts, including the potential for extensive job creation, increased efficiency, and enhanced skills. Innovations, especially in artificial intelligence, are driving employment growth by boosting productivity, introducing new decision-making tasks and job roles, and creating demand for labor in related fields. As a result, the labor force is adapting to higher levels of education to meet evolving skill requirements, thereby reshaping the future workforce landscape (Agrawal et al., 2019).

6. Conclusion and Future Directions

The impact of technological transitions on labor markets reveals both opportunities and challenges. I4.0 advancements, such as artificial intelligence and automation, promise increased productivity and new job sectors but also raise concerns about job displacement, inequality, and TU. This complex landscape underscores the need for adaptive policies and workforce strategies, emphasizing the importance of lifelong learning and adaptable education systems. While technological change may disrupt traditional employment, it also offers potential for economic growth and innovation. Effective collaboration among policymakers, businesses, and individuals, along with strategic investments in education and social security, is crucial to ensure inclusive growth and mitigate adverse impacts, ultimately shaping a future where technological progress benefits all.

Like other research efforts, this study has limitations that could be improved upon in future research. By utilizing additional research databases such as Scopus, Web of Science, Microsoft Academic, and SpringerLink, among others, might provide a more varied dataset related to I4.0, TU, and LMI, thereby improving the quality of the findings. Furthermore, combining databases (e.g., WoS and Scopus) could enhance the sample size and the overall quality of the research outputs, making the results more applicable. In addition, it is possible to investigate the impact of I4.0 on TU among sectors/countries, besides their implications on the Labor market globally/nationally.

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